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Preface

WCSS 2014 aims to bring together researchers and practitioners from diverse fields with an interest in social simulations. Researchers in theoretical, experimental, and applied contexts of social simulation will present their recent results. With a purpose of better understanding complex social systems this gathering of scholars from computing, social sciences, economics, social psychology, and other disciplines will discuss issues related to behavioral modeling, social simulation, and emergent phenomena.

The World Conference on Social Simulation (WCSS) is the largest academic and scientific event in the field of social simulation. It is a biannual event, sponsored jointly by three scientific societies: European Social Simulation Association (ESSA), Pacific-Asian Association for Agent-based Approach in Social Systems Sciences (PAAA), and the Computational Social Science Society of the Americas (CSSSA). Each of these associations has been promoting social simulation, for at least 10 years, and annual regional conferences. In 2005, these societies decided to create a biannual World Congress in order to better integrate various geographically dispersed communities working in the area.

The 5^{th} World Congress on Social Simulation (WCSS 2014) occurs in São Paulo, Brazil, on November 4-7 2014. It is organized by Universidade de São Paulo (USP), and more specifically by research groups from the Computer Engineering (Escola Politécnica), Computer Science (Instituto de Matemática e Estatística), Social and Political Sciences (Faculdade of Filosofia, Letras e Ciências Humanas) and Complexity Science (Escola de Artes, Ciências e Humanidades) Departments. Besides USP, researchers from Centro Universitário da FEI, Centro de Estudos da Metrópole (CEM) and Universidade Federal de Rio Grande (FURG) were also involved in the organization of the Congress.

The main objective of this 5^{th} edition of WCSS, which occurs in Brazil and South America for the first time, is to integrate researchers and students of all levels in the area and to promote the activities of the various research groups in Brazil and South America, thus enabling the exchange of knowledge and experiences. Thus, the event consists of a combination of invited lectures, delivered by experienced researchers, and presentations of peer-reviewed full papers and posters.

In this edition, 23 submissions were selected for oral presentation, and 12 for poster presentation. We received submissions from 14 different countries, distributed by North (Mexico, USA) and South (Brazil, Colombia) America, Europe (Estonia, France, Italy, The Netherlands, Portugal, Russia, Spain, Sweden, UK) and Asia (Japan). An international Program Committee, composed of experts in the field, to whom we thank for their excellent work, has reviewed all papers presented in the conference.

We also express our gratitude for our institutions, for the conference sponsors (FAPESP, CNPq, CAPES, CEM, EPUSP), organizers (Acquaviva, FDTE), and supporters (São Paulo Convention Bureau).

We hope that all WCSS 2014 participants will have an excellent and exciting time at the WCSS 2014 Conference and take some time to explore the cultural, gastronomic, and urban richness of São Paulo, as well as the natural beauties of Brazil.

São Paulo, October 2014

Jaime Simão Sichman
WCSS 2014 General Chair

Edward P. MacKerrow, Flaminio Squazzoni, Takao Terano
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Table of Contents

PAPERS

Finance, Economics, and Markets Modeling

Applications of Complex Adaptive Systems in Portfolio Management

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Abstract. Simulation-based methods are becoming a promising research tool in financial markets. A general Complex Adaptive System can be tailored to different application scenarios. This paper documents an application of a Complex Adaptive System approach to modeling in the context of portfolio management, based on the sector rotation strategy in the United States stock market. Sector rotation is a ubiquitous phenomenon regularly exploited in financial markets. With a proper sector rotation strategy, investors can outperform the market and achieve extra profits through optimized portfolios. A sector rotation multi-agent model is implemented using the Netlogo framework. The model utilizes historical data and produces returns that exceed Standard & Poor's 500 index returns.

1 Introduction

Sector rotation is a ubiquitous phenomenon in the stock market. It refers to the well-known phenomenon of certain sectors outperforming other sectors over a specific period of time. The concept of Portfolio Management refers to a strategy for investing in a combination of securities such as stocks and other investment instruments. With a proper inclusion of sectors in the portfolio, investors can earn above average profits with their capital. This is true even in a financial crisis, which often brings about more investment opportunities. In recent years sector rotation has become a hot strategy in portfolio management, as it can bring extra profits while minimize potential risks.

There are many approaches to portfolio management. A selection of them is briefly summarized in Section 2 of this paper. Our approach to portfolio management, Complex Adaptive System (CAS), is described in Section 3. Section 4 summarizes the results obtained in this research. Section 5 offers a description of issues encountered during the CAS implementation. The paper concludes with a discussion and results/future work (Section 6).

S&P 500 stocks were classified into ten sectors, shown in Table 1, by the Global Industry Classification Standard (GICS), which is developed by Morgan Stanley Capital International (MSCI). At the same time, S&P 500 index was used as a benchmark for evaluating the model performance. All the data used in the model range from year 1975 to year 2013.

In addition, the distribution of model investor returns was tracked to determine if it follows the fat-tail distribution, a common distribution of returns in financial markets.

Table 1. GICS Sector Classification

Financials	Information Technology	Energy	Industrials
Health Care	Consumer Discretionary	Materials	Utilities
Telecommunications	Consumer Staples		

2 Background

Investment methods are usually classified as passive and active portfolio management (Barnes, 2003). Passive portfolio management only involves limited buying and selling actions. Passive investors typically buy and hold investments, anticipating long-term capital appreciation and limited portfolio maintenance. As a result, active portfolio management strategies can bring investors extra profits simply because they bring the possibility of covering a wide range of stock price movements. An active equity portfolio management (Grinold & Kahn, 1995) requires periodic forecasts of economic conditions and portfolio rebalancing based on foretasted conditions.

Differing sectors will stand out and outperform other sectors under varying business conditions, thus creating a cyclical behavior of sector performance. On the cash flow side, sector rotation is the capital flow from one market sector to another as investors pursue sectors that will outperform the market in a given market cycle (Rasmussen, 2003). Sector rotation assumes four stages in the business cycle: early recovery, recovery, early recession, and recession. Investors favor different sectors at different stages of the business cycle (Stangl, 2010).

An equity allocation strategy that focuses on strategic shifts across U.S. equity sectors is usually efficient. At the same time, sector rotation strategy benefits from a monetary policy (Conover, 2008). As monetary policy plays a critical role in the capital market, it affects the market liquidity directly (Thorbecke, 1997).

A simple momentum and relative-strength strategy could outperform the buy-and-hold strategy 70% of the time tracing back to 1920s (Faber, 2010). Performance can also be improved by adding a simple trend before taking positions.

However, these methods are not on the agent level. They simply provide a retroactive simulation technique. Since the market consists of trading individuals, taking into consideration interactions between agents provides investors with an important lever for significantly improving portfolio performance. Zero intelligence model (Farmer, 2004) shows that agent-based models can produce a high fit to the real stock market. However, the strategy used in the zero intelligence model emphasizes investors' utility, as opposed to a sector rotation strategy. The Complex Adaptive Systems (CAS) framework offers a natural technique for augmenting sector portfolio management strategies, given that its main advantage lies in its focus on capturing interaction between and among agents in the market place. There was proven success in utilizing ABM in simulating the NASDAQ market on single stock (Darley & Outkin 2007). Further advantage of CAS stems from its ability to set up different rules for agent interactions, thus uncovering agent interactions that actually improve the portfolio performance.

3 Complex Adaptive System Approach to Portfolio Management

Complex Adaptive System tools offer a novel way of modeling nonlinear systems because of their ability to capture the essence of distributed, self-organizing, and nonlinear social and natural phenomena characterized by feedback loops and emergent properties

3.1 General Complex Adaptive Systems

The theory of complexity has been invented in Physics. Its computational counterpart, mostly known as Complex Adaptive Systems (CAS), is a computational paradigm developed in computer science to deal with the issue of complexity in the real world. Computers can act as simulators of physical and social processes. When a model simulates behavior of a system, it provides us with a unique way of studying the underpinnings of the system that result in observed system behaviors (Holland, 1992).

Financial markets are complex systems (Johnson, 2003). In financial markets, there are micro behaviors, interaction patterns, and global regularities (Cappiello, 2006). In order to understand and learn financial systems, one needs to master such concepts as asymmetric information, strategic interaction, and equilibria. Due to the fast expansion of knowledge in computational sciences, the latest analytical tools made it possible to study the above aspects quantitatively.

One of these tools is Agent Based Modeling (ABM), which can model financial markets as a dynamic system of agents. ABM is not the only way to implement a CAS, but it is a way to implement it within a controlled setting in a computational environment. In the past decades, there have been rapid development of ABM applications in fields as diverse as economics, government, military, sociology, healthcare, architecture, city planning, policy, and biology, just to name a few (Tesfatsion, 2006, Johnson, 2013, Dreau, 2009, Hadzikadic 2010).

In financial market simulations, a large number of agents engage repeatedly in local interactions, giving rise to global markets (Roberto, 2001, Bonabeau, 2002). Stock markets are a good example of financial systems. Local markets will interact with each other, thus contributing to the worldwide momentum of interwoven financial transactions. The momentum here simply implies that all markets closely follow each other through the same bull/bear cycles, although markets can change their status by targeted policy of their respective governments.

3.2 A CAS Sector Rotation Model

In our CAS Agent-Based Model (ABM), we built a sector-trading strategy that implements sector rotation as part of the overall portfolio management. Agents trade sectors based on the publicly available GICS sector data from January 2, 1975 to August 31, 2013. We also include interest in agents' holdings, computed based on their cash on hand, on a daily basis, using data from the Federal Reserve in the same timeframe. In addition, agents know the current status of the stock market, be it bull or bear, based on the recession data available from the National Bureau of Economic Research (NBER). Agents use this information to select their trading rules.

Agents

A collection of agents constitutes the "trading world" in this ABM simulation. In order to simplify the model as much as possible, we decided to look at the individual investors only. We understand that the institutional investors represent a large component of financial markets. However, we are hoping that even a subset of the market can reveal regularities that hold for the whole market. Agents are given a certain amount of money at the model initialization stage. Agents' transactions are triggered by their decision rules and the amount of capital they have. As they are aware of the current market status, agents at each time step choose between two sets of trading rules: bull and bear market trading rules. Table 2 describes the trading rules assigned to individual agents.

Table 2. Trading rules assigned to individual agents

Buy-Threshold	Minimum price change required for taking a long position
Buy-Period	Time window agents observe before evaluating the Buy-Threshold
Sell-Threshold	Minimum price change required for taking a short position
Sell-period	Time window agents observe before evaluating the Sell-Threshold

The following formulas describe agents' decision rules in detail.

- Basic trading rules:

- Buy Rule:
  - X > Y * (1 - self-confidence * *momentum of buying*) in past Z
  - Agents will buy
- Sell Rule:
  - X < Y * (1 – self-confidence * *momentum of selling*) in past Z
  - Agents will sell

- Momentum ranges in [0, 1]
  - Count how many people intend to buy/sell
  - If no one is *buying/selling*, *momentum of buying/selling* will be 0
  - If everyone is *buying/selling*, momentum of *buying/selling* will be 1
- X – Change in Sector Price
- Y – Buy/Sell Threshold
- Z – Buy/Sell Period

For example, if the values for *buy-threshold* and *buy-period* for an agent are 0.1 and 20 respectively, then the buying rule for this agent is: IF the stock price goes up 10% in the past 20 trading days, THEN take a long position on this stock. Similarly, if the values for *sell-threshold* and *sell-period* are 0.2 and 50 respectively, then the selling rule for this agent is: IF the stock price goes up less than 20% in the last 50 trading days, THEN agent will take a short position. Also, short selling is allowed at any point. An agent can short sell any amount of stock up to their available cash amount.

However, not everyone in the market is rational. Greedy and panic-prone investors will impact the market as well. Market momentum is also an important factor that impacts agents' decision rules. Heterogeneous agent models (Hommes, 2006) show that most of the behavioral models with bounded rational agents using different strategies may not be perfect, but they perform reasonably well. In order to allow for the potential increase in the performance of investors, market momentum was added as another part of the trading strategy. In the sector-trading model, momentum was generated by the overall buy/sell behavior of agents. The more agents are buying sectors, the higher bidding price. The more agents are selling sectors; sector prices will tend to be low as agents are trying to liquidate their inventories.

Market information is available to agents. All agents know the current sector prices and can also track all the past prices starting Jan, 02, 1975. Consequently, the bandwagon effect plays an important role in transactions. The bandwagon effect simply means that agent behaviors and beliefs, as well as their consequences, spread around. As a result, if there are a lot of agents buying stocks, then agents will increase their buy-threshold. At the same time, if there are many agents who are shorting stocks, then a substantial number of agents will correspondingly decrease their sell-threshold as they try to liquidate their assets as soon as possible. Agents have a variable called self-confidence, assigned randomly at the initial stage, which controls how much each agent believes in its own trading rules. If an agent is totally self-confident, it will only follow its trading rules instead of it being affected by other agents in the market.

In ABM implementations agents can learn from each other. They learn only from agents in their respective neighborhoods. The neighborhood structure is introduced for efficiency reason. With learning, the search space can be made smaller so that more runs can be included in the model. Also, the learning mechanism makes it possible to investigate alternative strategies that have not yet been discovered in the market (Outkin, 2012). In this implementation, to preserve computational time, there are only four neighborhoods/quadrants. Agents move around and learn trading rules from the most successful (richest) agents in their quadrants. Agents also have a variable called *aggressiveness,* which allows them to control how much they want to adopt from their neighbor's behavioral structure. However, before agents start to learn they are given a chance to prove their existing trading strategies for a certain period of time. Only then they are allowed to start learning form their more successful peers.

Global Environment

In the CAS sector rotation model, the world is represented in 2 dimensions. Both X-axis and Y-axis range from -10 to +10. There is a variable called *radius* defining how far agents can reach out to other agents to both initiate transactions and learn their trading strategies. The *Radius* has a different value for each agent, making it possible for agents to have diversified trading and differing learning preferences.

However, *radius* significantly slows down the computing speed. Because of that, we opted to divide the world in four quadrants instead of relying on the *radius* as the variable that determines what agents see. Agents have the knowledge of where they are and who else is in their quadrant. This replacement of *radius* with the concept of quadrants was possible due to the preliminary investigations that proved that the final outcome was not significantly different between the two environments.

Implementation

This sector trading CAS model was implemented using the Netlogo 5.0.5 programmable modeling environment (Wilensky 2009). Netlogo offers a user-defined grid and the possibility of defining agents, normally called turtles in NetLogo.

Initially, in Version 1(Ver. 1), the transaction types for agents included only the possibility of buying and selling from/to other agents. However, due to the limited number of agents (a computational efficacy limitation), it often happens that there are either no buyers or sellers for a particular sector. Consequently, no transactions happen even though there is an interest in transactions for that particular sector. In order to avoid this situation, in Ver.2, an updated transaction method was created to allow agents to buy or sell any amount of any sectors at any time, this time from the "system/market maker" rather than from individual agents. This updated method provided agents with an unlimited inventory of sector shares and buyers, which is more similar to the real world portfolio management where each agent can buy or sell sector shares almost instantaneously and whenever they want to. Still, we opted to limit the number of shares that can be purchased or sold at any moment (a tick in NetLogo parlance) to 10 shares during each trading day. Later versions of the model explored the possibility of unlimited trading as well.

The prototype of the model used many variables, which significantly increased the search space for finding the best trading rules. Section 5 summarizes these issues in some details. Consequently, we explored many variants of the reduced search space.

Regarding the mechanism for regenerating or eliminating agents, in Ver.9, a *hatch* and *die* concept of NetLogo were used for introducing new agents and eliminating underperforming ones. Agents who lose all their money are eliminated from the environment. At the same time, new agents are initialized and placed into the environment, thus keeping the number of agents constant. This mechanism makes sure that active trading among agents is maintained.

Interest for cash on hand and transaction costs are two most important factors that impact investors' returns. They are included in the later stages of the model development, which are Ver. 10 and Ver. 12.

When agents run out of cash, they face a dilemma whether to sell the currently owned sectors to get cash and buy a new sector or to just keep their inventory. This creates a new challenge for agents, because now they have to decide whether to sell inventory and buy a new sector. To solve this problem, Sharpe Ratio was introduced in Ver. 11 to compare the past performance of the sector to be sold and the sector to be purchased. As a result, agents must check Sharpe Ratios for the two sectors they want to buy and sell. The Sharpe Ratio (Sharpe W. 1994) was proposed by William Sharpe in 1994. It is a widely used indicator to inspect past performance of stocks. The formula is given as follows:

$$S = \frac{\mathrm{E[R]}}{\mathrm{Std.dev(R)}} = \frac{Rewards}{Risk}$$

Here R is the stock that we are inspecting. Sharpe Ratio computes the reward vs. risk in the past (agent specified) number of days. To most people, greater return and lower risk is preferable. As it can be seen from the formula, the higher the Sharpe Ratio the better it is because it means higher reward and lower risk. Therefore, agents swap the long position for the sector with a lower Sharpe ratio with the long position for the sector with a higher Sharpe Ratio when they are running out of cash.

A complete simulation includes two rounds. The first round represents the learning phase. Agents improve over time their trading knowledge as they cycle through the first round. In the second round agents trade with the rules they learned in the first round.

The following table summarizes a complete evolution of our model.

Table 3. Model Evolution

#	Change	Settings	Res.
1	One set of decision rule, long only *Radius* affects agent transactions and learning Agents buy/sell from/to other agents Agents buy/sell 10 shares of one sector at time 2 rounds simulation	Agent Quantity: 1,000 Thresholds: [-1,1] Step size: 0.01 Period: [1,1000] Step size: 1 Self-confidence: [-1,1]	59x
2	Change radius to unlimited	Radius: Fixed at 10	59x
3	Add short selling mechanism in decision rules		112x
4	Reduced search space and add mutation	Thresholds: [-0.4,0.4] Step size: 0.2 Period: [1,100] Step size: 20 Mutation rate: Fix, 0.1	213x
5	Historical market info available to agents Separate decision rules for bull/bear market		245x
6	Replace *radius* by *quadrant*		245x
7	Agents will no longer buy/sell from/to agents Agents will have unlimited stock supply		249x
8	Add delay module for market information	Delay: 120 Delay: 250	191x 176x
9	Add die and hatch mechanism. Agents die when lose all money. New agents created copying parameters from best nearby agents or mutation	Delay: 250	232x
10	Historical interest information available to distribute interest for cash on hand		248x
11	Agents will no long buy/sell 10 shares of the sector. Agents will now conduct transaction with maximal possible amount		721x
12	Add transaction cost	$10 per transaction	708x
13	Sharpe ratio as an evaluation standard for agents when they evaluate performance of 2 stocks		749x

The Current Model

To provide a trade-off between the computing speed and the space exploration, we set the agent number to 1,000. All transaction decision rules are randomized within the [-0.4,0.4] range for required returns and within [0,100] range for the trading periods. *Self-confidence* and *aggressiveness* at set to 0.3 and 0.1, respectively. However, in order to maintain the possibility of exploring the whole search space, a mutation mechanism is added, allowing a subset of agents to mutate from [-0.4,0.4] to [-1,1] for required returns and from [1,100] to [1,1000] for trading periods. Agents are assigned the initial capital in the amount of $50,000. The transaction cost is fixed at $10 per transaction. The mutation rate is fixed at 0.1, which allows 10% of all agents to get buy/sell threshold and buy/sell period generated in [-1,1] and [1,1000] respectively.

During the learning phase, agents wait for 5,000 days/ticks before they start to learn. This gives all agents enough time to prove their initial trading strategies.

4 Results

The benchmark for the evaluation of the performance of the model is the S&P 500 index. The S&P 500 index increased from 70.23 to 1632.97 during the period of 01/02/75 to 08/31/13. If buy-and-hold strategy is used by investors, they receive a 23.25 times return in this time period.

In the Ver. 1, agents had to buy/sell sectors from/to other agents, short selling was not allowed, and there was a global variable called radius defining how far they can reach out to other agents to suggest potential transactions and to learn their neighbor's trading strategies. In this model, agents have only one set of trading rules (no knowledge of bear or bull markets) and they can only buy and sell 10 shares of stock each time. The results are shown in Table 4.

Table 4. Results for the Initial Model

Radius	Period Range	Best Return
10	200	59x
10	1000	58x
5	200	57x
8	200	56x
10	500	53x
3	1000	36x

The return numbers indicate how many times agents multiplied their initial capital. It is easy to see that agents gain more return as the radius goes up, because they can reach out for more potential buyers and sellers. At the same time, the computing power limits the model to use only 1,000 agents. As the period ceiling decreases (thus reducing the search space), agents can explore the search space better, resulting in higher return rates.

Then, a reduced sample space is introduced in Ver. 4. The mutation includes only the trading thresholds. Agents are now allowed to short stocks. Agents have publicly available information on market conditions, as well as separate trading strategies for the bull and bear markets. The radius is set to 10, thus allowing agents to have access to all potential transactions and all possible learning targets (10 is the size of the environment). Many step sizes for parameter settings have been evaluated. The best return rate is shown in Table 5.

Table 5: Best Rates of Return for the Updated Model

Radius	Step Size	Best Return
10	0.01	112x
10	0.2	213x

With the step size increasing, it becomes easier to create agents covering the exploration space more readily.

The Ver. 5 of the model makes the historical recession data available to agents. With the historical data, agents will have 2 separate trading rules for bull and bear market respectively. The best agent now achieves a 245x return. Ver. 6 is created with quadrants replacing radius as the main way to define the extent of agent interactions in the model. This change enables the model simulation to be completed within a day. The best return remains at 245x.

Ver. 7 excluded agents who buy high and sell low. In this way, there will be less noise in the market. With this change, the model can explore more possibilities in one trial. This version boosts the best return to 257x.

The goal of the CAS sector rotation model is to simulate real world scenarios. In the current version of the model agents have the privileged information on the changes in the market status (bull vs. bear). However, in the real world there is a delay in understanding when the market actually goes from a recession into a recovery or vice versa. This delay is usually a yearlong. Consequently, a delay mechanism is introduced in the Ver. 8. It is clear that instant market status information offers a big advantage to agents (Table 6).

Table 6. Performance with Market Conditions Delay

Delay Length	Best Returns
0	257x
120	191x
250	176x

The latest model Ver. 12 includes the following conditions: interest and transaction cost is added, agents can transact in an unlimited fashion, and agents compare the Sharpe Ratio between two sectors when they are switching position on sectors when running out of cash. As a result of these changes, best performance returns to the 700+ times range. Fig 1 shows the return of the latest model.

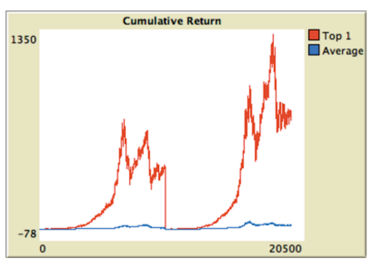

Fig. 1. Best and Average Performance

After learning, agents perform much better when they repeat a run using the same data. The return is now 749x for the best agent and 24x for average agents.

The following is the best trading rule set:

For bull market:
- If the sector price goes down 4% in last 20 trading days, take a long position.
- If the sector price goes up less than 25% in last 5 trading days, take a short position.

For bear market:
- If the sector price goes down 13% in last 6 trading days, take a long position.
- If the sector price goes up less than 47% in last 5 trading days, take a short position.

The rules above are updated based on the market momentum, which is described in Section 3.1. The narrative for the trading rule set basically states that an investor should *get in and get out of the market quickly*. Once the sector prices deviate from the expectation, investors should clear their positions immediately.

5 Issues

There are several issues that we have encountered during the implementation of the model. The first problem is the exploration space. The following table shows the original range setting for each parameter.

Table 7. The Initial Setting of the Parameters.

Parameter	Range	Possibility
Bull-Buy-threshold	-1 to 1 by 0.01	200
Bull-Sell-threshold	-1 to 1 by 0.01	200
Bull-Buy-period	1 to 1000 by 1	1,000
Bull-Sell-period	1 to 1000 by 1	1,000
Bear-Buy-threshold	-1 to 1 by 0.01	200
Bear-Sell-threshold	-1 to 1 by 0.01	200
Bear-Buy-period	1 to 1000 by 1	1,000
Bear-Sell-period	1 to 1000 by 1	1,000
Aggressiveness	0 to 1 by 0.01	100
Self-Confidence	0 to 1 by 0.01	100

Based on the above setting, we have a total search space of $1.6 * 10^{25}$, which means we need to create at least $1.6 * 10^{25}$ agents to cover the whole space. With the current computing power this is an impossible mission, even if we use high performance computers (HPC) to run the simulation. That is why we created a mutation mechanism. The mutation mechanism allows the agents to mutate and compute new values for their parameters outside of the defined range. Table 8 depicts the search space after mutation was enabled in the model.

Table 8. Performance with Mutation

Parameter	Range	Possibility
Bull-Buy-threshold	-0.4 to 0.4 by 0.2	5
Bull-Sell-threshold	-0.4 to 0.4 by 0.2	5
Bull-Buy-period	1 to 100 by 20	5
Bull-Sell-period	1 to 100 by 20	5
Bear-Buy-threshold	-0.4 to 0.4 by 0.2	5
Bear-Sell-threshold	-0.4 to 0.4 by 0.2	5
Bear-Buy-period	1 to 100 by 20	5
Bear-Sell-period	1 to 100 by 20	5
Aggressiveness	Fixed at 0.1	1
Self-Confidence	Fixed at 0.3	1
Mutation-rate	Fixed at 0.1	1

With mutation we successfully reduced the search space to 390,625 possible values. However, this is still higher than expected, and the computation can be performed on an HPC with an extremely low speed, meaning it may take years to run the simulation.

Thus, we went further in eliminating the possibility of existence of agents who deploy unreasonable trading strategies. The ranges *of Sell-thresholds* are changed as follows:

Table 9. New Values for Sell-thresholds

Parameter	Range	Possibility
Bull-Sell-threshold	Bull-Buy-threshold to 0.4 by 0.2	< 5
Bull-Sell-threshold	Bear-Buy-threshold to 0.4 by 0.2	< 5

Thus, we finally reduced the search space to 62,500 possible values/cells. With 1,000 agents in the model, we can explore around 1.6% of the search space. At the same time, Monte Carlo simulation (Fisherman, 1995) can be used to repeat experiments on an HPC, in order to get the best parameter set for agents that outperform the market the most.

6 Discussion, Conclusion, and Future Work

Computer simulations allow us to see behind-the-scene actions of agents, and to make possible forecasts on possible futures of the markets. Comparing with the return of the S&P 500, the CAS model presented here has achieved a much higher return, around 800x in the same timeframe as the S&P.

However, although the CAS sector rotation model achieved a much higher return than the S&P 500, the best achievement relies heavily on the interaction among agents. Momentum is a measure of the overall market sentiment (Scowcroft and Sefton, 2005). It is the desirability of buying or selling among all agents. Agents change their threshold based on the market momentum. With the benefits of momentum, the model achieves a much higher return than the S&P 500. However, we are aware that the best return is probably just an outlier, because it happens if and only if the market contains the same momentum as the one in the model.

A continuing refinement of the sector trading CAS model shows that CAS can be a powerful tool in portfolio simulation. An improved CAS can be very helpful to: define parameters that best characterize agents' trading strategies, discover and suggest suitable positions for different sectors at different times, and discover the factors affecting optimal sector rotation strategy. In the future, we are planning to diversify investors into individual and institutional ones. Value investment and technical analysis indicators will also be incorporated into agents' decision rules. These two methods can compensate each other's drawbacks and provide better results for the CAS model. A general simulation of financial markets is another direction for exploring the CAS sector rotation model. Finally, additional experiments will lead to refined parameters and trading strategies.

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Price of Invisibility: Statistics of centralised and decentralised matching markets

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Abstract. We simulate a model of a decentralized and a centralised two-sided matching market in order to compare the efficiency of the two mechanisms. Also we parametrise the preference structure with preference list correlation and length. We use well known better response dynamic matching for a decentralised marketplace. We compare the decentralised mechanism to a centralised clearing house based on the Deferred-Acceptance mechanism. We use median rank and the number of unassigned agents to measure the efficiency of a matching. We found that median rank is statistically at most five times worse on a decentralised market, which occurs when correlation in preferences is small and list are long. Also with longer preference lists the decentralised mechanism has many unassigned agents and the matching is unstable, whereas a centralised mechanism computes a stable matching and usually with almost no unassigned agents.

Introduction

Two-sided matching markets have been studied quite extensively in the past half a century, starting with the National Residency Matching Program in US and the seminal result by David Gale and Lloyd Shapley [7] on a stable matching mechanism. This mechanism has proved useful in many entry-level job-markets (see e.g. [13]) and school choice markets (e.g. [1,12]). The general model is a two-sided market, where both sides have preferences or priorities over the agents on the other side.

The main benefit of a matching mechanism is that it is centrally applied. All the market participants report their preferences to a central clearing house that then can compute an optimal matching using for example Gale-Shapley Deferred-Acceptance algorithm [7]. Optimal usually means that the result is the best possible stable matching for one side of the market as the optimality can not be guaranteed for both sides. Stability is defined as a situation where participants do not have an incentive to deviate - there is no participant on the other side that the agent would prefer to his current match and that would also prefer him.

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Roth [13] observed that in some situations where there was not a central clearing house in place, market participants still executed a very similar algorithm as proposed by Gale and Shapley. A major drawback of the execution was that usually it was time-capped, i.e. at some point the market had to be closed. This meant that the algorithm execution might not have finished and resulting matching may not be stable.

We model a situation where agents randomly interact and always select a better, compared to their current, match if available. This is also called a better response dynamic in [2]. Agents do not know all participants from the other side of the market, but rather become aware and form preference of them as they meet. Then they decide to change their match or not. In a real market setting there are always some cost related to a change , but in our current model we do not consider it.

Our main aim and contribution is to understand the benefit of having a centralised mechanism instead of a decentralised. Our secondary goal is to study the effect of preference structure on the outcome for both market mechanisms.

1 Market models

In a two-sided matching market there is a set $\mathcal{A} = \{a_1, ..., a_n\}$ of agents on one side and a set $\mathcal{B} = \{b_1, ..., b_n\}$ of agents on the other side. Although the number of agents on both sides can be different, we consider here only cases where the two sets are of equal size, i.e. the market is balanced. Each agent a_i from $\mathcal{A}$ has a strict preference relation $\succ_{a_i}$ over agents in $\mathcal{B}$, and similarly for $b_j \in \mathcal{B}$ there is a preference relation $\succ_{b_j}$ over agents in $\mathcal{A}$. A matching μ is a mapping from $\mathcal{A} \cup \mathcal{B}$ to itself, such that for every $a \in \mathcal{A}$, is matched to $\mu(a) \in \mathcal{B} \cup \{a\}$, and similarly for $b \in \mathcal{B}$, $\mu(b) \in \mathcal{A} \cup \{b\}$. When an agent is matched to itself, $\mu(a) = a$ or $\mu(b) = b$ respectively indicates that they are in fact unmatched. Also for every $a, b \in \mathcal{A} \cup \mathcal{B}$, $\mu(a) = b$ implies $\mu(b) = a$. A matching is unstable if there is are at least two agents, a blocking pair, a and b from opposite sides of the market such that $b \succ_a \mu(a)$ and $a \succ_b \mu(b)$. A matching is stable if it is not unstable.

1.1 Decentralised random matching model

For modelling a decentralised market we use NetLogo ([15]). As usual in NetLogo agents are positioned on a grid, we use the default size of 33×33, with each position occupied by at most one agent. After the preference profiles have been set, at each time step an agent selects a random free position on the grid in the distance of 10 positions, if the position is occupied the agent remains in his current position for this round. The grid has a periodic boundary condition, meaning when an agent selects a position out of the grid, he is just moved to opposite side of the grid as the grid is toroidal.

After all agents have found a new position, we find the closest neighbour to all agents, from opposite side of the market, on the neighbouring 8 positions. If there is more than one at the same distance, one is chosen randomly. Note that some agents might not have a neighbour at each step.

After all agents have been assigned a neighbour they start a transaction with the selected neighbour. First they both check if they are on each other's preference lists. If they are on each other's lists, the agents are myopic, they compare their current assignment with the neighbouring agent and decide to change their match if the neighbour is higher in their preference list (Algorithm 1). This is described as random better response dynamics in [2]. In one timestep t some agents might have multiple transactions if they were selected as closest neighbour by multiple agents, but only the best match will remain.

Algorithm 1 Better response dynamic

Require: a, b, $\succ_a$, $\succ_b$, μ
Ensure: μ is a matching
  $m_a \leftarrow \mu(a)$, $m_b \leftarrow \mu(b)$
  if $b \succ_a m_a$ **and** $a \succ_b m_b$ **then**
    $\mu(m_a) \leftarrow m_a$, $\mu(m_b) \leftarrow m_b$
    $\mu(a) \leftarrow b$, $\mu(b) \leftarrow a$
  end if
  return μ

1.2 Centralized matching model

We compare our results from the decentralised matching model to one that would be centrally managed. In this case both parties submit their preferences to a central clearing-house that then outputs a matching. A classical algorithm used is the Deferred-Acceptance algorithm (DA), discovered by Gale and Shapley in [7].

The DA algorithm always produces a stable matching as showed by [7]. Furthermore depending the side that initiates the proposing sequence also obtains an optimal stable matching where agents from that side are matched to the best possible partner. The A-proposing algorithm is presented in Algorithm 2, similarly we can construct B-proposing algorithm that outputs stable matching optimal for B. These matchings may be, but necessarily are not the same, as there can be multiple stable matchings. It is also known that in general that A-side optimal stable matching is the worst stable matching for agents in $\mathcal{B}$ and vice-versa, see for example [13].

2 Selected parameters

The preference structure is parametrised by the length of the preference list (k) and correlation between the preference lists (c). The preference list limit k is the

Algorithm 2 A-Proposing deferred-acceptance

Require: $\mathcal{A}, \mathcal{B}, \succ_a, \succ_b$
Ensure: μ is a matching
  while There are unmatched agents in $\mathcal{A}$ with proposals **do**
    for all $a \in \mathcal{A}$ **and** $\mu(a) = a$ **and** $\succ_a$ is not empty **do**
      $b \leftarrow FIRST(\succ_a, \mathcal{B})$ // Most preferred match for a in $\mathcal{B}$
      $\mu(a) \leftarrow b$, $\mu(b) \leftarrow \{\mu(b), a\}$
    end for
    for all $b \in \mathcal{B}$ **do**
      $a \leftarrow FIRST(\succ_b, \mu(b))$
      $\mathcal{A}' \leftarrow \mu(b) \setminus \{a\}$, $\mu(b) \leftarrow a$
      for all $a \in \mathcal{A}'$ **do**
        $\mu(a) \leftarrow a$, $\succ_a \leftarrow \succ_a$ without b
      end for
    end for
  end while
  return μ

same for all agents. Although the preferences themselves are not necessarily the same, they might be correlated to some degree or might be totally random as defined by parameter c.

In reality the limit on the preference list might be artificial, due to limited processing capacity of the clearing mechanism. Or it might also be driven by agents themselves, due to the cost of additional information processing. It is hard to evaluate all the alternatives in a market, so they settle on listing or evaluating just a few. Or when considering the labour market, the list might be limited because some agents lack the skill to be matched with some jobs. Similar limitations to length of preference have been studied in [16,11].

High correlations between preference lists are usually driven by similar information people receive over alternatives and also similar value systems. It is observed in [14] that high correlations limit the size of the core of stable matchings. In some aspects correlation has been investigated in [4], where they look at fully correlated preference (uniform) lists and the effect on convergence to stability.

There have been additional studies on the effect of correlation. Mostly correlation is defined as as a utility function of the agents in the form $u_{a_i}(b_j) = \beta \cdot \xi(b_j) + \xi_{a_i}(b_j)$ ([3,6,5]) and then sorted to obtain preference ordering. The parameter β is the correlation parameter and in case of $\beta = 0$ we recover the uncorrelated preferences. The $\xi(n_j)$ is global popularity of the agent b_j and $\xi_{a_i}(b_j)$ is the agent a_i specific utility for agent b_j. Note that β can be arbitrarily large, thus it is hard to have fully correlated preference lists. In ([5]) they define a similarity measure for preference lists after generation, but usually the results are far from total correlation.

Algorithm 3 Random permutation

Require: $n, k \in [0, 1], c \in [0, 1]$
Ensure: p is a permutation of unique numbers
  $p \leftarrow 1, 2, 3, ..., n$, $j \leftarrow n$, $l \leftarrow k \cdot n$
  while $j > 0$ **do**
    $r \leftarrow$ random number between 0 and 1
    $q \leftarrow \lfloor j \cdot r^{1-c} \rfloor + [c \neq 1]$
    $t \leftarrow p_q$, $p_q \leftarrow p_j$, $p_j \leftarrow t$
    $j \leftarrow j - 1$
  end while
  return $\{p_1, p_2, ..., p_l\}$

Table 1: Parameter spaces

Parameter	Values
Knowledge limit (k)	$0.02, 0.1, 0.2, ..., 1$
Correlation (c)	$0, 0.1, 0.2, 0.3, 0.4..., 1$

2.1 Generating the preferences

The preferences are generated using algorithm 3 with parameters k, c and n. This algorithm is taken from [9] and modified to generate correlated lists with parameter c. The algorithm starts with master list of n numbers. Then it iterates over the list from end to beginning, each time at position j randomly selecting a position $q \in [1, j)$ to exchange values with. The correlation parameter c just states how biased the randomly selected position is, higher values indicated that the exchange position is selected closer to the current position j. With $c = 0$ the selection is uniformly probable over all positions, until finally at $c = 1$ the exchange position is always the active position and all the generated lists are exactly the same.

2.2 Parameter space

We run our simulation for multiple combinations of parameters k and c with the pattern as in Table 1, altogether $11 \cdot 11 = 121$ combinations. Each set of parameters is executed 100 times, to account for some variability. Since we are interested in effects of k and c we fix the market size to $n = 100$ for both sides of the market. So altogether there are 200 participants in the market. There is some research on unbalanced markets [3], where there are more participants on one side of the market. Also there is most likely significant interaction with our selected parameters and the size and the balancedness of the market, but this currently remains future work.

3 Results

We define two measures for the outcome of a matching mechanism: median rank and the number of unassigned agents. And Price of Invisibility measure for comparing the two matching mechanisms.

Definition 1 *The rank of b_j in preference relation $\succ_{a_i}$ of an agent a_i is defined as $\rho_{a_i}(b_j) = |\{b' : b' \succ_{a_i} b_j\}|$. Similarly we define the rank of a_i in b_j preference list by $\rho_{b_j}(a_i)$.*

Definition 2 *Given a matching μ then side A's median rank r_a is defined as*

$$P(\rho_a(\mu(a)) \leq r_a) \geq \frac{1}{2}, P(\rho_a(\mu(a)) \geq r_a) \leq \frac{1}{2}, \forall a \in \{a' : \mu(a') \neq a', a' \in \mathcal{A}\} \ . \tag{1}$$

Similarly we define a median rank r_b for agents on side B.

Definition 3 *Given a matching μ the number of unassigned agents is defined as*

$$u = |\{a : a \in \mathcal{A}, \mu(a) = a\}| + |\{b : b \in \mathcal{B}, \mu(b) = b\}| \ . \tag{2}$$

Definition 4 *Given a better response dynamic matching μ_{brp} and a deferred-acceptance matching μ_{da}, the Price of Invisibility, with respect to metric $f(.)$, is defined as*

$$PoI_f = \frac{f(\mu_{brd})}{f(\mu_{da})} \ . \tag{3}$$

We currently cut-off the execution of the decentralised mechanism after 5000 steps. Ideally we would run the simulation until we reach a stable state, but the random model does not find a stable solution in polynomial time [2]. Also when we observe the details we see that already after 2500 steps the rate of change is really slow - Figure 1.

Fig. 1: Convergence speed

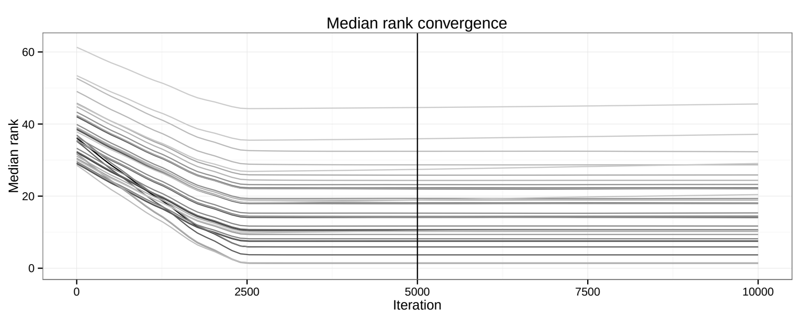
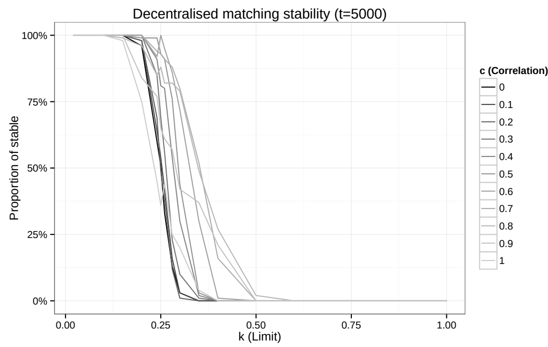


Fig. 2: Probability of a stable solution



3.1 Stability

As mentioned the decentralised market takes exponential time to find a stable match so we cut-off the execution at $t = 5000$ steps. Our selected random better response decentralised matching model operates by satisfying blocking pairs with each transaction. As these are not guaranteed to be the best blocking pairs that are satisfied some blocking pairs containing one of the agents might still remain.

The results of probability of stability with different parameters is presented on Figure 2. Similar results are reported in [4], where they look at $k \cdot n \leq 8$.

3.2 Median Rank

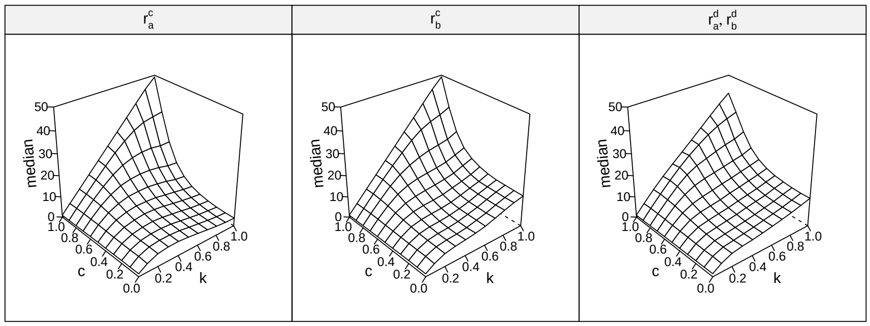
We select the median rank of a matching as a descriptive statistic for a matching. Main reason is that the distribution of matched ranks is exponential, most receive their first some their second and then the number of agents decays by rank, and median is much better statistic for an exponential distribution than the mean rank. Secondly median has a much better interpretation to it as half of the agents received a better and half a worse rank then the median, but there is hard to find an agent who received the average rank. Another alternative would be the the rate parameter of the exponential distribution, but the parameter describes more the skewness of the distribution than the outcome.

On Figure 3[1] we have plotted the median rank as a function of correlation and length of preference lists, respectively c and k. Interesting observations are that in a decentralised market both sides, A and B, have very similar median ranks, which can be expected as neither side has a definite advantage over the other. Also median rank from decentralised mechanism is really close to the median rank for the accepting side of a centralised DA matching.

These observations are also confirmed by other papers - [8] and [10] show that when the preference lists are short, even on one side, the set of stable matchings is likely to be small, and the difference in ranks is also small, which we observe

[1] Surfaces are smoothed with local regression

Fig. 3: Median rank dependence on k and c in centralised and decentralised markets



when $k \leq 0.4$. In [14] it is also observed empirically that the size of the core is small when preference lists are short.

Next we estimate the relationship to get the expected median rank in a matching as a function of c and k. Looking at various multiplicative functional forms, we arrive at the following form that has a reasonable trade-off between accuracy and complexity. In a later section we also have an overview of residuals. Fitting the parameters for decentralised matching we obtain (4).

$$r^d \approx e^{3.9-2\cdot k+1.9\cdot c\cdot k} \cdot k \ . \tag{4}$$

For the centralised (DA) matching expected median rank is different and depends on the proposing side. We denote the proposing side with a and the side b is the accepting/rejecting side as before. Similarly as before fitting the parameters we obtain (5).

$$r^c_a \approx e^{4.1-3.9\cdot k+3.8\cdot c\cdot k} \cdot k, r^c_b \approx e^{3.9-2.1\cdot k+2.1\cdot c\cdot k} \cdot k \ . \tag{5}$$

We can now approximately estimate the proportional difference in median ranks in decentralised and centralised markets. Price of Invisibility on median rank is defined as equation (6) where r^d and r^c are the median ranks from decentralised and centralised models respectively. With this we can estimate how much worse is expected median rank from a decentralised market compared to a centralised one.

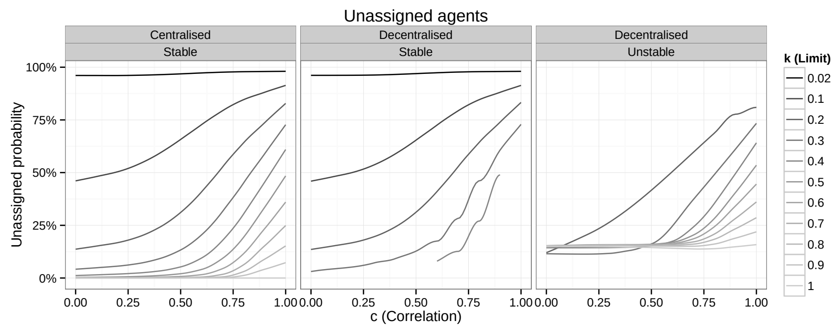
$$PoI_r = \frac{r^d}{r^c} \ . \tag{6}$$

For the proposing side a we obtain (7).

$$PoI_{r_a} \approx e^{-0.2+1.9\cdot k-1.9\cdot c\cdot k} \ . \tag{7}$$

First we observe that when $k = 1$ and $c = 1$ we actually obtain ratio < 1, which indicates that the decentralised matching might be better. Initially this

Fig. 4: Unassigned probability dependence on k and c in centralised and decentralised markets



seems counter-intuitive, but as we will observe in the next section there is a hidden cost, the number of agents who are unmatched in this case tends to be very large compared to a centralised match.

Also we observe that the greatest PoI_{r_a} occurs when k is big and c is small. For example when $k = 1$ and $c = 0$ then $PoI_{r_a} \approx e^{1.7} \approx 5$.

For the receiving side we obtain (8).

$$PoI_{r_b} \approx e^{-0.1 \cdot k - 0.2 \cdot k \cdot c} \leq 1 \ . \tag{8}$$

The median rank does not differ much for side B in decentralised and centralised markets, the PoI_{r_b} is very close to 1. But again we shall observe that the difference in the number of unassigned agents is significant. The PoI_{r_a} of averages over 100 executions is on Figure 5a.

3.3 Unassigned agents

A critical metric of a matching market is the number of unassigned agents. A centralised matching scheme guarantees that we have a minimal number of unassigned agent. In a decentralised market this is not always the case, as agents make choices using the better response dynamics, we are not usually guaranteed to have a minimal number of unassigned agents because of the dynamics.

We start by fitting the relationship of unassigned agents as a function of k and c in a centralised market. We observe on Figure 4 that the general form of the relationship is sigmoidal for each k, with minimum unassigned value (lower asymptote A) as $c = 0$ and maximum value (upper asymptote K) at $c = 1$. Thus we fit the parameters (A, K, B, M) of a generalised logistic equation (9). The asymptote parameters depend on k and logistic equation depends on c.

$$u \approx A + \frac{K - A}{1 + e^{-B(c-M)}} \ . \tag{9}$$

We also obtain different fitting parameter values for stable and unstable matchings on decentralised mechanism. For stable and centralised market we obtain the following lower and upper asymptotes as in (10).

$$A^c = e^{5.5-10\cdot k}, K^c = 200(1-k) \ . \tag{10}$$

As the length of the preference lists k grows the lower asymptote ($c = 0$) decays exponentially and becomes effectively zero after $k > 0.6$. In the case when agents have fully correlated preferences ($c = 1$) the decay in unassigned agents is merely linear as does not reach zero until the preference lists contain all the agents $k = 1$.

After the unassigned values are normalised using lower and upper asymptotes to be between 0 and 1 we fit a logistic function. We obtain that $B^c = 4 + 25 \cdot k$ and $M^c = \frac{1+27\cdot k}{5+24\cdot k}$. M is the position of maximum growth and B is the rate of growth. When k is small say $k = 0.1$ we observe that $M = 0.5$, so when $c \leq M$ the number of unassigned agents is closer to the lower asymptote and when $c \geq M$ the number of unassigned agents is closer to upper asymptote. If the growth rate B is large, it means that most of the growth happens near M. As k increases the growth rate B also becomes more rapid as correlation c passes the critical point M.

Next we look at the number of unassigned agents in a decentralised matching market. The number of unassigned is rather different due to the dynamics of the assignment process. We observe that the results are quite different when we obtain a stable match and when not, so we fit two separate logistic models. When we obtain a stable state we observe that the number of unassigned agents very closely resembles that of a centralised matching. On the other hand in the case of unstable matchings, approximately where $k > 0.3$, in decentralised matching we obtain the asymptotes in (11).

$$A^d = 30, K^d = 160(1-k) + 30 \ . \tag{11}$$

We observe that we can expect to have at least about 30 (15%) of unassigned agents as the lower asymptote indicates - even when we have full preference lists $k = 1$. Interestingly the lower asymptote is constant, which is an evidence that the number of unassigned agents is rather caused by the market mechanism than the inherent preference structure.

Similarly for unstable states in decentralised matching we obtain the position of maximum growth as $M^d = \frac{-4+55\cdot k}{54\cdot k}$ and growth rate $B^d = 54 \cdot k$.

Finally we estimate the average Price of Invisibility on number of unassigned agents as $PoI_u = \frac{u^d}{u^c}$. First we obtain lower and upper bounds based on previously obtained asymptotes where $c = 0$ and $c = 1$ respectively in (12).

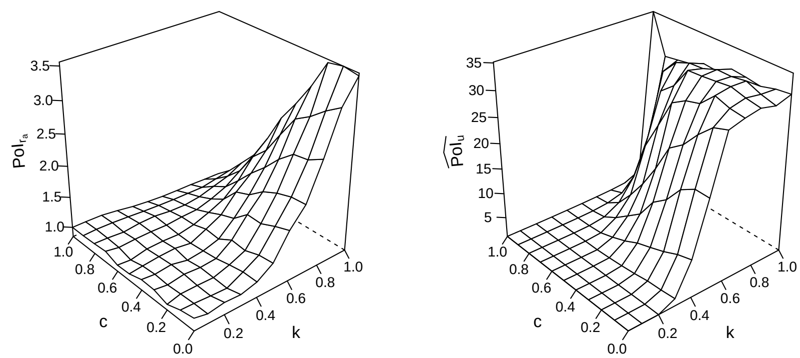
$$PoI_u \approx \begin{cases} 1 & \text{if stable} \\ \in (\frac{30}{e^{5.5-10\cdot k}}, \frac{160(1-k)+30}{200(1-k)}) & \text{if unstable} \end{cases} \ . \tag{12}$$

The PoI_u of averages over 100 executions is on Figure 5b. Since the number of unassigned agents in a centralised market can be zero in many circumstances the figure is plotting $\widehat{PoI}_u = \frac{\widehat{u^d}+1}{\widehat{u^c}+1}$.

Fig. 5: Price of Invisibility

(a) PoI on rank

(b) PoI on unassigned



3.4 Error analysis

The fitted functional forms of the relationships between matching metrics should be considered as approximations of the actual relationships. The error in the predictions tends to vary with the parameters. We define two error metrics:

Definition 5 *Root mean square error is defined as*

$$RMSE = \sqrt{\frac{\sum_1^n (\hat{y} - y)^2}{n}} \quad . \tag{13}$$

Definition 6 *Normalised root-mean-square error is defined as*

$$NRMSE = \frac{RMSE}{y_{max} - y_{min}} \quad . \tag{14}$$

In Table 2 we observe that the overall errors are small for r_a and u.

Table 2: Error levels

Mechanism	Function	RMSE	Normalised RMSE
	r_a	1.9	4.0 %
Centralised	r_b	3.1	6.3 %
	u	4.7	2.3 %
	r_a	2.6	5.6 %
Decentralised	r_b	2.6	5.8 %
	u	6.3	3.3 %

4 Conclusion and further research

Main conclusions

- the critical value to have a stable match with better response dynamic is to list less than 20 alternatives
- in a decentralised market there is always a significant number of unassigned agents - about 15%
- the median rank in the decentralised matching process produces very similar results as a centralised matching for the receiving side in DA

This research could be further extended by adding

- additional parameters for the size and balancedness of the market
- spatial properties like population density on a grid

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Impact of shadow banks on financial contagion

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Abstract. An asset network systemic risk (ANWSER) model is presented to investigate the impact of how shadow banks are intermingled in a financial system on the severity of financial contagion. Particularly, the focus of this study is the impact of the following three representative topologies of an interbank loan network between shadow banks and regulated banks. (1) Random mixing network: shadow banks and regulated banks are intermingled randomly. (2) Asset-correlated mixing network: banks having bigger assets are a regulated bank and other banks are shadow banks. (3) Layered mixing network: banks in a shadow bank layer are connected to banks in a regulated bank layer with some interbank loans.

Keywords: Financial contagion, regulated bank, shadow bank, systemic risk

1 Introduction

Understanding how the characteristics of a financial system govern the financial contagion of bank bankruptcies is essential in the argument to reform the capital requirement and other regulatory standards. Recently computer simulation models [10], [12], [13], [16] are developed to mimic the transmission of financial distress and predict the systemic risk [3], [6], which is the severity of financial contagion in a financial crisis. Both the external assets and interbank loans of banks can be the origin of financial distress in these models. Either distress may transmit separately in a peace time while compound distress transmits in a crisis time. A bank makes an investment in multiple external asset classes. The value of the total external assets may depreciate when the markets fluctuate. A defective investment portfolio of banks imposes financial distress on them. A failing debtor bank becomes insolvent in paying off the interbank borrowings. Any creditor banks suffer financial distress from the failing debtor bank. A bank goes bankrupt unless the capital buffer absorbs the total loss from the external assets and interbank loans. Bank bankruptcies bring about still more financial distress repeatedly. This is the mechanism of financial contagion.

A shadow banking system [2], [4], [5], [15] had grown rapidly to rival depository banks after 2000. A shadow bank is not a regulated bank, but such an unregulated financial intermediary as hedge funds, money market mutual funds, and investment

adfa, p. 1, 2011.

banks. It is not subject to the international Basel III requirements on capital buffer, and monitoring by government authorities. Shadow banks have a very high level of leverage, which is a very high ratio of debts to liquid assets, through off-balance sheet financing. Consequently, they have merely a very poor capital buffer. The vulnerability of the shadow banking system was one of primary factors to cause the global financial crisis in 2008 that ensued from the collapse of the US subprime mortgage markets. The US government authorities placed significant blame for the freezing of credit markets on a run on shadow banks, which had borrowed short-term in liquid markets to purchase illiquid risky assets.

In this study, we present a computer simulation model, which is called an asset network systemic risk (ANWSER) model [1], [8], [9], [11], to investigate the impact of how shadow banks are intermingled in a financial system on the severity of financial contagion. Particularly, we are interested in the impact of the following three representative topologies of an interbank loan network between shadow banks and regulated banks.

(1) In the random mixing network, shadow banks and regulated banks are intermingled randomly. It is a reference network topology. (2) In the asset-correlated mixing network, banks having bigger assets are regulated banks and other banks are shadow banks. It is less trivial than the reference network topology. Big banks are subject to regulatory standards worldwide. It was announced in 2011 that the international Basel III requirements would impose a relatively high level of capital buffer, which means additional loss absorbency, on global systemically important banks. The fraction of shadow banks may have a big impact on financial contagion. (3) In the layered mixing network, a financial system consists of two bank layers, and banks in the shadow bank layer are connected to banks in a regulated bank layer with interbank loans. It is even less trivial than the reference network topology. The number of interlayer loan relations may have a big impact on financial contagion.

2 ANWSER model

Models of interbank loans and investments are presented in this section.

The asset network systemic risk model (ANWSER) is founded on previous computer simulation models. They investigate the statistical characteristics of a financial system with a Monte-Carlo method. The Monte-Carlo method is a broad class of a computational technique to obtain many samples of numerical outcomes which are used to analyze the statistical characteristics. The technique relies on a sequence of random numbers generated repeatedly from a specified probability distribution. The initial financial distress on banks is the falling prices of their external assets in the market. When a debtor bank happens to go bankrupt, the consequent interbank loan defaults are the next financial distress to its creditor banks. Financial distress transmits from failing debtor banks to creditor banks repeatedly in an interbank network.

The number of banks is N. M is the number of external asset classes in which an individual bank makes an investment. The interbank loan ratio of a financial system $\theta = \Sigma l_n / \Sigma a_n$ is the total value of interbank loans as a fraction of the total value of assets. The assets of the n-th bank consist of the interbank loans l_n and external assets e_n. The external assets are securities and government bonds. An interbank loan is the credit relation between a creditor bank and a debtor bank which appears when the debtor bank raises money in the interbank market. An interbank network describes the all credit relations. It is a directed graph which consists of banks as vertices, and the interbank loans as edges from creditor banks to debtor banks. The liability consists of the equity capital c_n, interbank borrowings b_n, and deposits d_n. The equity capital includes common stock and disclosed reserves. The equity capital ratio (core tier 1 ratio) is $\gamma_n = \Sigma c_n / \Sigma a_n$. These need not be paid off and can be used to absorb the loss from financial distress immediately. The amount of the assets is equal to that of the liability in the balance sheet, $a_n = l_n + e_n = c_n + b_n + d_n$.

The denseness κ of a financial system is the average incoming or outgoing nodal degree of the interbank network as a fraction of $N - 1$. A more dense interbank network has a larger value of κ. The concentration ρ of a financial system is the sum of the interbank loan share of the five biggest banks. A more concentrated interbank network has a larger value of ρ.

Given N and M, a sequence of random numbers is generated to synthesize a number samples for fixed values of θ, γ_n, κ, and ρ. An individual sample includes:

(1) Interbank network topology $\boldsymbol{Z}$ (an $N \times N$ matrix) where the element $Z_{nn'} = 1$ means the n'-th bank makes a loan from the n-th bank, and otherwise $Z_{nn'} = 0$.

(2) Investment portfolio $\boldsymbol{X}$ (an $N \times M$ matrix) where the element X_{nm} is the fraction of the investment which the n-th bank makes in the m-th external asset class ($\Sigma X_{nm} = 1$, $0 \leq X_{nm} \leq 1$).

(3) Prices of the external assets in the market $\boldsymbol{v}$ (an M column vector) where the element v_m is the price of the unit of the m-th external asset class.

The initial financial distress on the n-th bank is $e_n \Sigma X_{nm} v_m$. It is assumed that failing debtor banks do not pay off any portions of the interbank loans to creditor banks. A bank goes bankrupt if the total loss from the financial distress is not absorbed by its capital buffer c_n. F is the number of banks which end in bankruptcy until the financial contagion comes to a halt. The empirical distribution of the number of bank bankruptcies $P(F)$ is obtained from those samples. The value of F is picked up at the 999-th 1000-quantile point as the representative in case of a financial crisis.

It is known empirically that the nodal degree of the network and the value of the transferred funds between banks obey a power law. In this study, $\boldsymbol{Z}$ is generated randomly by a generalized Barabasi-Albert model. This is a random graph with the mechanism of growth and preferential attachment which becomes scale-free as N goes to infinity. The distribution of the nodal degree k obeys the power law $P(k) \propto k^{-\alpha}$ where $\alpha \geq 2$. There is a significant probability of the presence of very big banks. This is the origin of heterogeneity.

The value of a loan $w_{nn'}$ from the n-the bank to the n'-th bank is determined from the incoming nodal degree k_n^{in} and outgoing nodal degree $k_{n'}^{\mathrm{out}}$ in the interbank network topology by the generalized law: $w_{nn'} \propto \left(k_n^{\mathrm{in}}\, k_{n'}^{\mathrm{out}}\right)^r$. The concentration ρ increases as $r \geq 0$ increases. The value of interbank loans is a constant if $r = 0$. Once the value of $w_{nn'}$ is given, the interbank loans and borrowings of individual banks are determined. Then the balance sheet of individual banks is determined from the values of θ and γ_n. A prerequisite that the external assets are no less than the net interbank borrowings are imposed because the bank has already gone bankrupt if this prerequisite is not satisfied.

A bank chooses multiple external asset classes to make an investment in randomly. When $M = 2$, X_{n1} and X_{n2} obey a uniform distribution. The prices of the external asset classes are independently and identically distributed. The absolute fluctuation in their prices obeys a uni-variate Student *t*-distribution. The prices rise or fall randomly. The degree of freedom is $\mu = 1.5$. This is a long tailed distribution which is suitable to describe a sudden large fluctuation. The amplitude of the absolute fluctuation is adjusted so that the probability of a bank with the equity capital ratio $\gamma = 0.07$ alone going bankrupt can be $p = 10^{-3}$.

3 Network topology

The focus of this study is the impact of the following three representative topologies of an interbank loan network between shadow banks and regulated banks. Empirically, some of real financial system may be close to the asset-correlated mixing network. Some of government authorities seem to believe the layered mixing network is relatively robust.

(1) Random mixing network: Shadow banks and regulated banks are intermingled randomly. It is a reference network topology. The number of shadow bank as a fraction of N is $0 \leq f \leq 1$. Fig. 1 shows an example topology when $N = 30, f$ =0.5. Blue nodes are shadow banks. Their number is $N_\mathrm{s} = 0.5N$. Red nodes are regulated banks. Their number is $N_\mathrm{r} = N - N_\mathrm{s} = 0.5N$.

(2) Asset-correlated mixing network: Banks having bigger assets are regulated banks and other banks are shadow banks. It is less trivial than the reference network topology. Big banks are subject to regulatory standards worldwide. It was announced in 2011 that the international Basel III requirements would impose a relatively high level of capital buffer, which means additional loss absorbency, on global systemically important banks. As a result, the equity capital ratio is correlated to the amount of assets generally in a real financial system. Such a core-periphery network as the asset-correlated mixing network is a simplified but still substantial replica of the real financial network. The number of shadow bank as a fraction of N is $0 \leq f \leq 1$. The fraction of shadow banks may have a big impact on financial contagion. Fig. 2 shows an example topology. Shadow banks are peripheral small banks. Regulated banks are central big banks.

(3) Layered mixing network: A financial system consists of two bank layers, and banks in the shadow bank layer are connected to banks in a regulated bank layer with interbank loans. It is even less trivial than the reference network topology. Some of government authorities believe separating a finan-

cial system into multiple bank layers is effective in mitigating the severity of financial contagion. The layered mixing network is reasonable in such a regulatory belief. The number of shadow bank as a fraction of N is $f = 0.5$. The number of inter-layer loan relations may have a big impact on financial contagion. The denseness of the inter-layer links is $q\kappa$, while the denseness in the intra-layer links is κ. The quantity $0 \leq q \leq 1$ adjusts the inter-layer denseness relative to the intra-layer denseness. The two bank layers are decoupled completely when $q = 0$. The denseness is uniform all over the network when $q = 1$. Fig. 3 shows an example topology. A non-trivial layer structure is visible clearly.

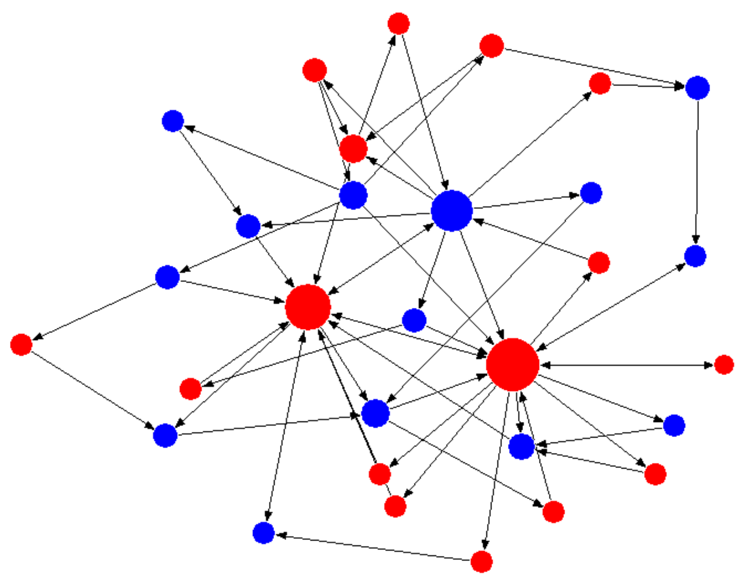

Fig. 1 Example topology of a random mixing network when $N_{\mathrm{r}} = N_{\mathrm{s}} = 0.5N, N = 30$. Blue nodes are shadow banks. Red nodes are regulated banks.

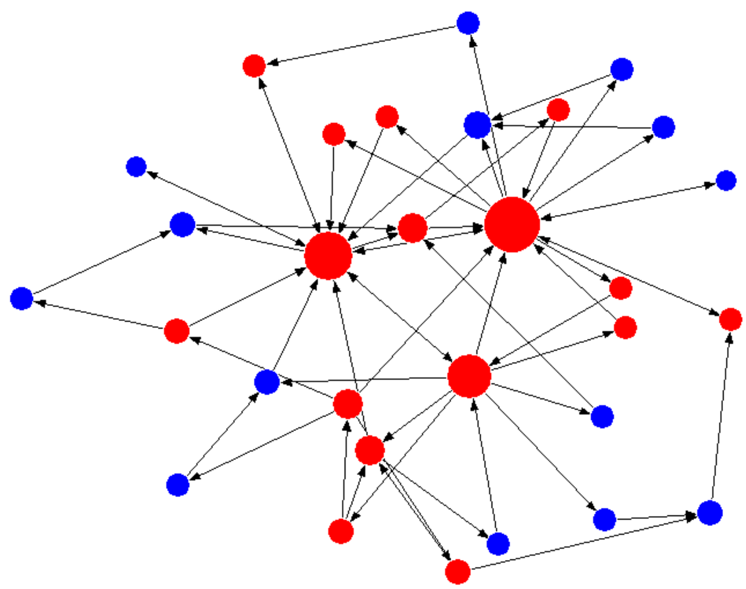

Fig. 2 Example topology of an asset-correlated mixing network when $N_r = N_s = 0.5N, N = 30$. Blue nodes are shadow banks. Red nodes are regulated banks.

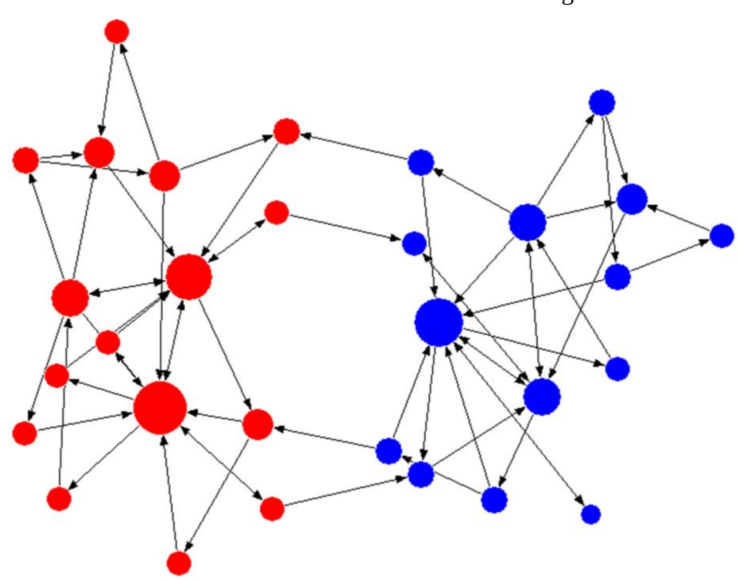

Fig. 3 Example topology of a layered mixing network when $N_r = N_s = 0.5N, N = 30$. Blue nodes belong to the shadow bank layer. Red nodes belong to the regulated bank layer.

4 Result

The experimental conditions are as follows. The number of external asset classes is $M = 2$. The values of the parameters are $\theta = 0.3$, $\gamma_s = 0.06$ for shadow banks and $\gamma_r = 0.1$ for regulated banks, $\kappa = 0.05$, and $\rho = 0.25$. The number of nodes is $N = 500$ for the random mixing network. The number of nodes is $N = 500$ for the asset-correlated mixing network. The number of shadow banks is determined by f in both topologies. The number of nodes is $N_r = N_s = 500$ for the layered mixing network. The fraction of shadow banks is fixed at $f = 0.5$. The creditor and debtor banks of an inter-layer interbank loan are chosen randomly.

(1) Random mixing network: The curve (a) in Fig. 4 shows the number of bank bankruptcies $F(f)$ as a function of the fraction of shadow banks. The number of bankruptcies is larger than that shown by the straight line (c) $F(f) = F(0) + fN$, which assumes every shadow bank goes bankrupt, when the fraction of shadow banks is 10% through 50%. This is a clear evidence of financial contagion from a shadow banking system to regulated banks.

(2) Asset-correlated mixing network: The number of bank bankruptcies shown by the curve (a) in Fig. 5 is much larger than that shown by the curve (b), which is the number of bankruptcies for a hypothetical network where the all banks have the average equity capital ratio $\gamma_s = \gamma_r = \bar{\gamma} = \Sigma c_n / \Sigma a_n$ uniformly. Given the total amount of capital buffer, banks having heterogeneous equity capital ratio is more vulnerable than banks having homogeneous equity capital ratio.

(3) Layered mixing network: Fig. 6 shows the ratio of increase in the number of bank bankruptcies as a function of q. The ratio is defined by $R(q) = [F(q) - F(0)]/F(0)$. The relative denseness q is the inter-layer denseness relative to the intra-layer denseness. $F_s(0) = 468$ (94%) shadow banks and $F_r(0) = 124$ (25%) regulated banks go bankrupt when $q = 0$ and $R = 1$. 592 banks (59%) go bankrupt in total. The number of bankruptcies increases even for very small values of $q \simeq 0.05$ because more regulated banks go bankrupt (see the curve (c)). There are few surviving shadow banks regardless of the value of q (see the curve (b)). This implies financial contagion from shadow banks to regulated banks. Decoupling a financial system into multiple layers does not necessarily mitigate the severity of financial contagion because q cannot be zero under a practical circumstance. On the other hand, the number of bankruptcies does not increase for large values of $q \simeq 0.2$. The financial distress from shadow banks is leveled off by many neighboring regulated banks. But the number of bankruptcies is still much larger than that when the layers are decoupled completely. Note that the reason why the curves fluctuate is not evident. This is for future study.

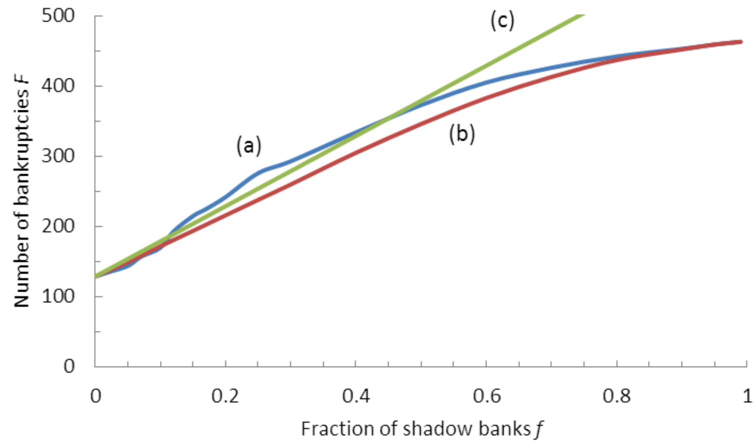

Fig. 4 Number of bank bankruptcies as a function of the fraction of shadow banks. (a) Random mixing network, (b) hypothetical network where the all banks have the average equity capital ratio ($\bar{\gamma} = \Sigma c_n / \Sigma a_n$) uniformly, and (c) $F(f) = F(0) + fN$.

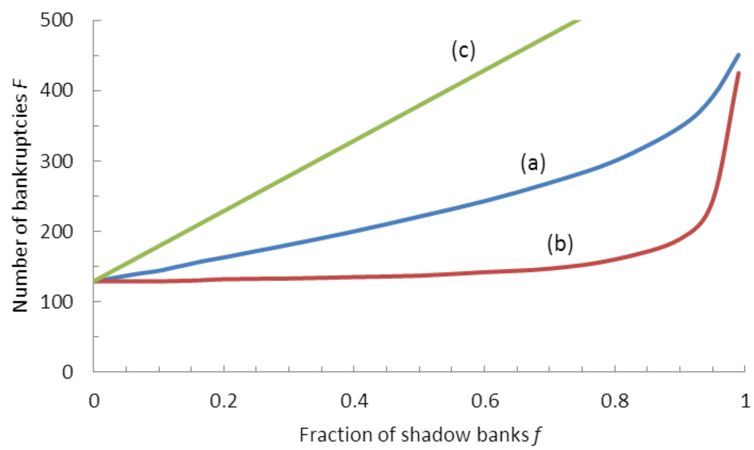

Fig. 5 Number of bank bankruptcies as a function of the fraction of shadow banks. (a) Asset-correlated mixing network, (b) hypothetical network where every bank has the average equity capital ratio ($\bar{\gamma} = \Sigma c_n / \Sigma a_n$) uniformly, and (c) $F(f) = F(0) + fN$.

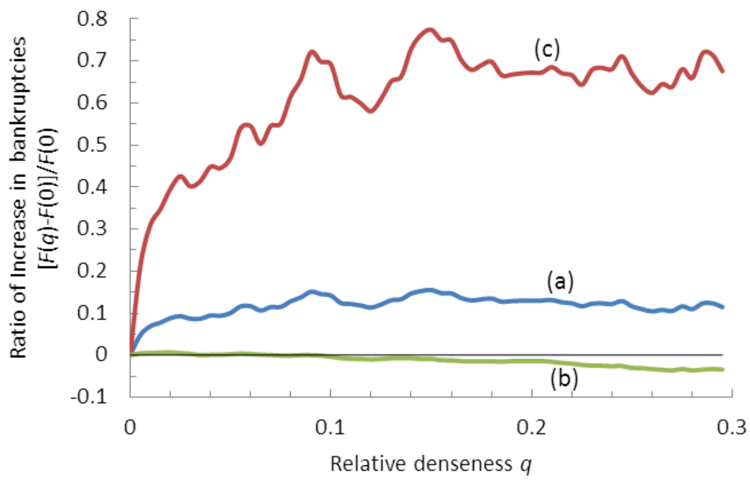

Fig. 6 Ratio of the increase in the number of bank bankruptcies $R(q) = [F(q) - F(0)]/F(0)$ as a function of q. The relative denseness q is the inter-layer denseness relative to the intra-layer denseness in the layered mixing network. (a) Entire financial system, (b) banks in the shadow bank layer, and (c) banks in the regulated bank layer.

5 Conclusion

The findings in this study include:

(1) Random mixing network: Financial contagion from shadow banks causes the bankruptcies of regulated banks when the fraction of shadow banks is 10% through 50%.

(2) Asset-correlated mixing network: The number of bankruptcies is much larger than that for a hypothetical network where every bank has the average equity capital ratio uniformly. This finding also holds true to the random mixing network.

(3) Layered mixing network: The number of bankruptcies increases even for a very small value of the inter-layer denseness relative to the intra-layer denseness.

The findings imply that failing shadow banks may affect regulated banks and consequently the entire financial system, banks having heterogeneous equity capital ratio may be vulnerable, and layer decoupling may not eliminate financial contagion. These implications are relevant to the argument to reform the capital requirement and regulatory standards.

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Model Structure of Agent-Based Artificial Economic System Responsible for Reproducing Fundamental Economic Behavior of Goods Market

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Abstract. Validation has been an important issue in using the ABM approach. It has been pointed out that deriving the necessary conditions for reproducing specific macro behavior is difficult due to the functional complexity of ABMs. However, based on the authors' experience with ABMs, we believe it is possible to define the necessary conditions for reproducing each macro behavior by using the structure of the system to express the input conditions. In the present study, a series of computer experiments are conducted to verify this idea. The study analyzes business cycles and the effect of tax reductions on GDP as examples of fundamental macro behaviors of economic systems. The results indicate that the most essential model structures for reproducing business cycles and the effects of tax reduction are credit creation for investment and factors relating to the efficiency of the government's, household's, and firms' expenditures, respectively.

Keywords: Agent-based modeling, Model structure, Business cycle.

1 Introduction

Agent-based modeling is a bottom-up modeling method in which we view artificial, computer generated societies as laboratories where we attempt to grow certain social structures. The purpose of these models is to discover the fundamental local or micro mechanisms that generate macroscopic social structures and collective behaviors [1]. Although agent-based modeling is a promising methodology that can deal with heterogeneity, individual agents' bounded rationality, and non-equilibrium dynamics in social systems, validation still proves to be a significant issue. As pointed out in the literature [2], one typical criticism by economists could be stated as follows, "you have presented one set of behavioral rules to explain your chosen phenomenon, but there must be many such sets which produce the same result, so how do you know yours is correct?" Some economists even go so far as to imply that it is excessively easy to construct an agent-based model (ABM) that produces desired phenomena. As argued by Marks [3], the problem behind this criticism is the functional complexity inherent in the ABM. It has also been argued that macro behaviors may be insensitive to many micro variables; and, as a result, it would be difficult to derive the necessary

adfa, p. 1, 2011.

conditions for the model to exhibit specific macro behaviors [3]. The severity of this problem increases when the model is described with greater detail and realism as this requires more variables and greater degrees of freedom [3]. For this reason, the model should be as simple as possible, and even then, it would be difficult to achieve quantitative predictions.

When input conditions are expressed by specific values of micro variables or parameters, there is a great deal of freedom. However, it should also be noted that the freedom of input conditions decreases if they are expressed by the system structure of the model (i.e., model structure) [4]. Here, the model structure includes the types of agents, the type of field (such as the market in which agents develop their activities), and the agent's behavioral rules. Consequently, it would be considered possible to specify the necessary conditions to reproduce the specific macro behavior. This is consistent with the argument of Ormerod [2] who pointed out that the current method used to build ABMs is a process of discovering the behavioral rules for agents that appear to be consistent with the phenomena we observe.

In this context, we believe that, although the model should be as simple as possible (based on the KISS Principle [5]), it is also important to consider all of the factors required to reproduce the desired phenomena. That is, the model structure should be the same as, or similar to, the real system in order for the characteristics to emerge as they do in the real world. The factors essential for reproducing the desired characteristics of the system can be discovered by running a series of computer experiments in which only one constituent factor of the model is changed at a time [4].

Although a number of ABM research studies have focused on macroeconomic aspects, these studies have not fully clarified the structural factors necessary for their reproduction.

Motivated by this deficiency, the authors have constructed a simple, artificial economic model consisting of consumers, three types of producers, a bank, and a government (some of which were reported in previous studies [4,6,7]).

In the present study, some additional simulations are conducted to clarify the model structure necessary for reproducing business cycles and the changes in GDP caused by a tax reduction (which were taken as examples of fundamental macro behaviors in a goods market). A series of simulation experiments are systematically conducted, changing the input conditions one by one. The study focuses on finding the model structure necessary to reproduce the above mentioned macroeconomic phenomena.

1.1 Outline of model

The ABM of the artificial economic system in the present study includes consumers, producers, a bank, and a government as autonomous decision-making agents. Consumers and producers are each divided into three types of agents, as shown in Table 1. Markets are also divided into three types: goods, stock, and labor. Each agent is heterogeneous in its state variables as well as in the other parameters included in their action rules.

Table 1. Outline of agents and their action rules.

Agent	Type	Output to be supplied	Product type to purchase	Outline of action rules
Consumer				Consumers work and obtain wage at producer,bank,or government, pay tax, and purchase consumption goods. Income is divided into the money for consumption and deposit by the Keynesian consumption function. Purchasing consumption goods is performed according to the utility which each consumer holds uniquely. Consumers transact in stock market, aiming to increase their assets, when stock market is
	Worker	The labor force for firms	Consumption goods	
	Executive	Management for firms		
	Public worker	The labor force for government		
Enterprise				Enterprises employ consumers, get profits from operating activities and pay wages and tax.
Enterprise: Producer				Producers supply and sell products in the goods market.
	Retailer	Consumption goods	Consumption goods, Materials, Equipment	Retailers and raw material producers decide both the amount and price of each class of product according to its state of amount of inventory. Moreover, they invest in equipment and expand production capacity according to demand,.
	Raw material producer	Material goods	Consumption goods, Equipment	
	Equipment manufacturer	Equipment	–	The equipment manufacturers produces equipment in line with the requirements of the retailers and raw material
Enterprise: Bank	Bank	The funds for producers	–	The bank keeps the surplus money of other agents in their respective bank accounts, and lends money.
Government	Government	Redistribution of wealth	Consumption goods	The government collects tax from other agents, pays wage to public worker and spends remaining money on expenditure of public money.

1.2 Sequence of actions

The set of actions for each agent is comprised of period-based units, where one period is assumed to correspond to one month in the real system. During each period, agents act according to a sequence of eight steps. At the end of the sequence for each period, a GDP value is calculated based on an input/output table obtained by summing each agent's account data. The eight steps dictating the agents' actions are as follows:

1. Agents pay any unpaid tax from the previous period. After paying taxes, agents create a budget plan for consumption, paying wages, or public spending.
2. Raw material producers decide on the quantity and price of products to be produced, produce several types of raw materials, and supply these to the goods market.
3. Retailers decide on the quantity and price of products to be produced, purchase raw materials in the material goods market, produce several types of consumption goods, and supply these products to the consumption goods market.
4. Consumers, retailers, raw material producers, and the government purchase products in the consumption goods market.
5. Each firm pays wages to employees and executive compensation to the executives while the government pays wages to public workers.
6. Retailers and raw material producers consider expanding production capacity based on total sales in the previous periods, and, if necessary, they decide to invest in expansion by either buying new equipment from the equipment manufacturer or employing a new worker.
7. When a stock market is included in the model, consumers buy or sell stocks aiming to increase their financial assets.

8. Each agent settles its accounts using the double-entry bookkeeping method. They calculate their income and profit for the current term, and then determine the amount of tax to be paid based on these figures.

1.3 Outline of agent's decision-making rules

1.3.1 Behavioral rules of consumers

Consumers create a budget for consumption $\boldsymbol{E_b^t}$. This budget is calculated by adding after-tax income $\boldsymbol{I^t\ (1\text{-}r_{i\_tax})}$ which represents the Keynesian consumption function [8]), to their bank deposit $\boldsymbol{D^t}$ multiplied by a withdrawal ratio $\boldsymbol{r_{wd}}$ at each fiscal period $\boldsymbol{t}$. The formula for the budget is shown in Equation (1). Here, $\boldsymbol{r_{i\_tax}}$ is the income tax rate, $\boldsymbol{a}$, is the consumer's basic consumption, and $\boldsymbol{b}$ is the marginal propensity to consume as per the Keynesian consumption function. The withdrawal ratio $\boldsymbol{r_{wd}}$ is selected randomly for each agent during each period.

$$E_b^t = a + bI^t(1 - r_{i\_tax}) + r_{wd}^t D^t \tag{1}$$

When purchasing products in the consumption market, consumers select goods based on their utility and affordability (as determined by the utility function for each class of products and the agent's budget constraint, respectively). Moreover, when a stock market is included in the model as an experimental level in order to analyze the reproducibility of business cycles, consumers buy or sell stocks aiming to increase their financial assets. Please refer to the authors' previous study in which consumers' action rules in the stock market are described in detail [7].

1.3.2 Behavioral rules of producers

The retailers and raw material producers both decide the quantity and price of their product at the beginning of each period. The price of each product is increased or decreased depending on the amount of goods they held in stock at the end of previous period. The quantity to be produced is decided in such a way that the probability of being out of stock must be less than 5%; this is estimated based on total sales from the last 10 periods.

The production capacity $\boldsymbol{Y}$ is defined by the Cobb–Douglas function [8] (as shown in Equation (2)) where $\boldsymbol{K}$ is the number of units of capital equipment, $\boldsymbol{L}$ is the number of employees, and α is assumed to be 0.25. In addition, $\boldsymbol{A}$ is a bounded proportionality constant that is randomly assigned to each producer. It is assumed that this value is unique to each producer and represents its technical capability.

$$Y_i(K, L) = A_i K^{\alpha} L^{1-\alpha} \tag{2}$$

Retailers and raw material producers initially have one unit of equipment and a specified number of employees. They will invest in order to increase their production capacity after they have passed a determined number of periods producing at maximum capacity. They decide to invest based on expected financial merit obtained by either buying a piece of equipment from the equipment manufacturer or employing a new worker from the labor market (when a labor market is included in the model as an experimental level).

When investing in equipment, they may finance the funds by borrowing from the bank, issuing new shares in the stock market, using their own internal funds, or using some combination thereof. The funds financed by the bank are repaid with interest in equal sized payments each period for a constant number of consecutive periods. An upper limit is placed on total investment so that, during the repayment period, additional investment will not be allowed. The equipment manufacturer produces equipment in accordance with the requirements of retailers and raw material producers as long as it is within their capacity. In the present study, the price of equipment is assumed to be constant. Please refer to the authors' previous study in which the decision-making rules for investment as well as for financing are described [7].

One executive and several workers are initially assigned to each of the producer agents. The producers pay wages to workers and wages plus executive compensation to the executive in each period. The executive compensation comprises a salary, a bonus, and long-term incentives. Wages comprise a fixed salary (randomly assigned to each employee between a lower and an upper limit) and a bonus when the producer's profit is positive.

1.3.3 Behavioral rules of bank

The bank lends money in the form of long-term loans to producers (in line with their demands for investment), charging a 3% interest rate. The bank also lends money to producers in the form of short-term loans so that they may meet their requirements when their working capital to pay fixed wages and/or purchase raw materials becomes sufficiently depleted. In the present study, the bank is initially given a very large quantity of funds so that there is no limitation on lending to producers, except in the case where long-term loan payments are not fulfilled during the repayment period.

1.3.4 Behavioral rules of government

The government collects corporate and income taxes, pays wages to public employees, and uses the surplus funds for public expenditure as dictated by their expenditure policy. Public employees' wages are calculated in each fiscal period so that they are equal to the average income of private employees.

Concerning expenditure policies, the study tests market purchasing, firm subsidies, and combinations thereof. Market purchasing is an extremely efficient form of public expenditure in which the government directly purchases goods at the market price. This policy is akin to the government placing job orders with firms, in a completely competitive situation, at the market price. Firm subsidies are an extremely inefficient form of public expenditure in which the government distributes funds to producers, without any limitations on their use. Most of the funds distributed could be transferred to the bank account without being used in the market. This policy is akin to the government placing job orders at a value far above the market price or paying money for jobs that have no economic value.

2 Simulation Conditions

The simulation conditions as experimental levels are divided into two categories: an analysis of the reproducibility of periodic changes in GDP (i.e., business cycles) and an analysis of the reproducibility of the effects of tax reductions on GDP.

In the former experiment, producers' decision making processes regarding investment in equipment (including the case where they do not invest) and the means of financing said equipment, as well as the types of markets are manipulated as input conditions in order to find the necessary model structure for reproducing periodic change in GDP (i.e., a business cycle). The periodic changes in consumers' wages and the amount of money spent investing in equipment are also analyzed. In the latter experiment, the types of agents included in the model system (including executives) and their behavioral rules relating to the efficiency of government', producers', and consumers' expenditures are all changed as input conditions so that the influence of tax reductions on GDP may be analyzed.

A series of simulation experiments are systematically conducted, changing the factors relating to the model structure (such as the type of agents, their behavioral rules, and the type of market) one by one. The simulation conditions for the experiment are shown in Table 2.

Table 2. Simulation conditions for the experiment in which factors relating to the model structure are changed as input conditions.

		Structure of basic model	Analysis of reproducing the periodic change of GDP			Analysis of reproducing the influence of tax reduction
			Analysis of investment rules	Analysis of financing rules	Analysis of MEC model	
Agent	Government	Without	Without			With
	Others	With	With			With
Rules of producers	The decision-making rule of equipment investment	Based on demand	No investment / Fixed interval	Based on demand	Based on an internal rate of return	Based on demand
	The rule of financing	Loan and internal funds	Loan	Using internal funds/ The issuance of stock	Using internal funds	Bank financing / Loan and internal funds
	The rule of executive compensation	Without	Without			With / Without
	The deletion of equipment	Without	Without		With	Without
	The price of equipment	Fixed	Fixed		Variance	Fixed
	The upper limit on the number of loans	Limited(1)	Limited(1)		Unlimited	Limited(1) / Unlimited(3)
Rules of consumers	The rule of withdrawal deposit	With	With			With / Without
Rules of governament	Taxation	Without	Without			With
	Inefficiency of government expenditure	Witout	Witout			With
Market	Goods market	With	With			With
	Stock market	Without	Without	Without / With	Without	Without
	Labor market	Without	Without			With / Without

3 Simulation Results

3.1 The necessary model structure for reproducing business cycles

As shown in Fig.1, the cyclical changes in the average price of consumption goods, average consumer income, and GDP are reproduced by the simulation under the base model conditions. The necessary funds for investment are all financed from the bank with constant repayment periods. It should be noted that these three macro indicators shows synchronized movement.

The business cycle mechanism reproduced by the base model is summarized as follows: In the beginning of the booming stage, some of the firms with strong sales decide to invest in equipment. This induces an increase in demand, wages, and investment at the aggregate level.

After the majority of producers have made their investments, the total amount of repayment per period becomes larger than the total amount of borrowing due to credit rationing. This induces a decrease in total sales, workers' wages, and investments, thus resulting in a recession. The details are presented in our previous studies [6].

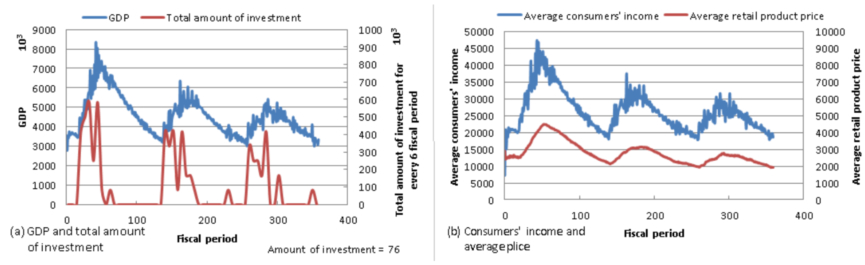

Fig. 1. The change in GDP and total amount of investment (a, left) and average consumer income and average retail price over time(b, right) under the conditions of the base model (bank financing and decision-making on investment on the basis of demand).

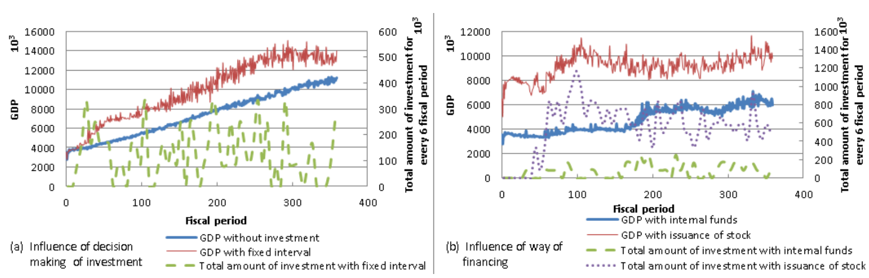

Fig. 2. Influence of investment decision making (a, left) and influence of financing means (b, right) on GDP and total investment.

When we assume that producers either do not invest (i.e., there is no debt), or that they invest randomly, with no regard to total sales, then there is no periodic change in GDP (as shown in Fig.2 (a)). Therefore, it might be concluded that the model must incorporate endogenous capital investment decision making (dictated by demand) in order to reproduce business cycles.

Financing from the bank (i.e., the existence of loans) is considered to be another important condition for reproducing business cycles. Fig.2 (b) shows the change in GDP when investment is financed either by the internal funds alone or by a combination of internal funds and the issuance of new shares in the stock market. In both cases, we can see the fluctuations in GDP and in the number of investments, but periodic changes in GDP (business cycles) do not occur. This is because, in both cases, there are almost no definite restrictions for conducting additional investment. When only internal funds are used, GDP shows slight cyclical variations (as shown in Fig.2), but this tendency is far less clear than that of the bank financing case. This is because some firms must wait several periods after enough funds have been raised in order to invest, but not all of the firms do. In addition, clear periodic change in GDP occurs in both cases when the bank financing rule is added (see Fig.2).

Therefore, in an ABM featuring producers' production and pricing activities as well as consumers' buying and working activities, it is reasonable that the most important conditions for reproducing business cycles would be the inclusion of bank financing and investment in the model structure.

On the other hand, Keynes proposed that the marginal efficiency of capital (MEC) is the primary determinant of the business cycle [8]. This, in turn, implies that the internal rate of return is the essential factor for creating business cycles. Based on this idea, an additional experiment is conducted in which producers decide to invest when the internal rate of return is expected to be greater than the current interest rate. Here, the internal rate of return is calculated using the expected value of the investment's marginal productivity, the price of the product, and the operating ratio of the equipment. The life of the equipment is assumed to be 60 and the price of the equipment is assumed to be $EP^t+1=EP^t(1+0.1(O^t/Y))$, where EP^t is the price of the equipment in period t, O^t is the amount of orders received in period t, and Y is the production capacity of the equipment manufacturer. However, cyclical change in GDP does not emerge in the simulation when bank financing is excluded from the model. The primary reason for this is that there is little to no change in the aggregate capacity of supply. The decreases in production capacity suffered by some producers due to the scrapping of equipment are balanced out by the surpluses of others. As such, without bank financing, variation in production capacity due to the scrapping of or investment in equipment cannot, by itself, influence the price of the retail product, and hence the expected return. Therefore, marginal efficiency of capital is not considered to be a major factor for generating business cycles when there is any degree of surplus in the aggregate production capacity.

3.2 The influence of a reduction in income and corporate taxes on GDP

In addition to the factors included in the base model (where the types of agents included are private and public workers as consumers; retailers, raw material producers, and equipment manufacturers as producers; a bank; and a government) each agent's behavioral rules regarding consumption are changed so that their influence on the relationship between the tax rate and GDP may be analyzed. The base level tax rate is initially set at 30%. In order to analyze the influence of a tax reduction on GDP, the tax rate is reduced from its initial level to 20% or 10% after 100 periods, while the average GDP over 360 periods is employed as the macro indicator.

The calculated relationship between the income tax rate and GDP is shown in Fig.4 (a). It should be noted that the negative correlation between the income tax rate and GDP is only reproduced when some inefficiency exists in government expenditure. It is also found that the level of inefficiency at which the correlation changes from positive to negative decreases when the effective marginal rate of consumption (which is dependent on the withdrawal ratio on bank deposits and the existence of executives) is increased.

If government expenditure is sufficiently inefficient, the negative correlation between the income tax rate and GDP is reproduced regardless of credit rationing (i.e., the upper limit on the number of loans), the existence of executive compensation, the usage of internal funds for investment, consumers' withdrawal ratio on bank deposits, or the labor market.

Consequently, it seems that the most important factor for reproducing the negative correlation between GDP and the income tax rate is the inefficiency of government expenditure. If government expenditure is 100% efficient, GDP increases even when income taxes increase. The reason for this tendency is that as the efficiency of government expenditure corresponds to the government's marginal propensity to consume. If the efficiency of government expenditure is larger than the consumers' marginal propensity to consume, some of the consumers' money to be deposited in the bank account will be transferred to the government by taxation and then consumed in the market, leading to an increase in GDP with an increased tax rate.

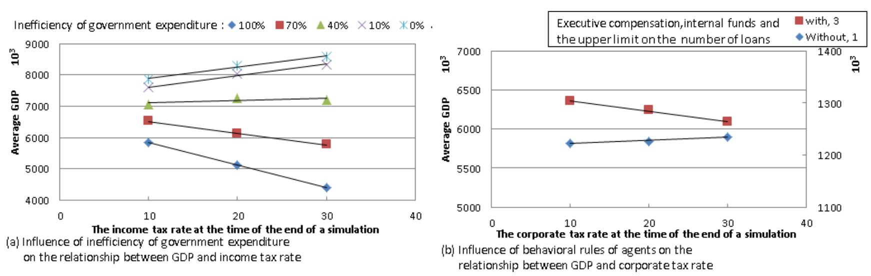

Fig. 3. Influence of behavioral rules (which are executive compensation, using internal funds, the upper limit of number of loans being three, and deposit withdrawal) on the relationship between GDP and income tax reduction (a, left) and corporate tax reduction (b, right)

However, the negative correlation between the corporate tax rate and GDP is not reproduced when only the inefficiency of government expenditure is accounted for. The negative correlation is only reproduced when executive compensation, the usage of internal funds for investment, and the inefficiency of government expenditure are all taken into account. The results also show that if the inefficiency of government expenditure is great enough, the negative correlation is reproduced regardless of the upper limit on the number of loans, the withdrawal ratio on consumers' bank accounts, or the existence of a labor market.

These factors might affect the critical level of efficiency at which the correlation changes from negative to positive.

Therefore, it seems that executive compensation, the usage of internal funds for investment, and the inefficiency of government expenditure are indispensable factors for the model to reproduce the negative correlation between the corporate tax rate and GDP. Although corporate tax reduction is known to reduce unemployment in the real system [9], the results show that the inclusion of a labor market in the model (which would account for unemployed workers) is not an indispensable factor in reproducing the negative correlation.

The reason for this tendency is that the surplus money from tax reduction promotes investment when the model accounts for the usage of internal funds, and directly increases demand when it accounts for executive compensation. If these two factors are not taken into account, the surplus money from the tax reduction is only transferred to the firms' bank account without increasing the market demand.

This finding suggests three things:

First, when input conditions are expressed by the model structure, it is possible to specify the necessary conditions to reproduce specific macro behavior. In addition, we can gain understanding of the underlying mechanisms that produce the specific macro behavior by discovering the necessary system structure for the model.

Second, corporate tax reduction increases GDP only when the government's effective marginal propensity to consume (expressed by the degree of efficiency in government expenditure) is smaller than that of aggregate firms'. That is, GDP is increased when producers receive surplus money from the tax reductions and effectively spend it in the market by means of investment or consumption by executives and workers.

Third, inefficiency of government expenditure harms the economy. The degree of inefficiency is defined as the ratio of firm subsidies to the total amount of public expenditure. In the actual system, inefficiencies might be caused by many factors such as public orders set above the market price, subsidies to firms in the industry, or rent seeking behavior [10].

4 Discussions: the validity of the model in ABM

As described in the introduction, the validity of the ABM has been widely criticized. It has been pointed out that, due to the functional complexity of the system in an ABM, one cannot assume that the factors that successfully reproduce the desired macro phenomena are necessary conditions.

On the other hand, the results of this study indicate that the necessary conditions for reproducing both business cycles and GDP reactions to tax reductions exist. Furthermore, these factors can be determined by running a series of computer experiments where each of the factors is changed one at a time. These necessary conditions are the factors of the model structure and they include the types of autonomous, decision making agents; their behavioral rules; and the types of markets or other fields where the agents develop their activities. Moreover, by revealing the necessary conditions for the model to reproduce the specific macro phenomenon, it is possible for us to gain a better understanding of the mechanisms that drive the macro phenomenon in question. The reason for this is discussed below.

A system is a set of interacting objects and is defined as a proper relation of sets [11]. Social systems consist of such objects as autonomous decision makers (i.e., agents, such as individuals and firms) and the field where they develop their activities (such as markets and cities). The macro behaviors of social systems are determined by the actions of interacting agents who develop their activities on the field.

Therefore, the macro phenomena that emerge in the model will be similar to that of the actual system if the set of agents (including their behavioral rules), the set of fields (such as the market where they act), and the set of attributes ascribed to the various types of agents are similar to those in actual systems. In other words, if the factors in the model are quite different from those of the actual system, then the macro phenomena in question will not be reproduced. Just how similar the factors must be in order to reproduce the desired phenomenon depends on the phenomenon in question as well as the form of similarity (i.e., whether the model factors are reproducing the qualitative or quantitative characteristics of the system). As evidenced by the results of present study, the most important of these factors are the types of agents and their behavioral rules. The results indicate that if these important factors are significantly different from those in the actual systems, the desired macro phenomena will not emerge either on a qualitative or on a quantitative level.

On the other hand, the model system does not need to exactly mimic the actual system in terms of the number of agents or the parameters on their attributes in order to reproduce the phenomenon, because, as pointed out by Marks [3], macro behaviors are insensitive to these factors. However, this study has found that the macro behaviors are not insensitive to the types of agents and their behavioral rules. This suggests that it is possible to specify the necessary structure of the model system by a series of computer experiments, if the types of agents and their behavioral rules are taken into consideration as integral factors.

It should also be noted that the model structure that can reproduce the desired macro phenomena might not be unique, because the emergence of macro phenomena could be influenced by several factors. However, this does not contradict the validity of the model, because each of the factors corresponds to a certain mechanism which would not be unique even in the real systems. Moreover, the mechanism of emergence for each phenomenon can be discovered by accumulating the knowledge on the model structures necessary for the reproduction of that phenomenon.

5 Conclusion

1. In an ABM where producers' production and pricing activities, as well as consumers' buying and working activities are included, the necessary conditions for the model to reproduce business cycles are the inclusion of bank financing and producers' capital investment decisions based on demand.
2. In order to reproduce a positive multiplier on income tax reduction under the balanced budget condition, the model must include inefficient government expenditure.

Furthermore, it is indispensable that the model include executive compensation and the usage of internal funds for investment in addition to the inefficiency in government expenditure in order to reproduce a positive multiplier on corporate tax reduction.

3. These results indicate that the necessary conditions for reproducing each of the macro phenomena can be identified if the input conditions of the model are expressed by the model structure (such as the types of agents, their behavioral rules, and the types of market). The model structure that reproduces the desired macro phenomena might not be unique. This does not contradict the validity of the model, though, because factors responsible for the emergence of macro phenomena might not be unique in the actual system. The mechanism of emergence for each phenomenon can be discovered by accumulating the knowledge on the model structures necessary for the reproduction of that phenomenon.

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The Regulatory Dilemma: An Agent-based Approach to Policy Making within Innovation Systems

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Abstract: Government regulation plays a pivotal role in influencing the innovation activities of companies, industries and whole economies. However, sound regulation must be based on an understanding of how a policy change will affect the behaviour of various actors in the market. This implies that some form of predictive modelling is necessary for intelligent policy formation. With this in mind, an 'almost zero-intelligent' agent-based model is developed to represent typical market dynamics. The agents make price and production decisions and decide whether or not to develop or imitate a product based on a pre-defined 'research' and 'imitation" ratings. The findings illustrate a Pareto Optimal line where both consumers and companies prefer the development of new products; however, different imitation rates create opposite results. Interestingly, policy changes in environments where imitation is already low, seems to cause larger impacts on the system. Furthermore, the findings also suggest that when regulation encourages imitation, improvements to consumers or companies can be made without hurting the other as much. These preliminary results set the foundation for future models that use regulation to steer the system of innovation towards these preferred outcomes.

Keywords: Agent-based modelling, Zero-Intelligence, Innovation, System of Innovation, Regulation

1 Introduction

In any industry where innovation plays a key role, we want to reward entrepreneurs for their investments in cumulative and sequential innovation. However, we want to do this without prohibiting follow-on creativity and without raising unreasonable barriers to market entry. Getting this balance right in sectors such as pharmaceuticals, entertainment and information and communications technology is a significant 21st century policy challenge [1].

A critical dimension of economic change [2] is the conversion of knowledge and ideas into a benefit, which may be new or improved products, processes or services [3]. This can be argued as critical for the development and competitiveness of firms, regions and nations. Therefore, policies that aim to improve or promote conditions for innovation have become increasingly important [4].

2 Innovation Policy

Just as innovation is a key determinant of economic change, regulation can have equally disruptive implications upon it – both positive and negative. For example, economic policies try to provide suitable conditions within the marketplace, such as increasing competition and reducing unemployment. Similarly, there are social policies that pressurize firms to focus on particular types of research, such as environment policies that try to reduce carbon emissions. Furthermore, there are administrative policies that try to control economic actors within the system. This is to ensure companies play by a certain set of rules and conditions, such as intellectual property and copyright laws [4].

Despite policy trying to serve the best interests of society, regulation can have negative implications upon it. For example, in some instances it can unintentionally erect barriers that may hinder the development of new research. A case in point is the Stop Online Privacy Act. This was a rejected bill put before the U.S. House of Representatives. It proposed several policies, such as increased powers for blocking websites, preventing search engines linking to them and consumers becoming responsible for the content that they view. However, fears arose regarding the long-term implications of such a policy. This was because despite trying to ensure that content creators receive the fruits of their labor, it could unintentionally hinder innovation in other areas. This is because innovations may not get the necessary funding for entrepreneurial exploitation if the legal ramifications and risk become too high. Therefore, if policies increase the uncertainty and costs of the development process, it could negatively affect the rate of technological diffusion [5].

2.1 Regulatory Dilemma

The aforementioned leads to a regulatory dilemma for policy makers. If there are "strong" penalties for firms imitating another product then a firm will have an incentive for the generation of new knowledge. However, this lack of competition can lead to less economic pressure to innovate which will subsequently reduce the speed that new technologies spread among enterprises [6][7]. Conversely, 'weak' regulatory protection entices competition by increasing pressure to develop ways of reducing costs or increasing revenue. However, this can lead to invention spillovers where firms copy new ideas without having to pay research costs, thus mitigating the reward for future invention [8] [9].

This dilemma highlights the regulatory problems within a system of innovation. It stresses the flow of technology and information between people, enterprises and institutions. The relationships between actors turn an idea into a process, product or service – and are fundamental to the innovative process [10]. Therefore, regulation can be used to try and control actors within the system. Such interactions within the system can be extremely complex. This is because actors within the innovation system can have conflicting goals and objectives. A case in point is the situation of consumers and corporations: arguably, consumers prefer the creation of new products as they will have more choice in price and quality, whereas companies, arguably, prefer less competition within the market so that they can set prices and production at their preferred rate, thus capitalising on their investment. However, the latter cannot enjoy this state of affairs if firms easily figure out how to imitate products similar to their own.

This raises the question of what would happen within a system of innovation for both companies and consumers under a set of different research and imitation scenarios. Traditionally, such strategic behaviour would be analysed using a game theory model [11]. However, this is a mathematical construct that assumes a small number of rational players that have a limited number of actions or strategies available. Thus, whilst it can be useful for determining future strategic outcomes, it does not allow one to analyse things such as human behaviour, randomness of events and outcomes, with heterogeneous agents that can perform different calculations and analysis [11].

3 Agent-based Modelling – An Improved Approach?

Agent-based modelling alleviates some of the limitations above. It is a type of computational model that simulates the actions and interactions of autonomous agents, where through a collection of decision-making entities each assess their own situation and makes a decision based on a set of predetermined rules [12] and repeated individual action leads to complex social institutions. Subsequently, this gives rise to patterns, structures and behaviours that are not explicitly programmed into the models. It offers a way to model social systems that are composed of agents that interact and influence one another, and they can learn from their experiences and adapt their behaviours so that they are more suited to the environment. Several benefits of Agent-based modelling are: 1) it's a natural representation of a complex system, 2) it allows modeling adaptive systems, 3) it allows heterogeneity of behaviors into the model, 4) and it has the ability to perform controlled computer experiments to study micro foundations of a complex system. Consequently, applications within agent-based modelling have been used across many different sectors (for examples see [13] [14] [15] [16]).

3.1 Agent-based Modelling in Policy

Agent-based modelling has been considered for some time within policy. It alleviates some of the concerns advocated by Lucas in his critique of macro-economic policy; for example, it takes into account the microfoundations of agents such as learning and adaption [17]. Similarly, Pyka and Fagiolo describe how it is easy to conceive frameworks where policy experiments are carried out to evaluate the effectiveness of different policy measures for a range of different institutional setups and behavioural rules [18]. A case in point is Antonelli and Ferraris looked at innovation as an emerging property of complex system dynamics based on external knowledge and internal learning, testing different intellectual property regulatory regimes [19]. They found that the dissemination of knowledge favours the emergence of creative reactions and hence fast rates of introduction of technological innovations. Nobel et al. developed a model that looked at the ageing population of the UK with regards to health and social care services. The agent-based model looked at demographic processes that influenced the supply and demand of social care and predicted that the pre-taxpayer cost of state-funded social care would double in forty years, unless suitable policy measures were used to correct it [20]. Additionally, Dilaver et al. looked at the role of entrepreneurship in regards to the emergence of regional industrial clusters. The authors found that an increase in entrepreneurship in one region had a negative effect in another. This was due to competition factors such as production and innovative outputs. Therefore, the authors illustrated the limitation on regional innovation and development policies that aspire to support clusters in similar areas of industrial specialization [21]. (See also [22] [23] [24] [25]).

Agent-based models are able to ask theoretical questions about different policy scenarios within the system of innovation. One type of approach that has been used to analyze market mechanisms is known as zero-intelligence agent-based modelling. This approach models agents that operate within a market mechanism, where they behave without strategy in order to determine the impact of the system and consequently the effect of the agent's behaviour [26]).

3.2 Zero-intelligence Agent-based Models

Zero-intelligence agent-based models have been one of the most successful applications of agent-based simulation [26]. The first application was developed by Gode and Sunder, who tested market experiments with zero-intelligence programs that submitted random bids and offers, thereby not seeking to maximize profits nor observe, remember or learn. They found that even without trader rationality, the market generated efficient allocations and "convergence of transaction prices to the proximity of the theoretical equilibrium price" [27]. Bollweslev and Domowitz extended this to analyse the effect of an order book, storing all price and quantity combinations sorted by price. The authors focused on varying or restricting the size of the order book and its effect upon the system. They found that as the order book size increased, the trade price within the market became less volatile. With the average spread and deviation in the spread reduced, liquidity increased and orders were executed more rapidly [26] (for other notable works on zero-intelligence, please see [28] [29] [30] [31] [32] [33].

Overall, the zero-intelligence framework has demonstrated to researchers that the market mechanism is capable of creating rational outcomes at the market level, even though individual participants may behave completely at random. Therefore, the models may display characteristics closely matching those of a real market, even though the traders differ in their sophistication. Considering this, we have chosen to build a zero-intelligence model that considers consumers, firms and regulators. Consequently, there will be three levels of adaption. Companies will make pricing and production decisions for the products that they own, and similarly make more strategic decisions regarding whether or not to create or imitate a product. There will be two adaptive algorithms for both of these. Regulation will then try to serve the interests of consumers by making decisions about how tight or loose patent and copyright law should be. However, as there is far too much to fit into this initial model, we will demonstrate an 'almost zero-intelligence' model comprised of corporate agents that make decisions about price and production, with different research and imitation probabilities. The outcome will be to find optimal states between consumers and corporations, and compare them to the different research and imitation scenarios within the system.

4 Agent-based Model Design

The model is designed to replicate typical market dynamics using a zero-intelligence framework. Each agent is initially assigned a starting product, which every consumer has its own utility for a product. The almost zero-intelligence agents make price and quantity decisions, initially started at random. Once in the marketplace, consumers make a purchase if the asking price is lower than what is perceived. Consumer satisfaction is measured by subtracting the difference between price and utility. After a day's trading, agents will vary price and production. This variance is randomly generated by moving price or quantity up or down by 1 and 5. The hill climbing algorithm works by recording the current day's profits against the previous day's profits, and if the current profits are greater than previously then that becomes the new best strategy. If not, it reverts back to the previous price or quantity – therefore allowing the agents to learn to maximize profits. Similarly, a mutation probability is included in the variance function, where price and quantity will randomly jump away from the hill climbing algorithm in order to allow the agents to find the optimal price and quantity. This is because agents will not necessarily get to the optimal price or quantity as they may be comfortable with the current profits that they are generating. For example, under a monopoly, as depicted in Fig. 1, the firm learns to profit maximize to the optimal amount over a period of about 50 days. The dips illustrate the mutational leaps, where they have tried a completely random price or quantity strategy.

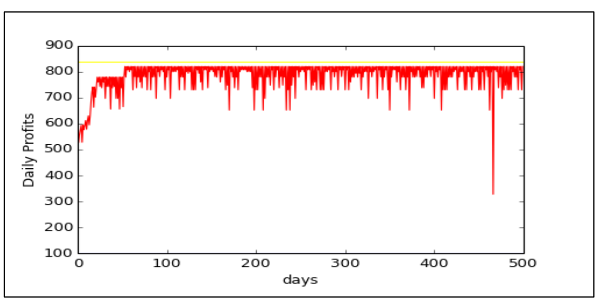


Fig. 1. An example of a company learning to profit maximize towards the optimal Price and Quantity.

At the end of every 'day' during the simulation, there is a pre-assigned probability regarding whether or not the firm will steal or research a new product. If a firm does enter an existing market, the agent will set a random price and quantity before adopting the hill climbing algorithm. Within a competitive marketplace, consumers will choose the product sold at the cheapest price.

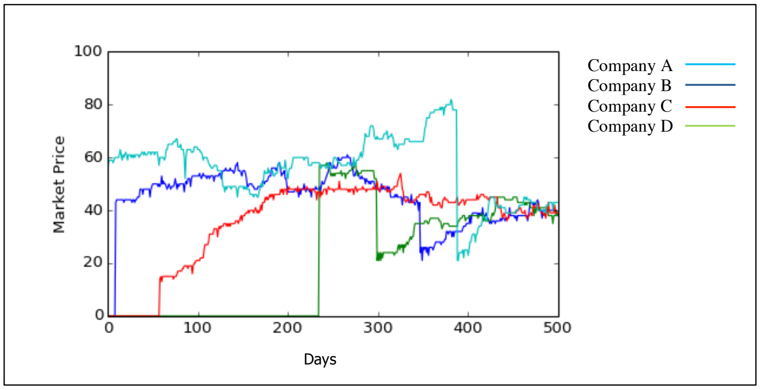
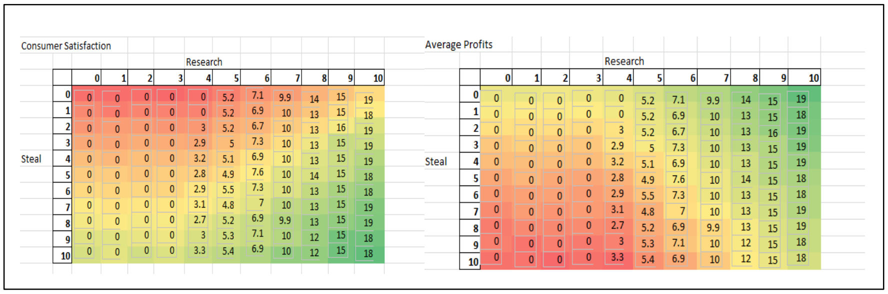


Fig. 2. An example of companies' pricing strategies that are competing within the same market

As more firms enter the market, agents will adapt and start trying to compete with one another. As illustrated in Fig. 2, companies (depicted by the colours) enter the market at different times, and slowly learn to undercut their competitors. This subsequently leads to a 'price war'. For example at around day 400, Company A tries to dramatically reduce its price through the mutation function. And, as that was a more effective strategy than the previous one, the company sets this as the new price.

4.1 Agent-based Model Results

In the results presented, the agent's parameters are randomly assigned for each experiment on the basis of 100 independent simulations (results are calculated into an average), based on a pre-assigned probability for both stealing and researching a new product. This is used to compare with other system states, which have different research and steal ratings. The steal/research ratings (1 to 10) are then turned into a probability, resulting in 100 different steal/research combinations. Within each of these system states a 100 simulation runs of each are completed and turned into an average in order to be compared. Finally, the market setup is consistent for each experiment (meaning the number of companies, consumers and so forth). There are 50 consumers per market and 12 companies each with their own randomly assigned manufacturing costs.



Consumer Satisfaction

Research

Steal	0	1	2	3	4	5	6	7	8	9	10
0	0	0	0	0	0	5.2	7.1	9.9	14	15	19
1	0	0	0	0	0	5.2	6.9	10	13	15	18
2	0	0	0	0	3	5.2	6.7	10	13	16	19
3	0	0	0	0	2.9	5	7.3	10	13	15	19
4	0	0	0	0	3.2	5.1	6.9	10	13	15	19
5	0	0	0	0	2.8	4.9	7.6	10	14	15	18
6	0	0	0	0	2.9	5.5	7.3	10	13	15	18
7	0	0	0	0	3.1	4.8	7	10	13	15	19
8	0	0	0	0	2.7	5.2	6.9	9.9	13	15	19
9	0	0	0	0	3	5.3	7.1	10	12	15	18
10	0	0	0	0	3.3	5.4	6.9	10	12	15	18

Average Profits

Research

Steal	0	1	2	3	4	5	6	7	8	9	10
0	0	0	0	0	0	5.2	7.1	9.9	14	15	19
1	0	0	0	0	0	5.2	6.9	10	13	15	18
2	0	0	0	0	3	5.2	6.7	10	13	16	19
3	0	0	0	0	2.9	5	7.3	10	13	15	19
4	0	0	0	0	3.2	5.1	6.9	10	13	15	19
5	0	0	0	0	2.8	4.9	7.6	10	14	15	18
6	0	0	0	0	2.9	5.5	7.3	10	13	15	18
7	0	0	0	0	3.1	4.8	7	10	13	15	19
8	0	0	0	0	2.7	5.2	6.9	9.9	13	15	19
9	0	0	0	0	3	5.3	7.1	10	12	15	18
10	0	0	0	0	3.3	5.4	6.9	10	12	15	18

Fig. 3. Two heatmaps illustrating Consumer Satisfaction and Corporate Profits. This is measured under a range of different imitation and research scenarios.

Two heatmaps are displayed in Fig. 3 above (red is lowest, green is highest). The left diagram displays consumer satisfaction and the right depicts the average profits of the companies, where the x-axis illustrates the steal rating between 0 and 10 and the y-axis is the research rating between 0 and 10. The ratings are turned into a probability by simply dividing by 100. The change of each state is therefore simply increasing it by 10%. The numbers within the boxes depict the degree of innovation that has been produced.

As demonstrated, consumer satisfaction is optimized in an environment where there are a lot of new products discovered and research is 100%. This is in alignment to corporations' objectives. However, the antipodal difference is that consumers prefer the imitable world whereas companies prefer a world where imitation is reduced. This is to be expected, as companies prefer to be able to capitalize on their investments.

Considering this, a Pareto analysis was undertaken. This was in order to find optimal states between consumers and corporations, and compare the outcomes to the other system states. The aim was to allow us to see if we can improve one without making the other worse off.

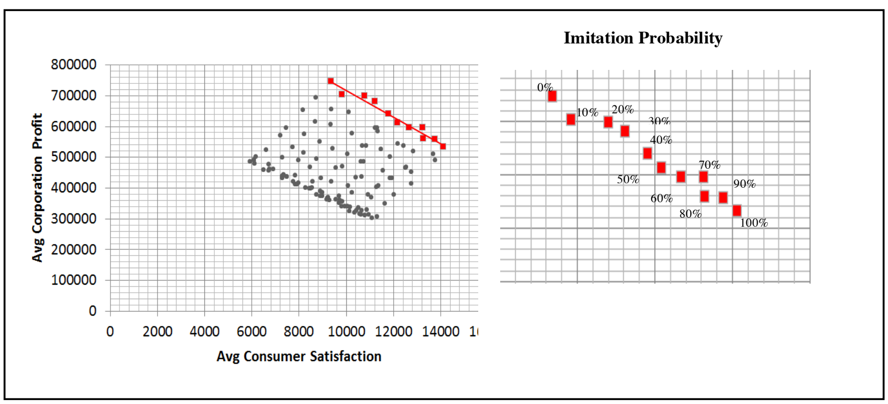


Fig 4. A Pareto Analysis illustrating different states of the system between the research and steal scenarios

The dots on the left diagram depicted in Fig. 4 show the different states of the system between the steal and research scenarios; for example, a world where research was at 10% and imitation at 20%, or research was at 30% and steal was at 40%, and so forth. Represented by the square dots in red, it becomes clear that the optimal solution for both parties is to encourage as much innovation as possible. For consumers this is only achieved when imitation is at 100%, whereas for companies this is achieved when imitation is at 0%, thus it is impossible to satisfy the optimum solution for both parties simultaneously. Therefore, a trade-off arises with regards to how much imitation is allowed.

The diagram on the right depicted in Fig. 4 illustrates this trade-off, where research was at 100% with imitation probabilities from 0% (farthest dot on the left) to 100% (farthest dot on the right). Therefore, it appears that the introduction of changing policies where imitation is at a low rate tends to have a larger causal effect on the system than changing policies where imitation rates are high. Similarly, a policy that entices imitation between 0% to 10% has a linear correlation with consumer satisfaction and companies' profits. However, changes to policies which encourage imitation from 10% to 20% create an uneven distortion, where consumer satisfaction can be improved without hurting corporate profits too much. As you move towards a weaker regulatory environment it increases imitation at around 30% to 40% another interesting anomaly occurs, creating a big change between the two, albeit in even proportion to each other. In middle range policies (20% to 60%) there is a small linear correlation between the two variables, albeit 30% to 40% having a big impact in terms of change between the two. In environments where a policy allows imitation to be high, an interesting occurrence happens between 60% and 90%: each state can be improved upon without much of a negative impact on the other.

These preliminary results suggest the aligned goals for research, highlighting the anti-podal differences between consumers and companies. Interestingly, policies where imitation is low, seems to yield larger impacts on the system than ones where imitation is high, where these changes are more evenly correlated between consumers and companies. However, it seems easier to improve the system when imitation is high without hurting the consumer or the company as much.

5 Conclusion

The agent-based model developed illustrates different outcomes under a set of research and imitation scenarios, illustrating that innovation is mutually beneficial for both consumers and companies, with interesting differences between policies that change imitation rates. This seems to align with the neo-classical equilibrium models of innovation and intellectual property. Greater analysis of the changes of imitation suggests that in environments where imitation is already low, it seems to cause larger impacts on the system. However, these changes are largely in linear correlation with each other. Conversely, in environments where regulation encourages imitation, there is more of a non-linear relationship, where changes to policies within this area can often lead to improvements for consumers or companies without hurting the other.

Overall, this foundational agent-based model sets a precedent for future simulations and it is planned that this work will be extended. Future work will introduce two new adaptive algorithms for both research and stealing, where firms can adapt their strategy in the hope of maximizing profits. Regulation will then be used to try to steer the system towards optimal outcomes.

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Social Institutions and Economic Inequality

Modeling the onset of the Kuznets Curve

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Abstract. Theoretical models of the Kuznets Curve have been purely analytical with little contribution to the timing of the process and to the presence of additional mechanisms affecting its timing. This paper proposes an agent-based version of Acemoglu and Robinsons model of the political economy of the Kuznets Curve. In extending their analytical framework we include heterogeneity of agents' income and a mating mechanism that together represent elements of social mobility. These two simple changes proved to be enough to shed light on the length and timing before high inequality implies regime change. Thus, this work may contribute to an effective empirical assessment of the Kuznets curve as it explicitly considers the time dimension of the process and the effects of considering social dynamics.

1 Introduction

In 1955 Simon Kuznets hypothesized that there exists an inverse U-shaped pattern in long-run processes of economic development [12]; that is, economic inequality increases as an economy develops, before decreasing after a certain level of income is reached. Although the hypothesis has been subjected to extensive examination, there remain many open questions in relation to this theory. In particular, these questions relate to: a) evidence for the theory's empirical validity; b) theory explaining why the curve arises; and c) shape and onset of the curve in different countries.

In their 2002 paper, Acemoglu and Robinson [2] (AR) offer a political economy theory of the Kuznets Curve. They propose that "*capitalist industrialization tends to increase inequality, but this inequality contains the seeds of its own destruction,*

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because it induces a change in the political regime toward a more redistributive system" [2, p. 184]. In contrast to other theories they argue instead that political factors and institutional change are crucial. They model redistribution and the associated reduction in inequality as a process where poor agents force political instability and the political elites extend redistribution through taxation to avoid a revolution. Society, therefore, moves from an autocratic to a democratic regime.

However, they make several unrealistic assumptions in their analytical model and do not consider the dynamics of the Kuznets Curve explicitly. In this paper, we take their paper as a starting point and formalize their interpretation of the Kuznets Curve in an agent-based model. This allows us to explore the effects of relaxing some of the assumptions made on the shape and onset of the Kuznets curve and to consider the time dimension explicitly. Specifically, we extend the model to include heterogeneity in the agents (both poor and rich) by allowing for an income distribution, and we include also a mating mechanism that allows mobility between the two classes, rich and poor, via the social institution of marriage.

The paper is structured as follows. In section 2 we present an overview of the current literature highlighting gaps in the theory, and consider the discussion related to the existing empirical evidence on the Kuznets Curve. In section 3 we develop the model, showing both the features that we reproduce and those we introduce as novel. Section 4 covers assumptions and special cases. Section 5 describes the implementation of the agent-based model. Section 6 presents the parameterization, a brief sensitivity analysis and the results. We conclude the paper in section 7.

2 Literature survey

In his original paper, Kuznets [12] used time series data for England, USA and Germany for the formulation of his stylized facts about the dynamics of growth and inequality, namely an increasing inequality for early stages of development (i.e. for aprox. 50 years) and a shrinking inequality thereafter. He expected the then underdeveloped countries to follow a similar pattern. He was, however, skeptical of the quality of his data set and pointed out that "the results [can be] considered as preliminary informed guesses" [12, p. 4].

When providing a theoretical explanation for the income dynamics, he mentioned the importance of political interference, which is expected to become more pronounced at later stages of development [12, p. 18]. The major mechanism for him was, however, that more and more people move from the countryside to the cities and move from the agricultural to the industrial sector. The result would be an increase of the income share of the poorest in the cities, which is also related to their increased political influence. Since the theory was first proposed, there has been an extensive body of literature assessing the validity of the hypothesis. The contributions can be grouped into theoretical assessments and empirical studies.

Theoretical contributions The motivation for theoretical models yielding a Kuznets relationship is the belief that empirical regularities as such (if they exist) can only be interesting to the extent that "they can be viewed as providing some clues to the mechanisms through which the development process affects the degree of inequality" [3, p. 338]. If such deeper mechanisms could be identified, reasonable policy advice could be derived from the observations, a goal that has been articulated throughout the entire literature on inequality.

The first important theoretical contribution is the paper of Lewis [13] in which he coined the idea of dualistic development, i.e. the coexistence of two sectors with important differences in at least one relevant dimension, mostly productivity. In this paper, the author used the example of a capitalist and a subsistence sector and as capital is only used in the first sector, it has a higher output per head and higher wages. If more capital is produced, more workers move from the subsistence to the capitalist sector and their income rises. Kuznets idea of the population shift from agricultural to urban employment was certainly inspired by this paper. The dualistic development models were further extended and refined in further papers by Ranis and Fei (1961), Harris and Todaro (1970), and Anand and Kanbur (1993).

An important step was the work of Robinson [15] who provided a more formal two-sector model that deals with the inequality dynamics explicitly and considers different income distributions in the sectors and a shift of the relative population of one sector. He showed that such a setting will frequently produce a Kuznets pattern. These theoretical considerations have been used to justify a great set of policy measures.AR, while building on previous work in the political science literature are the first who propose a political economy explanation for the Kuznets curve.

Empirical contributions The empirical assessment of the Kuznets curve has been characterized mainly by discussions about the quality of data and the choice of estimation techniques. Although Kuznets himself used time series data for the formulation of his theory, the vast majority of empirical work until recently has focused on cross-sectional data , simply because other data was not available [3, p. 307].

The most famous papers of the early era concluded with support for the Kuznets relationship and triggered a huge policy debate [3]. Later, Anand and Kanbur [5] took these papers as a starting point for their critique of the Kuznets concept and highlighted the insufficient data and the lack of consensus about the adequate estimation techniques. Until 1998, studies used exclusively cross-sectional data and the resulting evidence was mixed, with a tendency to be negative ([10], [14]). But the overall explanatory power of these cross-sectional studies has frequently been questioned. The Kuznets hypothesis is about how inequality develops within one country, not how it develop across countries, what is tested if one relies on cross sectional data.

In 1996, Deininger and Squire (DS) were the first who provided a panel data set that allowed the consideration of country specific effects [9]. After the release of this first panel data set, a new wave of empirical studies about the Kuznets Curve emerged. While DS find a statistically significant Kuznets-like relationship for a pooled regression, they reject the presence of the Kuznets Curve when they use fixed effects estimation. Savvides and Stengos (2000) using a threshold regression model did not find evidence for the Kuznets relationship (or any other well-defined relation) either and Higgins and Williamson (1999) found evidence for the curve only if they controlled for demographic and globalization effects. Many authors used the data set to argue for the importance of additional mechanisms such as policies and openness, thereby rejecting the idea of an unconditional relationship and explaining the resulting differences across countries ([16], [8]). Later, the data set provided by DS received heavy critique for including inconsistent inequality measures and providing in-accurate time series [6]. After this, almost no study was published using the original data set any more. In contrast to earlier praxis, some non-parametric studies were conducted using a refined version of the DS data set, finding mixed evidence. Another issue not adequately dealt with in the empirical literature is the time period over which the Kuznets Curve develops: The existing theoretical contributions do not make concrete statements about the time horizon of the Kuznets curve. Because of data scarcity most studies assessed a time span of at most 40 years.

We conclude that the evidence for the Kuznets curve is very mixed. While the evidence from cross-sectional studies cannot be trusted, more recent studies suggest that Kuznets patterns can be observed in some individual countries, which suggests an important role for country and region specific influences. There has never been a trustworthy study considering the Kuznets curve over more than 60 years, and considerations about data quality and adequate estimation techniques are not yet fully resolved.

3 The theoretical model

Environment As in the original model [2] we consider an infinite-horizon non-overlapping generation model in which parents invest in their offspring's education. In the benchmark model, a discrete population of N agents is divided in two groups N_t^r and N_t^p, respectively, the total number of rich and poor agents in period t. In every period, every agent in the population meets another agent, which might or not be from the same social class, and they beget two children. It is assumed that $1/2 < N_0^p/(N_0^p + N_0^r) < 1$ so that rich agents are a minority elite in the beginning. Political power is initially concentrated in the hands of the elite, where decisions will be taken by the median voter.

There is a unique consumption good y with price normalized to 1 and a unique asset h. At $t = 0$ each agent i has human capital h_0^{ip} or h_0^{ir} indexed with p for poor agents and with r for rich agents. Note that we allow heterogeneity of individual capital endowment within the two classes. Capital endowments are drawn from a given Pareto distribution. The distinction between rich and poor depends solely on their capacity to invest, represented by γ, in the education of their children e_{t+1}.

The final good is produced by each agent using a linear technology. Individuals can choose to allocate their capital between the formal sector, using a market technology $y_t^{im} = Ah_t^{im}$, and the informal sector $y_t^{ib} = Bh_t^{ib}$, where h_t^{im} is the amount of capital used in the formal sector or market production by agent i in period t and h_t^{ib} is the amount of capital he devotes to informal production. In the model $A > B$, so production in the formal sector is always more productive. Production in the informal sector has the advantage of being untaxed. The relation between A and B will determine the maximum possible tax.

Aside from the heterogeneity of the agents, this formalization is the same as that of AR [2].

Mating The mating mechanism is not included in the original paper. We consider two agents in the population $i, j \in \{r, p\}$ who select each other in order to form a family. We denote the total probability of an agent i mating another agent j as P_t^{ii}. If mating is perfectly random, for a large N the probability of a poor agent mating with a poor agent is $\lambda_t = N_t^p / (N_t^p + N_t^r)$. If mating is perfectly assortative the probability of a poor agent mating with a poor agent is unity. We define such probability as: $P_t^{pp} = \lambda_t + \alpha(1 - \lambda_t) = \alpha + \lambda_t(1 - \alpha)$ where α is a measure of assortativity. Hence, when $\alpha = 0$, random mating results, while for $\alpha = 1$, mating is perfectly assortative. Following the same logic, given $1 - \lambda_t = N_t^r / (N_t^p + N_t^r)$, the probability of a rich agent mating with a rich agent is simply given by $P_t^{rr} = (1 - \lambda_t) + \alpha\lambda_t = 1 - \lambda_t(1 - \alpha)$

The remaining probabilities are easily computed as $P_t^{pr} = (1 - \alpha)(1 - \lambda_t)$ and $P_t^{rp} = (1 - \alpha)\lambda_t$. α is then our inter-class mating parameter (assortativity).

In every period t the expected number of poor agents that mate outside their class is $N_t^p P_t^{pr} = N_t^p[1 - (\alpha + \lambda_t(1 - \alpha))]$. The expected number of rich agents that mate outside their class is $N_t^r P_t^{rp} = N_t^r[1 - (1 - \lambda_t(1 - \alpha))]$. It is easy to see that expected values match.

The consumption-investment decision When two agents mate they become a family, for which the total amount of wealth or final good is the sum of the individual . For family z, made up of agents i and j $y_t^f = y_t^i + y_t^j$, where for a generic agent i, $y_t^i = y_t^{im} + y_t^{ib}$; this holds also for the agent j and, in principle, is expression of both formal, m, and informal, b sector.

We assume that both parents are altruistic towards their children, regardless their social origin. Accordingly, the decision about how much of the final good to consume and how much to invest on the children education is jointly taken between the two members of the family, e_{t+1}^z, following preferences,

$$u^z(c_t^z, e_{t+1}^z) = \begin{cases} (c_t^z)^{1-\gamma}(e_{t+1}^z/2)^\gamma & \text{if } e_{t+1}^f z > 2 \\ (c_t^z)^{1-\gamma} & \text{if } e_{t+1}^f z \leq 2 \end{cases} \tag{1}$$

where $\gamma \in (0, 1)$, c_t^z is the joint consumption of the parents in period t, and e_{t+1}^z is the investment in children education. These preferences imply an investment rate equal to γ. We assume that parents invest the same in both children, and so the utility function implies that a family will invest in education if and only if the amount they can dedicate to this is larger than 2 (1 for each of the children). Hence, the investment in offspring education will be

$$e_{t+1}^z = \begin{cases} \gamma \hat{y}_t^f & \text{if } \gamma \hat{y}_t^z > 2 \\ 0 & \text{if } \gamma \hat{y}_t^z \leq 2 \end{cases} \tag{2}$$

For each new child, k, his human capital is given by

$$h_{t+1}^k = max\{1; Z(e_{t+1}^z/2)^\beta\}, \tag{3}$$

with $Z > 1$ and $\beta < 1$. This guarantees that accumulation of capital does not continue indefinitely. Notice also that equation (3) guarantees that the minimum amount of capital is 1.

Taxes and transfers No matter how forward-looking the parents would be for their children, their investment decision depends on the tax regime. We assume that taxes cannot be made person-specific and so they are proportional to the amount of market-produced good. However, we have introduced the family unit as agent performing the investment and voting decisions, then, for every family, post-tax total income is simply $\hat{y}_t^z = (1 - \tau_t)Ah_t^{zm} + T_t + y_t^{zb}$ which simplifies to

$$\hat{y}_t^z = (1 - \tau_t)Ah_t^{zm} + T_t \tag{4}$$

if both parents produce all of their final goods in the formal sector. This will be the case in equilibrium. τ_t is the tax rate and T_t, the transfer in each period, is just given by

$$T_t = \frac{\sum_{i=1}^N y_t^{zm}}{N}. \tag{5}$$

The government's budget constraint is given by $NT_t = \tau_t AH_t^m$, where $H_t^m = \sum_{i=1}^m h_t^{im}$ is the total production in the formal sector of the economy. Initially the tax rate will be set by the median voter among rich agents. However, poor agents can overthrow the existing government and take over the capital stock at any period t. We assume that a revolution is triggered when more than half of the population are materially better off than under the government of the rich elite. If it is triggered, a revolution always succeeds, with a proportion $1 - \mu$ of the capital stock being destroyed, and the remaining of it being shared equally among the whole population. Therefore, μ indicates how costly the revolution would be. Hence, if there is a revolution at period t, each family receives

$$y_t^z = \frac{\mu AH_t}{N} \tag{6}$$

in every future period. For simplicity, we assume that when deciding whether agents prefer a revolution to take place, parents only think about their current period endowment of final good, and not about their offspring's.

For the median rich agent it will always be preferable to extent the franchise and open the regime to democracy than to let the revolution happen (see section 4). Hence, if the revolution constraint binds at any given period, the elite will introduce democracy, allowing the whole population to vote. The equilibrium tax rate in the first democratic period will be

$$\hat{\tau} = \frac{A - B}{A}, \tag{7}$$

the maximum tax level which does not imply agents allocating their capital to production in the informal level. The timing of the model in each period is as follows:

1. Parents die and the new generation receive education bequests. Upon receiving the bequest, the new generation makes a marriage decision. Social mobility can be improved by marriage.
2. The median voter among the rich agents sees everybody's capital endowment and finds out if a revolution is optimal for half of the population or more, in which case he will choose to extend the franchise and open the regime to democracy.
3. If the franchise has been extended, family, the two parents, decide if they prefer to vote and select the optimal tax level or to support a revolution, which never happens in equilibrium.
4. Each family allocates his capital stock between formal sector and informal sector production and the family's consumption and bequest levels.

4 Analysis

In this section we comment on the model assumptions and the case we choose for the simulation.

For the assumptions of the model the reader is referred to AR[2]. The main assumptions we keep are: the zero bequest assumption, the steady state assumption, the fact that median rich agent prefers democracy to revolution, and initial conditions which ensure that rich agents who marry other rich agents are able to accumulate capital when there are not taxes. These conditions imply that poor agents cannot accumulate wealth even in the absence of taxes, while economic growth exists in the economy because rich agents start with less than steady state human capital, and are able to accumulate wealth until they reach the steady state level.

Autocracy, the rich accumulate and a rich agent and a poor agent together create a rich family Since in our model poor agents cannot accumulate (unless they mate with a rich enough agent), and rich agents do (unless they mate with a poor agent and they are not rich enough), for high enough α, i.e. low enough inter-class mating, inequality will increase during the first periods, before rich agents' capital reaches the steady state level. The franchise will be extended when wealth under autocracy becomes lower for at least half of the population than what they would get after a revolution. Increasing inter-class mating has two effects: On the one side it increases economic growth, on the other it decreases inequality. When a rich agent and a poor agent together create a rich family, the case chosen for our experiment, inter-class mating decreases social inequality and increases economic growth. Then, the effects of introducing inter-class mating ($\alpha < 1$) in an environment in which the franchise would be extended at a certain period $t = k$ will be either:

1. To modify the time for a revolution to be optimal for at least half of the population, depending on whether the growth or the inequality effect dominates. Our simulations suggest a domination of the growth effect, by increasing the number of families which are able to accumulate wealth, increasing inter-class mating increases total wealth in the autocratic regime, making the revolution optimal for the poor proportion of the population earlier in time.
2. If inter-class mating is high enough, it might prevent the revolution constraint from ever being triggered. Since we are assuming the median voter of the rich takes the political decisions, democracy arrives just because all agents become rich at some point.

Democracy When democracy is trivially reached because everybody becomes rich or because everybody becomes poor, then there will be no taxes, and consequently no political decision is taken. If democracy is reached through the revolution, the median voter will choose the maximum possible tax rate in the first democratic period. After this, inter-class mating and redistributive taxes will decrease inequality. At some point, it might occur that the median voter is not interested in positive taxes anymore. Formally, he chooses τ as to optimize:

$$\tau^m \in \text{Argmax } (1 - \tau_t)Ah_t^m + \frac{\tau^m Y_t}{N} \tag{8}$$

So the optimal tax level is simply given by:

$$\tau^m = \begin{cases} 0 & \text{if } Ah_t^m > \frac{Y_t}{N} \\ \frac{(A-B)}{A} & \text{if otherwise} \end{cases} \tag{9}$$

In the next section, we consider the implementation of the theoretical model as an agent-based model.

5 Model Implementation

The model was implemented as a discrete-time, agent-based model written in Python. The code is available at github [1]. The simulation began by instantiating 1,000 agents with a wealth distribution according to a Lorenz curve where $\delta = 0.82$. The simulation was executed for 200 timesteps. Agents were considered rich if their initial wealth was above the poverty line $1/(\gamma A))$. After the initialization, the simulation was executed in the following manner:

1. Each agent calculates post-tax income as $(1-\tau)Aw + r$ where w is wealth and r is the transfer.
2. Each agent computes its savings as savings rate time post tax income.
3. A regime choice is made. If the richest poor agent's potential income under democracy ($\mu AH_t/N_p$) is greater than its current post-tax income, the democracy is set and democracy continues through the execution.
4. If democracy is the current regime, the median agent, sorted by wealth, sets the tax rate. The rate is zero if this agent has above average wealth or $(A-B)/A$ otherwise.
5. Transfers are calculated as $r = \tau A/N$.
6. In assortative mating, agents were paired based on the assortative parameter and a new generation was generated where two 'parents' begat two 'children'. The children wealth were set as the average between their parent's savings. Each agent is classified as rich or poor depending on their wealth relative to the poverty line.
7. In one-to-one mating, each agent generates a 'child' and its savings are passed down.
8. This generation is processed just as in steps 1–8.

6 Results and Discussion

Parameterization and Sensitivity Analysis Where possible, we use empirical data to inform the model parameterization. Some parameters are derived from the same equations as given in AR, the remaining parameters were set explicitly. Table 1 shows the origin of the parameters and values used in the baseline scenario. In all runs $N = 1,000$ and $H = 1,000$.

Table 1. Parameter Values

Parameter	Baseline	Origin
Gini Coefficient	0.10	Informed by data [7]
δ: Lorenze curve parameter	0.82	Derived from other parameters
Δ: % of poor	0.99	Model initial condition
I: Threshold agent	990	Derived from other parameters
H_m: Threshold agent (90th percentile)	1.87	Derived from other parameters
A: Parameter on modern sector production function	2.67	Derived from other parameters
B: Parameter on informal sector production function	2.13	Derived from other parameters
γ: Savings rate	0.20	Informed by data [7]
Z: Parameter on ospring human capital function	3.37	Set as initial condition
β: Exponent on ospring human capital function	0.75	Set as initial condition
μ: Proportion of economy remaining after revolution	0.85	Set as initial condition
τ: Tax rate	0.20	Informed by data [7]

For the sensitivity analysis we will consider the case of assortative mating and how parameters other than α influence the results. Both the initial inequality and the share of savings imposed to the economy determine the value of productivity on the formal sector. Derived from that, the equations provide the productivity on the informal sector. For δ close to 1 and derived productivity much higher than empirically observed, inequality rises for all values of α. The model also allows for a variation in the size of the economy that is left after a revolution. Results vary little with most distributions showing an increase in inequality followed by a short decrease before simulation is stopped with no more poor agents.

All considered the sensitivity analysis showed that the model is robust to transformations in the parameters as long as they are within the constraints and conditions imposed by the construction of the model itself.

Results Figure 1 presents the results associated with the baseline parameterization. For alternative values of α, we plot the time series of income inequality and poverty. Income inequality is measured by the Gini coefficient and poverty is captured by the number of poor agents. Recall that $\alpha = 0$ corresponds to perfectly random mating, $\alpha = 1$ corresponds to perfectly assortative mating, and a unit of time corresponds to a generation. Three interesting conclusions emerge from Fig. 1: higher assortativity in mating is associated with (1) a later onset of the Kuznets curve; (2) greater inequality; and (3) an increased persistence of poverty.

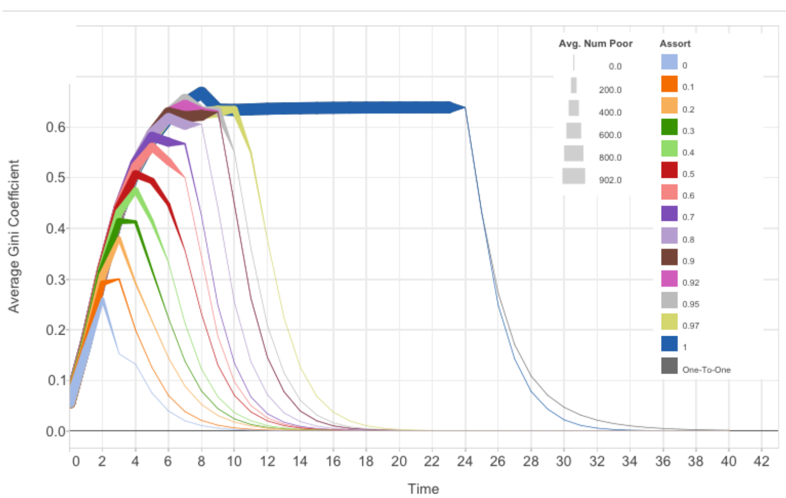

Fig. 1. Results. The Figure shows the evolution of the Gini coefficient for $\alpha = 0$ to $\alpha = 1$ (i.e. from random to perfectly assortative mating). The width of the line is proportional to the number of poor agents at a given time step.

Regarding the first conclusion, we see that for $\alpha = 1$ the turning point occurs at $t = 8$ whereas for $\alpha = 0$ the turning point occurs at $t = 2$. Taking into account all intermediate values of α reveals that the turning point increases monotonically with assortativity in mating. The second conclusion follows immediately from the first: for those values of α that correspond to a later onset of the Kuznets Curve we see that higher levels of inequality are obtained. Specifically, we see that for $\alpha = 1$ peak inequality nearly reaches 0.70 whereas for $\alpha = 0$ peak inequality remains relatively low at approximately 0.25. Analogous to the first conclusion, it is then evident that peak inequality increases monotonically in the assortativity of mating. With respect to the third conclusion, it is evident that for greater values of α poverty appears more persistent. That is, for $\alpha = 1$ a non-negligible quantity of agents remain impoverished until $t = 23$ whereas for $\alpha = 0$ poverty is nearly completely eradicated by $t = 2$. Thus, in examining all intermediate values of α we see that the third conclusion echoes that of the first and second: we see yet another monotonic relationship as the duration of poverty is increasing in α. Regarding intuition, first consider the case where $\alpha = 1$. In this scenario, marriage induces no social mobility and redistribution can only occur with taxation under democracy. For a given parameterization, the revolution constraint dictates that the franchise will be extended when per capita wealth (i.e. H/H^p) is sufficiently greater than the wealth of the wealthiest poor agent. The model outcomes for $\alpha = 1$ thus depend primarily on the growth rate of the economy relative to that of the wealthiest poor agent. When $\alpha = 0$, social mobility manifests through interclass marriage, which exerts influence on the transition to democracy. From Fig. 1, we see that this case is characterized by an immediate reduction in the number of poor agents, which exerts upward pressure on per capita wealth through both decreasing H^p and increasing H. This phenomenon leads to a more rapid transition to democracy and thus the earlier onset of the Kuznets curve. For $0 < \alpha < 1$ we observe that the higher α, the longer the Kuznets process lasts.

7 Conclusion

In this paper we present two major contributions to the debate around the theory of the Kuznets Curve. The first is of theoretical interest. Although we have only considered our baseline parameterization, our simulations show that social institutions (namely, interclass marriage) appear to play an important role in the timing or onset of the Kuznets Curve. Such social institutions may thus represent a crucial source of omitted variable bias in the existing empirical and theoretical work on the Kuznets Curve and future research may benefit from its consideration. We were also able to provide insights about the dynamics of the Kuznets relationship. Our model illustrates the possible variation in timing of the Kuznets Curve and is more explicit about the time span in which the relationship operates, namely up to 24 generations. If the model is calibrated to empirical data, such a consideration can help derive the time horizon to be considered in empirical studies and can thus help to bring more clarity to the empirical assessment of the hypothesis.

The second contribution is of a methodological kind. Our model takes a purely analytical model as a starting point, replicates the behavior of this model in an agent-based simulation, and then relaxes some of the assumptions required to keep the original model tractable. So it allows the consideration of the dynamics explicitly. While there are only a few models of this kind (e.g. [4] and [11] for the standard general equilibrium model), our model illustrates the usefulness of this approach. The rigor of the previous analytical model is sustained, but in our approach we are able to go beyond its application and assess its sensitivity to the rigid assumptions previously made. Our agent-based model will allow for further exploration of the factors affecting the timing and onset of the Kuznets Curve, and can also be applied to understand economic inequality in different countries with different levels of social mobility.

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Transitioning Saudi Arabia for an expat driven economy, to and endogenous wealth creating society

Davoud Taghawi-Nejad[1]

Abstract Like the other oil-rich GCC countries Saudi Arabia relies on an expat workforce and pays with its oil-wealth to support this. But with falling oil prices and depleting oil fields, Saudi Arabia risks to run out of oil in the foreseeable future. Saudi Arabia has to transition to a society that creates its own wealth. This change needs to be created by a training human capital and developing industry sectors that can create wealth with the Saudi population.

We are developing an Agent-Based decision support system, that enables Saudi policy makers to explore different policy options: such as hiring quotas for Saudis as well as taxation of expat labor and minimum wages for expats or expats and Saudis alike.

Saudi Arabia is at a cross road. As the oil prices decrease, because of unconventional oil extraction, and on the other hand Saudi Arabia's oil fields become more expensive to drill, Saudi Arabia might be unable to support its large expat workforce. To secure Saudi Arabia's standard of living, it must start creating wealth with it's own workforce.

In order to capture the ability to create wealth we need to model the particularities of the Saudi Arabian labor market. The Saudi Arabian labor market is special as it is characterized by a very low participation of Saudis in the private sector labor market, about 680.000 out of 20 million inhabitants. The low participation rate is caused by firms preferring not to hire Saudis as well as by Saudis choosing not to work in the private sector.

Foreign workers might be more attractive to firms, because they have lower bargaining power. Out of the ca. 7 million expatriates 6.5 are low and medium skilled and come from very poor countries. [1] Therefore they are willing to work for very low wages and put very much effort in their work. What is more Expatriate workers come on sponsored visas. That means that under the threat of deportation they can only work for their sponsoring firm. Thus once they are in Saudi Arabia their employer can act as a quasi monopolist, this additional factor forces them to put much more effort than Saudis and accept lower wages. What is more there are disincentives for Saudis to work: temporary unemployment assistance and high public sector employment. Job security and a lax environment make the government is still the preferred option.[1].

Saudi Arabia implemented the Nitaqat quota system to increase the participation of Saudis in the private labor market. Nitaqat establishes minimum quotas for Saudis in each sector. The quotas vary with firm size. Firms that employ a lower percentage of Saudis do not get new visas issued for expatriate workers.

The Nitaqat quota system poses a particular challenge on the model. Firms can fulfill the quota by firing expatriates or hiring Saudis. When firms choose to expand they can hire a combination of Saudis and expatriates. The combination of foreign and Saudi workers now become subject to strategic hiring. In order to captures this strategic behavior in the model, firms hire a combination of foreigners workers and Saudis, on the basis of a discrete optimization algorithm. It has even been observed that firms hire unproductive Saudis, who might even not be expected to show up to work, in order to hire productive expatriates. [2] While theoretically the model can capture an offer of pretending to work for a wage. It is currently not employed as we are lacking the data, to calibrate the model accordingly.

[1] This project was undertaken as part of the Labor Market Decision Support System at the Center for Complex Engineering Systems at MIT and the King Abdulaziz City for Science and Technology. I thank Jennifer Peck, whose empirical work was the basis of this policy simulator and for her support and discussions. As well as the CCES and the LMDSS team for their work.

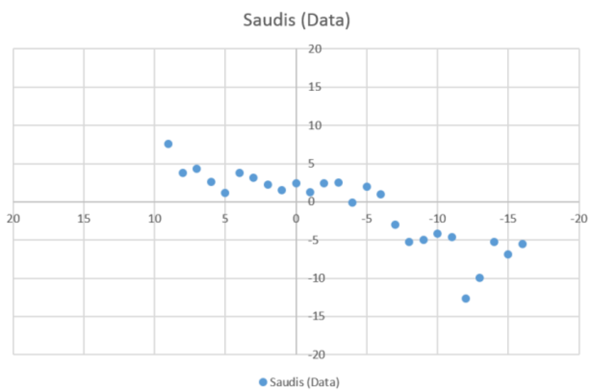
Building up human capital has two components, education and leaning on the job. In this paper we concentrate on the second. We will explore different policy options that could increase the Saudi participation in the Labor Market by sector. In this conference paper we will concentrate on the manufacturing sector.

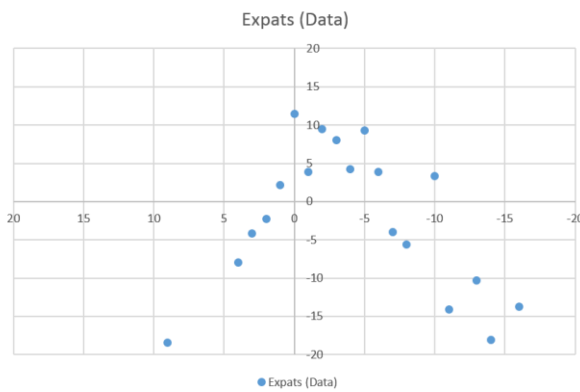
Empirical Findings

Between november 2011 and february 2012 Saudi Arabia faced in a comprehensive quota system - Nitaqat - for firms in all sectors. Jennifer Peck in her paper: “Can Hiring Quotas Work? The Effect of the Nitaqat Program on the Saudi Private Sector”,[8] finds that the during the program Saudi employment by increased by 96.000, but only 73.000 can be attributed to the program the rest would have been created also without it. Further Nitaqat had significant negative effects on employment. Overall the private sector employment decreased by 418,000 workers.

One particular phenomenon observed is that of poaching. Firms that were not in compliance with the Sauditization quota, hired away Saudis from compliant firms. While the quota could be met by both decreasing the number of expatriates as well as increasing the number of Saudis, firms largely increased Saudi employment. At this point, we can not distinguish, between real and fake employment. But research on this topic is underway.

As an example in this paper we will show and simulate the manufacturing sector.





In the two graphs above, every point on the y-axis is a bin of firms that need to hire a certain number of Saudis to comply with Nitaqat, if it would be in place in July 2011. Firms in the bin at 5 on the y-axis, for example need to hire 5 Saudis to comply with the quotas. Firms with negative y value, could lose Saudis and still be compliant. The x-axis on the first graph, shows the average number of Saudis firms with a particular compliance level actually hired by october 2012. The second graph shows the number of expatriates the firms lost in this interval. The y-axis is restricted to values, we can reproduce with a 1 to 100 scale model of the manufacturing sector.

We can observe that firms increase Saudi employment rather than decrease expatriate employment. On the first graph we see that non compliant firms on the left hire Saudis, but overly compliant firms, lose Saudis. The phenomen of hiring away Saudis from compliant firms is called poaching. First described in Jennifer Peck’s paper. The Expatriate graph has an inverse U shaped response, strongly non compliant forms are forced to decrease the number of expatriates, but also some over compliant firms decrease the number of expatriates.

Time-series data will be discussed along with the modeling results.

Model

Accessing the reactions of the Saudi labor market on policies requires a model that captures the behavioral responses of workers as well as interaction of workers and strategically behaving firms. Modeling the behavioral responses of workers would be meaningless without capturing the heterogeneity between different types of workers in the Saudi labor market. To address all this issues the model has five components: workers, firms and two newspapers for Saudis and Expats and final good markets.

Workers are either Saudi or expatriate, they have a corresponding reservation wage derived from empirical data. Unemployed workers apply for a job and when hired provide labor. Saudi worker can also engage in on-the-job search.

Firms use labor as their only source of production. They set prices, wages and a target production capacity according to their observed demand and labor supply. Firms hire new Staff, when the current production capacity is below the target production capacity and the individual hire is profitable. If minimum wages or quotas are in place firms comply with them. When quotas are in place firms hire Saudis even when the individual hire is unprofitable, but allows the firm to hire productive expats. Firms than quote their price and produce the demanded amount of goods, if their production capacity suffices. Profits are distributed.

There are 52 sectors, each company produces for one sector. The demand in each sector is derived calibrated, based on the Saudi supply and use tables.

Overview:
Firms and Workers are individual software agents. Every round, which represents a day, they go through a 7 step process:

1. Firms advertise for Saudi and expatriate labor, quoting their respective wages in a newspaper.
2. Workers apply, when their reservation wage is met.
3. Firms hire / fire (according to visa-status and tenure).
4. Firms quote a price and observe the demand. If their production suffices they sell the quantity demanded at the quoted price.
5. Firms pay wages and distribute profits
6. Firms adjust their prices and wages for new hires.
7. Bankrupt firms get removed

Modeling of the Workers
The workers in this model have individual characteristics: Visa status; saudi, non-saudi a reservation wage and an individual productivity. These attributes are derived from data from the Ministry of Labor and from the Social Insurance Entity GOSI. In a future extension of this model, the individual characteristics of workers will be modeled in more detail. The reservation wage will then be a function of the workers characteristics.

Workers in this model are not consumers. The final goods market is fixed and its parameters are part of the calibration. In the context of Saudi Arabia that is much less of an restriction, than it would be for other countries, because the demand is primarily driven by oil-financed government expenditures and therefore to a large degree independent from the workers income. What is more the large share of remittances in the labor market, that have a low share in the current account balance also decouple the income from sector demand.

The two secondary characteristics that impact the model directly are their reservation wage and and their productivity. Reservation wage and productivity are sector specific. When workers are generated these characteristics can be conditional to primary characteristics such as age, education, saudi/non-saudi, family income… Currently the distribution and mean is unconditionally calibrated.

A worker, is either employed or unemployed. Saudis and Expats apply at one firm per day, if they find a firm that offers a wage that meets their reservation wage. Saudis also engage into on the job search. Their search intensity is a parameter, which we use for calibration.

Firms
A firm produces a representative good of one of the 52 sectors. Goods in each sector are differentiated. Firms use labor as their only source of production using a constant economics of scale production function.

Price, and production target setting. Firms planned production and prices are set adaptively. Planned production is adaptively increased, when there is excess demand, with regard to the planning - decreased in the opposite case.

Prices are modified, whenever the firm doesn't find workers to meet its production target. (which feeds back to the observed demand). The price setting mechanism in the final goods market is inspired by [7].

A firm's production is:

$$x_{i,t} = \sum_{j} a_{i,j}$$

where a is the productivity of worker j in firm i. $\underline{a}_i$is the average workers productivity in firm i. A firm's production target (planned production) is $pp_{i,t}$.

When a firm's actual production exceeds their planned production, by more than the productivity of the average worker in that firm, the firm decrease it's price. But never below it's marginal costs. If the production falls short by more than the average productivity of a worker, the price is increased. The increase/decrease of the price is a uniform random percentage. The mean is a sector parameter.

$$x_{i,t-1} > pp_{i,t-1} + \underline{a}_{i,t} \qquad p_{i,t} = max(p_{i,t-1}(1-\sigma_\eta), \mu \underline{w_i}/\underline{a}_i)$$

$$x_{i,t-1} < pp_{i,t-1} - \underline{a}_{i,t} \qquad p_{i,t} = p_{i,t-1}(1+\sigma_\eta)$$

When observed demand exceeds/falls short of planned production, planned production is increased/decreased. Planned production falls never below the actual demand and is unaltered when it is close to actual production.

$$d_{i,t-1} < pp_{i,t-1} - \underline{a}_{i,t} \qquad pp_t = max(d_{t-i}, pp_{t-1} * (1-\sigma_\tau))$$

$$d_{i,t-1} > pp_{i,t-1} \qquad pp_t = min(d_{t-i}, pp_{t-1} * (1+\sigma_\tau))$$

Wage setting. The wage a firm offers to new workers is determined separately for Saudis and Expatriates. The respective advertised wage is the firm's average wage in the respective category plus a random gaussian variable. The standard deviation is a model parameter.

$w^{o,s}{}_{i,t+1} = \underline{w}^s{}_{i,t}(1+\sigma_\phi)$ and $w^{o,e}{}_{i,t+1} = \underline{w}^e{}_{i,t}(1+\sigma_\phi)$

While an wage offer is a random variation, the wages actually accepted by the worker and the firm, by hiring the worker at this wage is subjected to market forces.

Firms adjust wages, if minimum wages are required by law and add taxes[2] if applicable.

Firms hire and fire. When a firm has a production target above the current production they hire new workers. All hiring decisions are profit maximizing given the current prices and assuming that the current planned production is the maximum the firm can sell. Firms can observe workers productivity. A firm keeps all workers which can not be currently laid-off. From the stack of workers with expired contracts or visas and new applicants a firm employees the most profitable subset, that is in accordance with the quotas and other laws.[3] The profitability is calculated assuming the current prices and that only the planned production can be sold. Firms can not hire more workers than it can pay from their net worth. Employees that are not kept are laid-off.

When the planned production is below the current production workers are laid-off, if its possible and profitable to do so.

[2] Currently Saudi has no taxes on labor
[3] It is also possible to model partial compliance.

Firms can only fire Saudis in a 90 day period and at contract end. After 3 years Saudis receive tenure and can not be fired. We assume 1 year contracts before this date. Expatriate labor can be fired at the visa expiration: one year. Firms can not renew visas for expatriates if a quota is binding.

Selling, paying wages and distributing profits. Firms quote the price to the (representative agent) final good market, which it turn determines the demand $x_{i,j}$ for their good. Firms sell the good and receive their revenue$p_i x_i$. Workers are paid their wages. If a company's profits are lower than a certain percentage % of their net worth profits are distributed.

Bankruptcy. Bankrupt firms are removed from the simulation.

Final Goods Markets

There are 52 sectors, with an endogenous number of firms in each sector. The firms create a differentiated good. As this model is interested in the labor market, we use a standard representative agent framework to model the final goods markets. The demand for each sector is represented by a Cobb-Douglas utility function, where the demand an individual firm encounters is determined by a CES utility function, to represent diversified products or geographical diversity of the firms. The final good markets are calibrated to the input-output tables and are represented by a Dixit-Stiglitz type monopolistic competition[3]. $u = U(V_1(x_1`, x_2, \dots, x_n), V_2(.), \dots, V_n(.))$where U(.) is Cobb-Douglas and V(.) is a Constant Elasticity of Substitution function. This leads to the following demand equations

$$x_{i,j} = \frac{\alpha_i I}{q_i}\left[\frac{q_i}{p_j}\right]^{1/(1-l)} \text{ where } q_{i,j} = \sum_j^n \quad p^{l\backslash(l-1)}$$

where i is the index of the firm and j the sector. I is a modeling parameter.

For the single sector simulation exposed in the remainder of this paper, we will only use the inner CES function. The two parameters to calibrate it are love of variety and the share of income spend in this sector.

Calibration

Strategy

We calibrate the model using a kriging model:

The agent-based model is run with different parameters. The parameters are chosen employing a latin hypercube sample technique, to insure optimal efficiency. Runs are repeated with different random seeds. The outcomes of the simulation are transformed with a weighted sum of squares to reproduce certain stylized facts. The correspondence between the parameters and the weighted sum of squares is employed to build a kriging model. The parameter with the lowest sum of weighted square is our best candidate parameterization (BCP). A kriging model employs a gaussian process, to build a meta model $f(x_1, x_2, \dots, x_n) = ss$. The kriging model asymptotically produces the same results as the agent-based model, but its several hundred times faster. We use the sweep the kriging model to find a small number of candidates for a parameterisation that reproduces the stylized facts best. In other words we run the simulation for every every point on a multi-dimensional lattice, that spans all parameters. We double check with the real model that this candidates are indeed better than the best candidate parameterization (BCP). If we find a new best candidate we narrow down our search space and make this candidate our new center of the search. If no better new candidate is found, but the best n candidates did correctly predict the agent-based model's weighted sum of squares, we also narrow down the search space. After this, we run the agent-based model again, restricting the parameters employed in the latin hypercube to the smaller search space. And the process continues from the beginsig.

Calibration Criteria

The simulation is a scale model of reality, we simulate for example one firm and one worker for every 100 firms or workers in the economy.

We minimize sum of squares of a set of stylized facts at two points of time, to correspond to our dataset:

- number of expatriates employed in each sector.
- number of Saudis employed in each sector.
- output in this sector
- average Saudi wages in each sector
- average expatriate wages in each sector

The parameters we systematically variate using a latin hypercube sampling technique are:

- love for variety in the demand function for a single market
- the number of expatriates that are in the labor pool for each market
- productivity mean and variance of expats (later, that should be a conditional mean and variance)
- productivity mean and variance of saudis
- reapplication probability
- mean and variance of the reservation wage of expats
- mean and variance of the reservation wage of Saudis
- sector spending

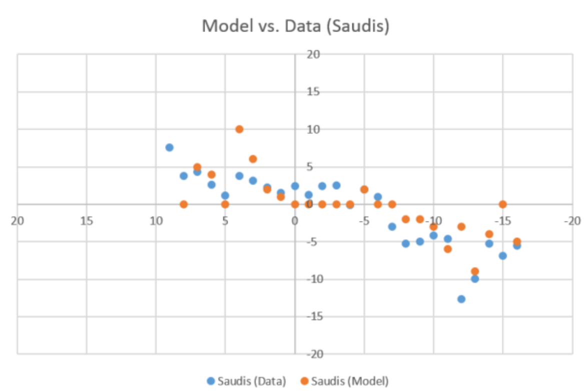
On the other hand, the parameters we obtain from our data and the policies are

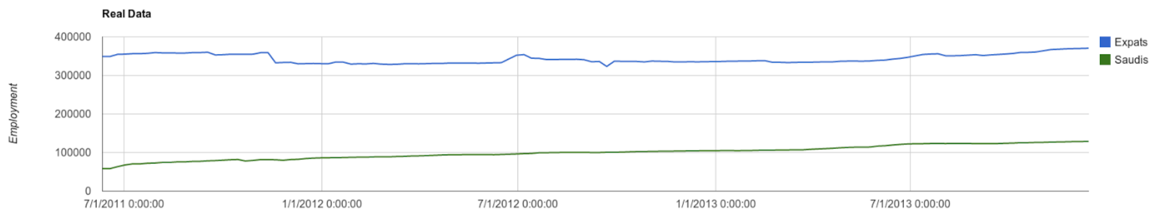
- number of saudis in the labor pool
- the number of firms
- Initial policies
    - expat minimum wage
    - expat tax per head
    - expat tax percentage
    - saudi minimum wage
    - saudi tax per head
    - saudi tax percentage
    - sauditization percentage
    - visa length

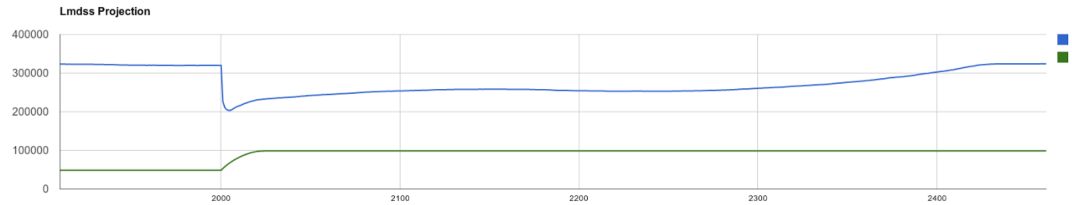
Validity check

The simulation needs to reproduce the change in the stylized facts for at least one policy change. Where the model has not been calibrated, using data after the day of the policy change.

Below we show the the, number of Saudis hired for a particular compliance level and in the second graph the number of expatriates lost accordingly. We see that the model reproduces observed reality in the manufacturing sector.







The timeline of the real data and the simulation, show that our simulation captures the essential dynamics of the policy change, although our levels, are not yet completely correct. Expectedly the model exhibits less fluctuations. And while we can observe preparatory hiring of Saudis in the real date, the inability of thinking about the future makes the software agents incapable if this behavior.

Policy Simulation

There is a large debate, whether a quota system is the best response to the low share of Saudis in the private labor market. Instead of a quota system we introduce a mandatory minimum wage for expatriates of 1000 riyals every month. We create an as if scenario pretending, the minimum wage would have been introduced instead of a quota system.

We can see that even with myopic agents, the transition is smoother and the effect is sustained for a longer time.

Conclusion

Employing Agent-Based Modeling and Kriging to calibrate the model, we created a model of the manufacturing sector of Saudi Arabia. Other sectors will follow. We are able to reproduce a policy intervention: Nitaqat. The effect of it's quotas is captured in the model. Both in the created time-series as well as in a closer inspection of cross-sectional data on the firms' response sorted by compliance level. The model can be used to explore a variety of alternative histories simulating alternative policies, such as expatriate taxes and minimum wages, for expats or for expats and Saudis. In the same manner future policies can be tested, before they are implemented.

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Analysis of Market Signaling with Mutual Learning Agent-Based Model

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Abstract. When there is asymmetrical information between buyers and sellers, goods in market often appear unstable in quality. Akerlof explained, using a game theoretic model, that as the price of the goods falls, the quality will fall in the automobile market. This problem is generally called a lemon market problem. The signaling of the buyers is typical behavior to be seen in such asymmetrical information market. So far the lemon market problem have been analyzed mainly in game theory by considering equilibrium under the rationality assumption on decision makers.

This paper supposes the situation of the heterogeneous market participants in the market where there is asymmetrical information among buyers with a seller. Then this paper expresses such situation using an agent-based model in which agents mutually learn other agents' signals. First this paper regenerates the lemon market situation, then observes the market dynamics where the equilibria move when signaling is introduced, and analyses the effectiveness of the signaling by performing simulation.

Keywords: lemon market, signaling, agent-based model, Vickrey bid method

1 INTRODUCTION

Akerlof [1] showed that it can be observed in a market that goods are unstable in quality. As an example, using a game theoretic model of the automobiles market in which typically the individuals in this market buy a new or used car without knowing whether the car they buy will be good or bad (which is known as "lemon" in America), he explained that under asymmetrical information between buyers and sellers, in equilibrium the supply of the cars must equal the demand for the given average quality, and as the price falls, the quality will fall.

This kind of problem on quality and uncertainty is generally called "A lemon market problem" where there is asymmetrical information between buyers and sellers. Because it is difficult for a seller to show the accurate quality of the product to a buyer in the lemon market, even if a product is defective, the buyer can show only an allowable purchase price, and the seller will sell the product in the prices that a buyer shows. The seller cannot sell a product to become in the red by selling it at the price that a buyer shows. As a result, the market is full only with defective products.

adfa, p. 1, 2011.

The signaling is a phenomenon to be seen in the market where there is asymmetrical information. The signaling information is originally unrelated to the quality of the product directly. However, cost to show signaling information is related to quality closely. Therefore a buyer should consider the signaling information to make a good deal.

The signaling information has been shown as useful even in a real market, for example, in the labor market. For example, education in the job market can be modeled as a signal and analyzed its equilibria in the model [7]. It is shown, for example, even if higher education does not substantially contribute to the ability improvement of the person at all, that it is fair that a company employs the person who received higher education positively. In other words, from the viewpoint of the company as an employer, the information "that received higher education," which should be not necessarily related to the ability of the person at all, takes the role of the "signal." This means that any signal is not necessarily related to the quality, e.g. higher education. The study on signaling has been carried out mainly in a framework of game theory in which equilibrium analysis is used for explanation under the rationality assumption on decision makers. However, the conventional game theory cannot express the way on how the action of each player changes as the equilibrium moves even if the movement of the equilibrium can be expressed in game theory. A typical example is a change of the actions in the markets which a large number of heterogeneous bounded rational players trade all at once based on experience.

This paper expresses such situation using an agent-based model in which heterogeneity is naturally expressed. This paper first regenerates a lemon market situation in asymmetrical market without any signaling. Then we observe the behavior of the market under the situation of the equilibrium movement when signaling is introduced into market and analyzes how effective the "strategic" signaling is by performing simulation. These results can be interpreted from the viewpoints of "mutual learning" of agents.

2 Approach

The model that can handle the dynamic change of the system and the learning of the market participants is necessary to achieve the purpose of this study. To that end, the framework of conventional game theory is insufficient to describe the dynamic change of players actions on issue of lemon market. At first, in the market where signaling can be produced for each of the buyer and seller, we model their learning and decision making and formulate a simulation model for generating behavior of the whole market from their micro interactions. Then, the values of the parameters are determined to reproduce the market behavior where signaling becomes effective. Finally, under the calibrated parameters, the signal considered as a market strategy is provided to the seller. This paper analyses the difference in effect by a timing to carry out the strategy.

3 Model

Figure 1 shows the summary of the model used in this study. By this model, the mutual learning to the signal of the buyer and seller can be realized using a simple algorithm described in the following sessions.

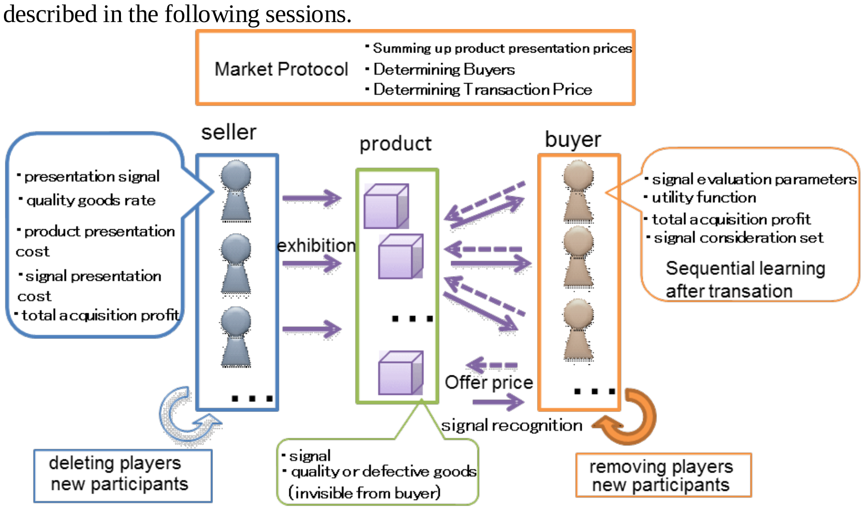

Fig. 1. Outline of Model

3.1 Market Model

In the model of this paper, a seller first offers a product to the market. The product has a signal with N bits, each of which has the value of either 0 or 1. A buyer evaluates the product based on the signal and shows his or her valuation to the market. The valuations for all buyers are added up and are handled according to an auction form shown below, and a buyer is selected to make a deal. The seller stochastically provides a quality goods according to his or her quality goods rate which he or she is assigned as a decision parameter. Then the buyer who is his or her trading partner gets a utility from the bought product and learns about the signal afterwards by the given learning algorithm.

3.1.1 Auction Form

In this paper, Vickrey bid method is basically applied as a protocol of the auction. In this method, when the amount of products presented in the auction reaches N units, which is given as an experimental parameter, buyers show their valuations for the products to the market, and the N-1th rank priced buyer among the top N rank buyers of the high-priced adducers trades with the seller. Then the product is sold to the N-1th rank buyer at the price presented by him. This strategy by this method is well known as the most suitable for the buyer (without collusion), since it just shows the valuation of the product and can make agent decision quite simple. For example, eBay, which is one of the most popular auction site, uses actually the method slightly different from the Vickrey bid method: i.e. the second price that should be considered to be a secret is open to the public. This paper adopted this protocol for ease of the mathematical interpretation and the simplicity of the model.

3.1.2 Volume of Transaction per Auction

The volume of transaction per auction is assumed commonly set to each seller and does not change during simulation.

3.2 Seller Agent

Each seller agent has two types of signals: to show and not to show. The type of the signal is assigned to each agent at the step of agent generation. Each agent also has a quality goods rate as a parameter that characterizes the agent heterogeneity. In the trade, the seller shows his or her own presentation signal and decides whether a product to provide is a quality goods or a defective article according to the assigned quality goods rate. As the result of the trade, the seller gets the gain subtracting product offer cost and the signal presentation cost from the sales. The agents who had low gain for an experimentally fixed period are deleted at a constant ratio, and alternatively other new agents are regenerated. The sellers agent who do not have any merit of the market participation is in this way excluded from the market.

(1) Quality Goods Rate

Seller agent i has quality goods rate $r_i \in [0,1]$ to express the probability that a product to offer is quality goods.

(2) Presentation Signal

Seller agent i decides by binary parameter $Signal_{in} \in \{0,1\}$ (the number of $n=1,2, \ldots ,N$(= signals))that he or she holds a signal to show. Agent i shows signal n if $Signal_{in} = 1$ and does not show otherwise.

(3) Product Offer Cost and Signal Cost

Seller agent i needs offer cost (*ProductCost*) proportional to a quality goods rate for making a product offer. $ProductCost_i = a \times r_i$ (a: constant parameter). In addition, signal presentation cost (*SumSignalCost*) showing a signal is defined by the following expression: $SumSignalCost_i = \sum n(Signal_{in} \times SignalCost_n)$ The value of $SignalCost_n$ is described in 4.1.

(4) Sales by the Trade

Seller i gets sales $Sales_{it}$ in period t by trade as follows: $Sales_{it}$= *(the number of the trade per auction)* × *(sale price)*. The sale price is decided according to the given market protocol.

(5) Total Acquisition Rate

After trade, seller i gets the gain subtracting product offer cost and signal cost from the sales for the profit and adds it to his or her total acquisition gain.

(6) Periodical Deletion

After every periodical deletion period defined as an experimental parameter, the total acquisition gain of seller agents is added up, and the agents of lower *m* % are excluded from the market. The same number of agents as the excluded agents are newly generated under the same condition as in the initial generation and participate in the market. This process means that agents behaving in an irrational way are excluded, and sellers learn the characteristic of the signal. In addition, at this time, the total acquisition profit of all agents is set to 0 (zero)

3.3 Buyer Agent

The buyer agent evaluates the signal of the product using a signal evaluation parameter and decides an offer price. When the trade is established, the agent pays a transaction price and gets a utility from the product. An agent learns whenever he or she makes a deal and updates a signal evaluation parameter.

The buyer agent has a signal to consider or one not to consider. This process is executed when agents are generated in the simulation step and represents the heterogeneity of the buyer agents.

In addition, like the seller agent, the agents who get low gains of the total acquisition are deleted in a constant ratio for a certain period of time and next generation agents are regenerated. This process can be seen as the replacement of players in the market.

Excluded from the market are the buyer agents who do not have any merit of the market participation because they evaluates a signal excessively and shows a large amount of price, or evaluates the signal much lower than the proper value.

(1) Acquisition Utility and Total Acquisition Benefit From Trade

Whenever buyer agent j makes a deal, he or she gains the profit $Profit_j$ subtracting the amount of payment C_j from utility U_k of product k. In addition, total acquisition profit $SumProfit_j$ is updated as follows:

$Profit_j = U_k - C_j$

$SumProfit_j \leftarrow SumProfit_j + Profit_j.$

(2) Signal Consideration

Each buyer agent has a consideration signal set and a non-consideration signal set and classifies existing signals s_n ($n = 0,1, \ldots ,N$) in these two sets.

(3) Signal Evaluation Parameter

To evaluate the signal of the seller, each buyer agent holds N parameters *SignalEvalParam* of the same number with the signals.

$SignalEvalParam_{jn} \in [0,1](n = 0,1, \ldots ,N)$

(4) Determination of Offer Price

For signal s_n included in the consideration signal set,

$\Sigma(s_n \times SignalEvalParam_{in})$/ (number of elements of the consideration set) is calculated. The presentation price of buyer agent *j* is given as the value multiplied the above value by the standard value 100 of the buying price. This value is given by averaging expected quality goods probability in the consideration signals.

(5) Sequential Learning

When trade is completed, buyer agent *i* memorizes a shown signal whether a product traded in his or her purchasing experience area was quality goods. In a past purchasing history e.g.100 periods, the ratio of the good quality products is calculated, and an evaluation value of signal s_n is updated as new $SignalEvalParam_{in}$. The evaluation values of all signals are updated similarly.

(6) Periodical Deletion

In every periodical deletion period, the total acquisition profits of the buyer agents are added up, and agents of lower *p* % are excluded from the market. Agents of the same number of the excluded agents are regenerated under the same condition as the initial generation and participate in the market. The total acquisition profit of all agents is set to 0 (zero).

(7) Quality Goods Utility and Defective Article Effect

The buyer agent has a utility (*goodProductUtility*) to get from a product of the quality goods and a utility (*badProductUtility*) to get from a defective article. These utilities are uniformly given to all buyer agents. Utility U_k of product *k* is U_k= *badProductUtility* if *k* is a defective article and (U_k= *goodProductUtility* if *k* is quality goods.

3.4 Initial Generation

3.4.1 Buyer Agent

All signal evaluation parameters *SignalEvalParam* are initially set to 1. The total acquisition gain is initially set to zero. The buyer agent determines whether he or she considers a signal in probability 0.5 about each signal.

3.4.2 Seller Agent

The total acquisition gain is initially set to zero. The quality goods rate is determined randomly from the uniform distribution on [0,1]. The seller agent determines whether he or she presents a signal in probability 0.5 about each signal.

3.5 Simulation Flow

The simulation is conducted according to the simulation flow shown in figure 2. The simulation end is 1 trial from this simulation start.

4 SIMULATION EXPERIMENT

4.1 Simulation Scenario

A strategic signal (*signalα*) is analyzed as a simulation scenario. The presentation cost (*SignalCostα*) of this signal is given continuously according to the next expression by quality goods rate *r* of the seller: $SignalCost\alpha = b \times (1-r)$ (*b*: fixed number).

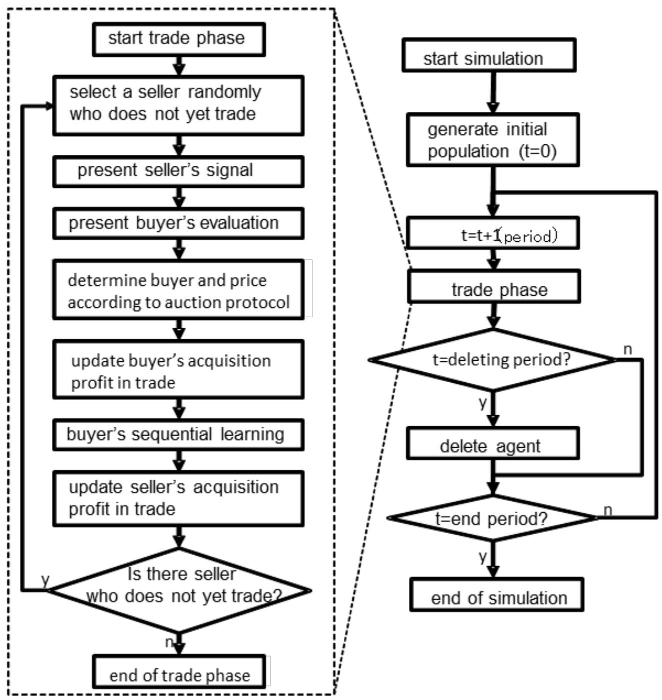

Fig.2. Simulation flow

Because the experiments focused especially on changing strategic practice timings, all the strategy signal presentation parameters of the seller agents were initially set to zero so as not to be able to present strategy signals before the period determined by the experiment scenario for agents.

4.2 Parameter Setting

There are tons of parameter sets possibly taken in the model. Our principle of selecting parameters is to regenerate the stylized fact of a lemon market in the current situation (figure 3). Hence after lots of preliminary experiments were conducted, the parameters of the model that made signaling effective were finally calibrated as follows. This suggests that other sets of parameters do not always regenerate the target problem situation, i.e. a lemon market.

Table 1. Calibrated Parameters

parameter	value
The number of signals	3(including strategic signal)
Production cost coefficient	5
The number of the trades per auction	40
goodProductUtility	200
badProductUtility	0
SignalCostα coefficient *b*	120
The number of sellers	100
The number of buyers	100
Periodical exclusion periods	25
Seller exclusion rate	5%
Buyer exclusion rate	1%

A mean quality goods rate of the whole seller agent was calculated in every term. The transition of the calculated mean quality goods rate from 0 quarters to the 96000th were added up for 100 trials. We basically describe the simulation results in the graphs that show those transitions in the subsequent figures. The simulation result of all the trials is drawn on ONE graph that distinguishes the trials by indicating different colors.

Simulation was conducted using the parameter mentioned above. At first we need to confirm if the market actually behaves like lemon market when no strategic signal is used. If the situation of lemon market is regenerated, we can see from the viewpoint of internal validity criteria that the model is valid. Figure 3 describes a simulation result that shows the regeneration of lemon market situation in which a mean quality goods rate falls to around 0.1-0.2.

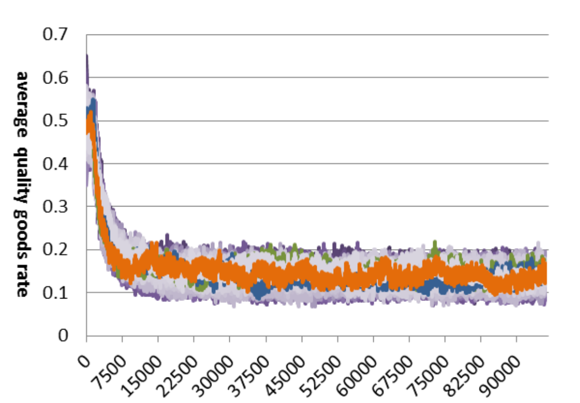

Fig. 3. Average Quality Goods Transition (no strategy signal, 100 trials) : The simulation without any strategic signal regenerates the lemon market situation.

When we applied a strategic signal available from the 0th period, we observed the case that the situation was improved by making a strategic signal (figure 4). In this case, the quality goods rate converged in 0.4-0.65 in many trials.

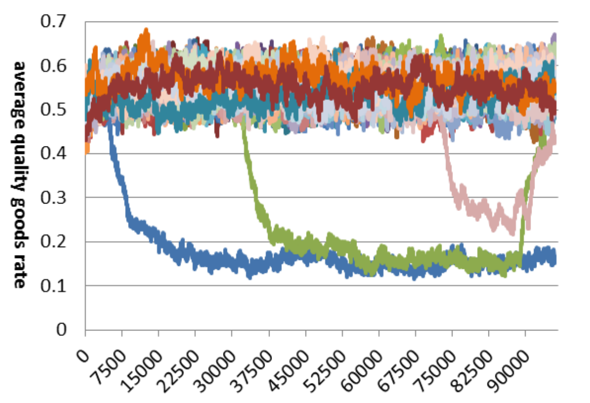

Fig. 4. Average Quality Goods Transition (strategy signal, 100 trials): When a strategic signal was applied, the lemon market situation was improved.

4.3 Results of Experiments Changing a Strategy Practice Timing

After the preliminary experiments described in 4.2, we conducted the experiment that delayed a timing to make a strategic signal up to the 1500th. The results were classified in three patterns:
Pattern 1: A quality goods rate in each trial is converging to around 0.1-0.2 (figure 5.).
Pattern 2: A quality goods rate is improved in the middle of a trial and converges to around 0.45-0.6 (figure 6).

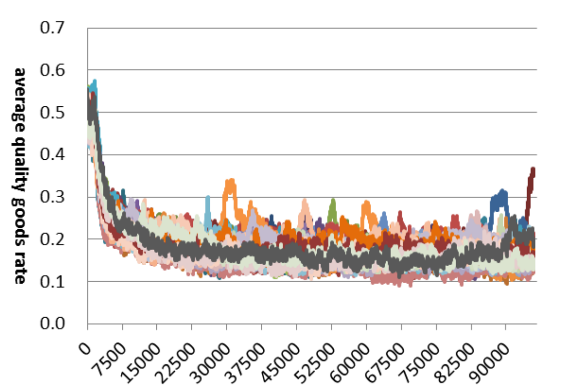

Fig. 5. Average Quality Goods Transition (delayed strategy signal, pattern 1)

Pattern 3: A quality goods rate is improved at a particular period, but falls after that period (figure 7).

During 100 trials, pattern 1 was observed in 65 trials, pattern 2 in 33 trials, and pattern 3 in 2 trials respectively. Figure 5, figure 6 and figure 7 show the quality goods rate transitions in each pattern respectively.

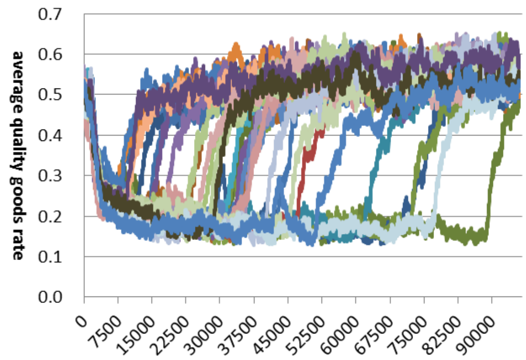

Fig. 6. Average Quality Goods Transition (delayed strategy signal, pattern 2)

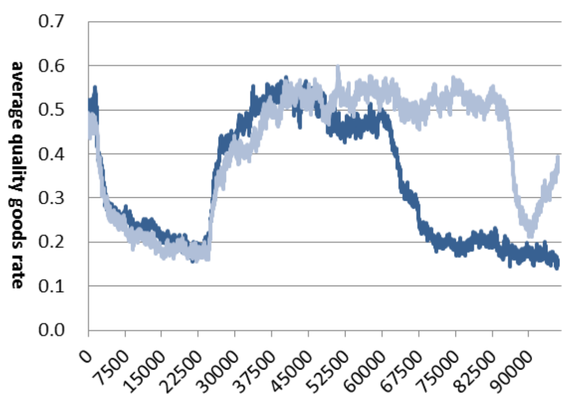

Fig. 7. Average Quality Goods Transition (delayed strategy signal, pattern 3)

5 DISCUSSION

We can see from figure 6 that while the convergence points of figure 6 look similar with the case of figure 4 in which strategic signals are used during the all periods, the timings and paths of the convergence strongly depended on trials. It can be partly implied from the model that the learning process of the signal evaluation by buyers randomly meets with the learning process of the presentation rate of signals by sellers. This convergence point is not always achieved because it reached this range. As seen in figure 4 and figure2, a quality goods rate may turn worse.

For example in the experiment of figure 4, the remarkable drop-off of the quality goods rate is seen only in 3 trials during 100 trials. This can be said to be smaller probability than in pattern 2 having appeared in 33 trials during 100 trials.

As for pattern 1, the convergence ranges can be observed in almost the same area as in figure 3 in which no strategic signals are applied during all the periods. It is suggested that the effect of the strategy signal may not appear during the limited period which has the potentiality which can improve a quality goods rate like in pattern 2.

Next we looked into the relationship between the market behavior and the learning of signals by analyzing individual actions. Picking up typical agents from the case of a lemon market situation and the case of the situation recovered from a lemon market situation, we analyzed how agents considered signals.

In the lemon market situation, as the quality goods rate falls, the consideration rate of signals also falls. This is partly because the agents considering signals can buy goods more than the agents not considering signals, who suffer from defective goods and get negative utility as a result of trading.

On the other hand, in the situation recovered from a lemon market, we focus on the strategic signal that as the quality goods rate becomes higher, the presentation cost of it becomes lower. Then it is observed that such strategic signal works quite effectively in raising the quality goods rate in the market. This behavior of the market mainly comes from the mutual learning of the agents. By the mutual learning of the agents, increasing the agents who consider highly the strategic signal and no other signals improves incentive for sellers to present the strategic signal to raise the quality goods rate.

6 CONCLUSION

In this paper, we supposed the situation that the heterogeneous market participants learning in the market where there was asymmetrical information among buyers with a seller. Then building the agent-based market model that can describe the lemon market, we analyzed how effectively and influentially the signaling strategies were applied by scenario analysis in simulation.

As a result, we saw that the behavior of the whole market greatly changed by a timing when the strategic signals were introduced in the learning situations. In addition, we identified typical three patterns as possible behavior when signals are introduced.

Finally we can give a comment from the management viewpoint. It might be important for a market manager to make possible the signal worth considering for buyers. Even if there are few sellers who present the strategic signal in the early stage trading, if the signal is actually effective for buyers, then the quality of goods should be improved in the market.

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Computing Methods &Algorithms

Application of Supercomputer Technologies in Agent - Based Models

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Abstract. This work contains a brief excursus on the application of supercomputer technologies in social sciences, first of all, – in part of the technical implementation of large-scale agent-based models. So, in this article we will consider the experience of scientists and practical experts in the launch of agent-based models on supercomputers, as well as on the example of an agent model developed by us of the social system in Russia we will analyze the stages and methods of effective projection of a computable core of a multi-agent system on the architecture of the acting supercomputer.

Keywords: agent-based models, parallel calculations, supercomputer technologies

1 Introduction

Computer modeling is the broadest, most interesting and intensely developing area of research and is in demand today in many spheres of human activity. The agent-based approach to modeling is universal and convenient for practical researchers and experts because of its benefits. These models allow modeling a system very close to reality. The emergence of agent-based models may be regarded as a result of the evolution of modeling methodology: a change from mono models (one model – one algorithm) to multi-models (one model – a set of independent algorithms). At the same time sets high requirements for computing resources. It's obvious, that for direct modeling of sufficiently long-term social processes in the country and the planet as a whole, significant computing capacities are necessary.

Supercomputers allow to enormously increase the number of agents and other quantitative characteristics (network nodes, the size of territory) of models, originally developed for use on ordinary desktop computers. For this reason, supercomputer modeling is a logical and desirable step for those simplified models, which have already passed practical approbation on conventional computers. Unfortunately, the specific architecture of modern computers does not guarantee that the software of a computer model will immediately work on a supercomputer. At least the paralleling of the computable core, and often its deep optimization is required, because otherwise the use of expensive supercomputer calculation will most likely will not pay off.

2 Experience of Some Scientists and Practical Experts

2.1 Well-known Examples of Launching Agent-Based Models on Supercomputers

In September of 2006 a project on the development of a large-scale ABM (agent-based model) of the European economy — EURACE, i.e. Europe ACE (Agent-based Computational Economics) was launched, with a very large number of autonomous agents, interacting within the socio - economic system (Deissenberg, van der Hoog, Herbert, 2008). Economists and programmers from eight research centers in Italy, France, Germany, Great Britain and Turkey are involved in the project, as well as an advisor from Columbia University, USA, -Nobel laureate Joseph Stiglitz.

According to the developers, virtually all existing ABMs either cover only a single industry or a relatively restricted geographical area and accordingly, small populations of agents, while the EURACE presents the entire European Union, so the scope and complexity of this model is unique, and its numerical computation requires the use of supercomputers as well as special software.

The information about 268 regions in 27 countries was used to fill the model with necessary data, including some geo-information maps.

In the model there are three types of agents: households (up to 10^7), enterprises (up to 10^5) and banks (up to 10^2). They all have a geographical reference, and are also linked to each other through social networks, business relationships, etc.

EURACE was implemented using a flexible scalable environment for simulating agent-based models - FLAME (Flexible Large-scale Agent Modeling Environment), developed by Simon Coakley and Mike Holcombe[1] initially to simulate the growth of cells under different conditions (Coakley, Smallwood, Holcombe, 2006). With the help of the developed model several experiments were conducted in order to study the labor market. Without going into detail about the obtained numerical results, we note that, according to the authors, the main conclusion of the research is that the macroeconomic measures of two regions with similar conditions (resources, economic development, etc.) during a long period (10 years and more) may vary significantly, due to an initial heterogeneity of the agents[2].

In ABM EpiSims, developed by researchers from the Virginia Institute of bioinformatics (Virginia Bioinformatics Institute), the movement of agents is studied as well as their contacts within an environment as close as possible to reality and containing roads, buildings and other infrastructure objects (Roberts, Simoni, Eubank, 2007). To develop this model a large array of data was necessary, including information about the health of individual people, their age, income, ethnicity, etc.

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[1] For more thorough information see www.flame.ac.uk

[2] More thorough information can be found on the website of the project: www.eurace.org.

The original goal of the research was to construct an ABM of high dimension (according to the number of agents) to be launched on the supercomputer, which could be used to study the spreading of diseases in society (Roberts, 2012). However, afterwards, in the course of work, another task was also being resolved, regarding the creation of specialized ABM++ software, which allows to carry out the development of ABM in the C++ language, and also contains functions, facilitating the allocation of the program code in use among the cluster nodes of the supercomputer. Apart from that, ABM++ provides for the possibility of dynamic redistribution of currents of calculations, as well as the synchronization of on-going events.

ABM++, the first version of which appeared in 2009, is the result of the modernization of the instrument, developed in 1990-2005 in the Los Alamos National Laboratory during the process of constructing large-scale ABMs (EpiSims, TRANSIMS, MobiCom).

Specialists of another research team from the same Bioinformatics Institute of Virginia created an instrument for the study of the particularities of the spreading of infectious diseases within various groups of society — EpiFast, among the assets of which is the scalability and high speed of performance. For example, the simulation of social activity of the population of Greater Los Angeles Area (agglomerations with a population of over 17 million people) with 900 million connections between people on a cluster with 96 dual- core processors POWER5 took less than five minutes. Such fairly high productivity is provided by the original mechanism of paralleling presented by the authors (Bisset, Chen, Feng et al., 2009).

Classic standard models of spread of epidemics were mostly based on the use of differential equations, however, this tool complicates the consideration of connections between separate agents and their numerous individual particularities. ABM allows to overcome such shortcomings. In 1996 Joshua Epstein and Robert Axtell published a description of one of the first ABMs, in which they reviewed the process of the spread of epidemics. (Epstein, Axtell, 1996). Agent models, which differ from each other in their reaction to the disease, which depends on the state of their immune system, are spread out over a particular territory. At that, in this model, agents, the number of which constitutes a mere few thousand, demonstrate fairly primitive behavior.

Later on, under the supervision of Joshua Epstein and Jon Parker at the Center on Social and Economic Dynamics at Brookings, one of the largest ABMs was constructed, which included data about the entire population of the US, that is around 300 million agents (Parker, 2007). This model has several advantages. First of all, it allows to predict the consequences of the spread of diseases of various types. Second of all, it focuses on the support of two environments for calculations: one environment consists of clusters with an installed 64-bit version of Linux, and the other of servers with quad-core processors and an installed Windows system (in this regard, Java was chosen as the language of the programming, although the developers did not indicate which particular version of Java they used). Third of all, the model is capable of supporting from a few hundred million to six billion agents.

The model in question (US National Model) includes 300 million agents, which move around the map of the country in accordance with the mobility plan of 4000×4000 dimensions, specified with the help of a gravity model. A simulation experiment was conducted on the US National Model, imitating the 300-day long process of spreading a disease, which is characterized by a 96-hour incubation period and a 48-hour infection period. In the course of the study, among other things, it was determined that the spreading of the disease was declining, after 65% of the infected got better and obtained immunity. This model has repeatedly been used by the specialists of the Johns Hopkins University, as well as by the US Department of National Security, for research, dedicated to the strategy of rapid response to various types of epidemics (Epstein, 2009).

In 2009 a second version of the US National Model was created, which included 6.5 billion agents, whose actions were specified taking into consideration the statistical data available. This version of the model was used to imitate the spreading of the A(H1N1/09) virus all over the planet (Parker, Epstein, 2011).

Previously, this kind of model was developed by the Los Alamos National Laboratory (USA), and the results of the work with this model were published on April 10, 2006 (Ambrosiano, 2006). One of the most powerful computers which existed at the time known by the name of "Pink", which consisted of two 1024 processors with a 2,4 GHz frequency and a 2 GB memory each was used for the technical realization of the model. This large-scale model, composed of 281 million agents was used to study scenarios of the spreading of various viruses, including the H5N1, taking into consideration several possible operational interventions such as vaccinations, closing of schools and introducing of quarantines in some territories.

2.2 RepastHPC – Environment of Designing Agent-Based Models for High-Performance Computing

Special attention should be paid to the software, developed for the projecting of the ABM with the subsequent launching on supercomputers, - Repast for High Performance Computing (RepastHPC). This product was implemented using the C++ language and the MPI – a program interface for the exchange of messages among processors, executing the task in parallel mode, as well as the library Boost, which expands the C++ (Collier, North, 2011).

A dynamic discrete-event scheduler which carries out program instructions with conservative algorithms of synchronization, which provide for the delay of processors so as to follow a certain order of their completion, was implemented within the framework of RepastHPC.

In RepastHPC agents are divided between processors and every processor is connected to an agent, which is *local* in relation to this processor. In its turn the agent is local to the processor completing the program code, which describes the behavior of this agent. In addition to that, copies of other – *non-local* – agents may be present in any processor, which allows agents of the entire model to interact with these copies. For example, suppose the user, in his model, which presupposes parallel calculations, a will use two processors – P1 and P2, each of which creates a certain number of agents and has its own scheduler of completion of program instructions. Agents, the behavior of which is calculated on the basis of processor P1, are local in relation to this processor, and only within the framework of this processor can the program code change their condition (the same applies for processor P2). Suppose processor P1 requests a copy of agent A2 from processor P2. Agent A2 is not local to the processor P1, and therefore the program code executed within the P1 processor cannot change the condition of agent A2. At that, agents implemented within the framework of the P1 processor, when necessary, may request information about the condition of agent A2, but the copy of A2 will remain unaltered. The alteration of the original A2 is possible only within the P2 processor, however, in this case RepastHPC synchronizes the changes of the condition of the agent amongst all processors3.

3 Adaptation of Agent-Based Models for The Supercomputer: Our Approach

In March of 2011 the model was launched on the supercomputer "Lomonosov", which simulated the socio-economic system of Russia for the next 50 years. This ABM is based on the interaction of 100 million agents, which hypothetically represent the socio-economic environment of Russia. The behavior of each agent is set by a number of algorithms, which describe its actions and interaction with other agents in the real world.

Five people participated in the project: two specialists of the Central Economic and Mathematical Institute of the Russian Academy of Sciences (V.L. Makarov, A.R. Bakhtizin) and three researches of the Moscow State University (V.A. Vasenin, V.A. Roganov, I.A. Trifonov). The data for the modeling was provided by the Federal Service of State Statistics and by the Russian Monitoring of the Economic Conditions and Health of the Population. A model for a standard computer was developed in 2009, and in 2011 it was converted into a supercomputer version. Below, we will examine the main stages and methods of effective projection of a computable kernel of a multi-agent system on the architecture of a modern supercomputer, which we have developed during the process of resolving the issue in question.

3.1 Parallel programming

It is important to understand that the scaling of programs for supercomputers is a fundamental problem. Although the regular and supercomputer programs carry out the same functionalities, the target functions of their development are usually different.

During the initial development of the complex application software the first and foremost goal is to try to minimize the costs of programming, personnel training, enhance the compatibility between platforms etc., and leave optimization "for later".

[3] More thorough information on the S/W can be found in the User Manual (Collier, 2012); a new version of the 1.0.1. package (dated March 5, 2012) can be downloaded from the following website: http://repast.sourceforge.net/repast_hpc.html

This is quite reasonable, since at the early stages, the priority of development is exclusively the functionality.

However, when the developed software is already being implemented, it is often discovered that there is not enough productivity for real massive data. And since modern supercomputers- are not simply computers, which work thousands of times faster than personal computers, in order to launch the program on a supercomputer it is necessary to introduce significant alterations first. Doing this effectively without special knowledge and skills is by far not always successfully achieved.

When the work is done properly and correctly significant increase in efficiency is usually achieved on the following three levels:

1. multisequencing of calculation;
2. specialization of calculative libraries by task;
3. low-level optimization.

3.2 Specialization and Low-Level Optimization

Before seriously talking about the use of supercomputers, the program must be optimized to the maximum and adapted to the target hardware platform. If this is not done, the parallel version will merely be a good test for the supercomputer, but the calculation itself will be highly inefficient.

To use a supercomputer without optimization and adaptation of the program to the target hardware platform is the same as sending a junior regiment on a combat mission: first it is necessary to teach the recruits how to properly carry out their tasks (specialization, optimization of software), as well as how to efficiently handle weapons (low-level optimization of software), and only then it can be considered an effective use of resources.

In the universal systems of modeling of the AnyLogic[4] type, the procedures presented are universal. And a universal code can often be optimized for a particular family of tasks.

3.3 Selection of a Modeling Support System.

Certainly, ABM can be programmed without a special environment, in any object - based language. In addition, the main shortcoming of the existing products for creating ABM except for RepastHPC, is the inability to develop projects that would run on a computing cluster (i.e. there is no mechanism for paralleling the process of executing the program code).

However, a more reasonable approach would be to use one of the proven systems for ABM - because of the unified implementation of standard ways of interacting agents. To save space, here, we will only consider the ADEVS system[5].

[4] AnyLogic – is an instrument for imitational modeling, which supports all approaches for creating imitational models: process-oriented (discrete event), system dynamic and agent-based, and any combination of the above. See http://www.anylogic.ru.

ADEVS is a set of low-level libraries for discrete modeling done in C++ language. Some of the advantages worth mentioning are the following:

- ease of implementation;
- high efficiency of models;
- support of basic numerical methods used for modeling ;
- built in paralleling of simulation with the help of OpenMP;
- the possibility of using standard means of paralleling;
- fairly rapid development of libraries in the current time;
- Cross-platform software;
- low-level software (current functionality does not impose any restrictions on the model);
- independence of the compiled code on unusual libraries;
- open source code.

However, significant shortcomings of this product is a complete lack of means of presentation and quite complicated modeling, when compared to, for example, AnyLogic. Therefore, this product cannot be used to build models on the consumer level, however, is an effective platform for implementing parallel simulations.

The main elements of the program when using the ADEVS library to build an ABM are the following:

- adevs simulator:: Simulator< X >;
- primitive of adevs agents:: Atomic< X >;
- model of adevs (container of agents):::: Digraph< VALUE, PORT >.

It was decided to develop the supercomputer version of the program described below, based on the ADEVS system, in view of its advantages listed above. Within the framework of this project, an MPI-version of the ADEVS simulator was created, as well as a visualization system of the calculation process based on the Qt library- a cross-platform set of tools for creating software written on the C++ programming language.

Next, we turn to a brief description of the developed model and the procedures for its subsequent run on a supercomputer.

3.4 The initial agent -based model

The first stage of development of the ABM described below, is to construct a tool that effectively solves the problem of research on conventional computers, as well as adjusting the parameters of the model. After its successful testing with a small number of agents (about 20 thousand - is the number of agents, with which conventional computers are able to perform calculations at a satisfactory rate and with good productivity, given the complexity of agents) it was decided to convert the model so

[5] The ADEVS system and its description can be downloaded from here:: http://www.ornl.gov/~1qn/adevs/

that it could be used on a supercomputer— this was the second stage of development. During the first stage the AnyLogic product was used, the technical capabilities of which, allowed to debug the model at a satisfactory speed and to configure its settings. Thus, the model for an ordinary computer was built in 2009, and in 2011 it was converted into a supercomputer version.

Fig. 1 shows the operating window of the developed ABM (dots - agents). During the operation of the system current information can be obtained on the socio-economic situation in all regions of Russia, including the use of cartographic data, changing in real time depending on the values of the endogenous parameters.

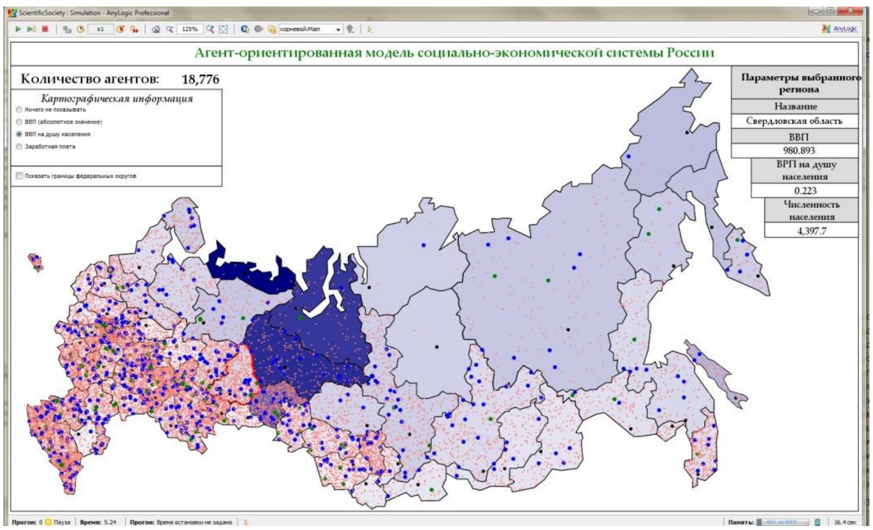

Fig. 1. Operating window of the developed ABM

The specification of the agents of the model was carried out taking into consideration the following parameters: age; life expectancy; specialization of parents; place of work; region of residence; income and others.

The specification of regions was carried out, taking into consideration the following parameters: geographic borders; population; number of workers (by type); GRP; GRP per capita; volume of investments; volume of investments per capita; average salary; average life expectancy; index of population growth, etc.

The major actions of agents are:

• aging (change from the category «children» to category «working age adults», and then - to «pensioners»);

• creating family;

• giving birth to a child;

• acquiring profession;

• religious activity;

• change of job;

• migration to other regions (or countries).

These actions are accompanied by the change in the number fo agents within corresponding groups with respect to (a) ethnicity, (b) religion, (c) nationality etc.

Statistics manuals of Rosstat, as well as sociological databases of RLMS (The Russia Longitudinal Monitoring Survey) were used to fill the model with the necessary data.

3.5 Conversion of the Model into a Supercomputer Program.

Earlier we had already discussed the problems of using ABM development tools for the realization of projects, carried out on the computing clusters of the supercomputer. Due to the difficulties in separating the computing part from the presentational part, as well as to the realization of the code using a high level of the JAVA language the productivity of the implementation of the code is significantly lower for AnyLogic than for ADEVS. Apart from that, it is extremely difficult to reprocess the generated code into a concurrently executed program.

Below is the algorithm of the conversion of the AnyLogic model into a supercomputer program.

3.6 Translation of the Model.

The models in the AnyLogic project are kept in the format of an XML-file, containing the tree diagram of the parameters necessary for the generation of the code: classes of agents, parameters, elements of the presentation, descriptions of the UML-diagrams of the behavior of agents.

During the work of the converter this tree diagram is translated into code C++ of the program, calculating this model. The entry of the tree is executed "depth wise". At that, the following key stages are marked, and their combination with the translation process is carried out.

1. *Generating the main parameters.* The search for the root of the tree and the reading of the parameters of daughter nodes, such as the name of the model, address of assembly, type of model, type of presentation.

2. *Generating classes.* Generating classes (more detailed):

- configuration of the list of classes;
- reading of the main class parameters;
- reading of the variables;
- reading of the parameters;
- reading of the functions;
- generating a list of functions;
- reading the functions code;
- conversion of the functions code Java -> C++;
- reading of the figures and elements of control that are being used;
- generating the code of initialization of figures and elements of control;
- generating constructor, destructor and visualizer codes;

- generating the class structure;
- generating header code and source-files.

3. *Generating the simulator.* Search for the peak, containing the information about the process of simulation (controlling elements, significance of important constants, elements of presentation etc.).

4. *Generating shared files of the project* (main.cpp, mainwindow.h, mainwindow.cpp и etc.)

3.7 Import of Incoming Data

Data from the geoinformation component of the initial model (map of Russia), containing all of the necessary information is imported into the model as input data.

3.8 Generating Classes and the Transformation of the Functions Code

When generating the functions from the tree the following information is read: name of function, return type, parameters and its body.

Based on the list of classes constructed earlier, changes are introduced into the arguments of the functions, replacing the "heavy classes", i.e. all generated classes, classes of figures and other classes, which do not form part of the standard set, with corresponding pointers. The purpose of this is to save memory space and avoid mistakes when working with it. After that, the titles of the functions are generated, which are later inserted into the title and source-files. In the course of such reading the body of the function, by the means of the relevant function is transformed from a Java-based code into an analogical C++ code (this is possible due to the fairly narrow class of used functions; as for more complicated functions manual modification of the translated code is required), after which it is added to the list of bodies for this class.

In the course of the translation the need for the transformation of the initial functions code from the Java language to the C++ often arises. It can be presented in the form of sequential replacements of constructions, for example:

- *Transformation of cycles*: Java-format.
- *Transformation of pointers*. Java, unlike C++, does not contain such an obvious distinction between the object and the object pointer, hence the structure of the work with them does not differ. That is why a list of classes is introduced, in which it is important to use operations with object pointers, and not with the object itself, and all of the variables of such classes are monitored with the subsequent replacement of addresses to the objects with corresponding addresses to the object pointers within the framework of the given function.
- *The opening of "black boxes"*. In Java, and in the AnyLogic library in particular, there is a certain number of functions and classes, which do not have analogues in the C++ itself, nor in the ADEVS library. Due to this fact additional libraries shapes.h, mdb-work.h had been created, which compensate for the missing functions.

- *During the generating stage of the main parameters of the lists of classes* the name of the main class and the names of the modulated agent-classes are obtained. The procedure of adding an agent into the visibility range of the simulator is introduced into the code of the main class.

3.9 Generating Outside Objects

In the process of generating outside objects a separate function «Main::initShapes()» is created, which contains all of the "graphic information", i.e. the initialization of all figures, the classes of which had also been implemented in the shapes.h., is carried out within the framework of the function. The relevant example is presented in the following code fragment.

3.10 Generating Classes and the Code of the Title and Source Files

Based on all the data that has been read and generated the title and source files of the corresponding class are created.

3.11 Generating Simulation

For the generation of simulation it turned out to be enough to have the main.cpp, mainwindow.cpp, mainwindow.h files, written beforehand, in which the templates define the type of the main class and the added title files. When compiling the initial code the templates are replaced with the names of the classes received earlier (at the generating stage). This is enough for the double-flow simulation, which can later be replaced with a corresponding module for a multiprocessor simulation.

3.12 Additional Attributes

At the stage of analyzing the tree (see above) a tree, similar in structure, is formed for the generation of a C++ code, with the help of which the necessary attributes of compilation can be set (visualization of certain parts, visual validation of code recognition, additional flags of assembly etc.) , during the stage of preparation for translation.

After that, at receiving the command for transformation, the final compilation takes place, taking into consideration all of these attributes.

3.13 Assembly of the Ready Project

For the assembly of the translated project the QtCreator is used — cross-platform shareware integrated environment for work with the Qt framework.

3.14 Agent Code

With the help of the translator described above an initial code (except for the behavior pattern of agent) has been generated from the data of the files of the AnyLogic project (model.alp and others).

The behavior pattern of the agent must be generated from the diagram of conditions, however, currently the automation of this process has not yet been implemented. Therefore, a certain volume of the code had to be added to the generated code.

After the introduction of the necessary changes, a cross-platform application, repeating the main functionality of the given model, was achieved as a result of the compilation.

3.15 Statistics and Visualization of Time Layers

Given the non-interactive mode of the launching of the program on big supercomputers the collection of data and visualization were separated (this has to do with the load imbalance on clusters at various times of the day; as for exclusive access, it is simply impossible). After the recalculation of the model the information obtained can once again be visualized, for example, in the following manner (Fig. 2).

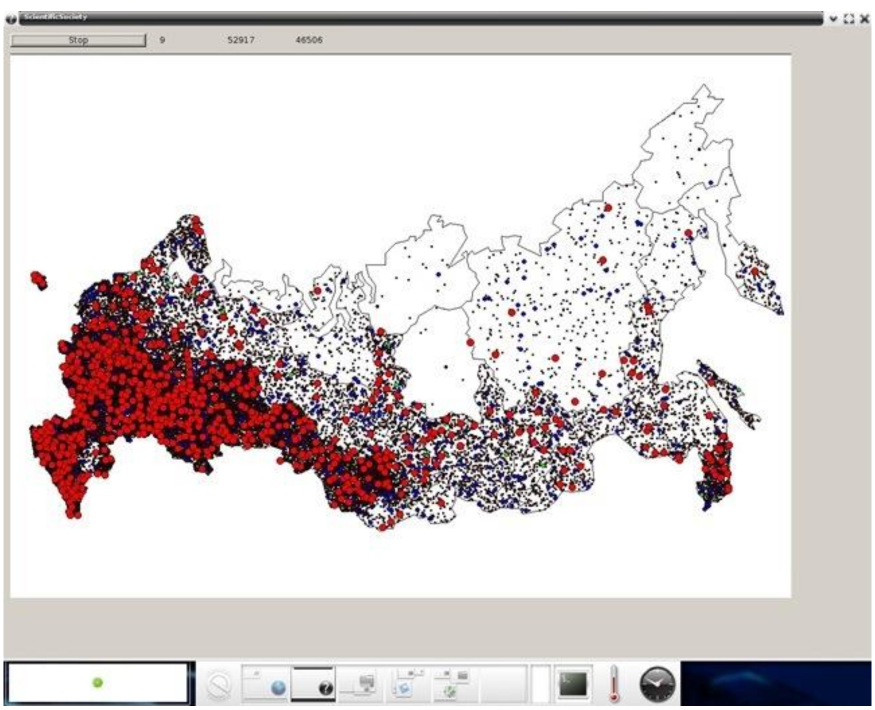

Fig. 2. Result of the work of the supercomputer program in graphic format

3.16 Supercomputers Available for Calculations

At the moment of making the calculations three supercomputers were available to us (Table 1), which were in the top five of the supercomputer rating of the Top-50 supercomputers in the CIS countries.

Table 1. Supercomputers available for research group

Position in Top -50	*Supercomputers*	*Nodes*	*CPU*	*Kernels*	*RAM/ node*	*TFlops*
1	«Lomonosov» (Moscow State University)	5 130	10 260	44 000	12GB	414
4	MVS-100K (Inter-agency Supercom-puting Center of the RAS)	1 256	2 332	10 344	8GB	123
5	«Chebyshev» (Moscow State University)	633	1 250	5 000	8GB	60

For our calculations we used two supercomputers – the «Lomonosov» and the MVS-100K.

4 Results

By using supercomputing technologies and optimizing the program code we were able to achieve very high productivity.

The optimization of the code and the use of C++ instead of Java allowed for the increase in speed of execution of the program. The model was tested in the following initial conditions: 1) number of agents — 20 thousand; 2) forecasting period — 50 years. The results of the calculations showed that the count time of the model using ADEVS amounted to 48 seconds using one processor, whereas the count time of the model using AnyLogic and a single processor amounted to 2 minutes and 32 seconds, which means that the development framework was chosen correctly.

As has already been noted before, an ordinary personal computer with high productivity is able to carry out calculations with satisfactory speed with a total number of 20 thousand agents (the behavior of each is defined by around 20 functions). At that the average count time of one unit of model time (one year) amounts to around one minute. When dealing with a larger number of agents, 100 thousand for example, the computer simply “freezes”.

Using the 1000 processors of the supercomputer and executing the optimized code, allowed to increase the number of agents to 100 million, and the number of model years to 50. At that, this enormous volume of research was carried out in a period of time, which approximately equaled 1 minute and 30 seconds (this indicator may slightly vary depending on the type of processors used).

Then we continued to increase the number of processors (under the same model parameters) in order to establish a dependency of the time for computation from the resources involved. Corresponding function is depicted on Fig.3.

Results of the modeling showed, that if the current tendencies ensue the population of the Siberian and the Fareast Federal Districts will significantly decrease, while in the Southern Federal District, on the contrary, there will be a significant increase in population. In addition to that, the modeling carried out gives reason to predict a gradual decrease of the GDP, as well as several other macroeconomic indicators.

The results of the experiments carried out using the developed ABM revealed that the scaling of the model in itself has certain meaning. For example, when launching the same version of the model for 50 model years using the same parameters (except for the number of agents: in the first case there were 100 million agents, in the second – 100 thousand agents) the results received, that is the scaled number of agents, had a difference of about 4,5%.

It can be assumed that in complex dynamic systems the same parameters (birth rate, life expectancy etc.) may produce different results depending on the size of the community.

Note a considerable increase of model productivity from the number of processors. At the same time we should mention that the model excludes almost any type of inter-agent interactions (which is conducted at macro-level). Therefore, we agenda for further research is to develop the complexity of the links between agents and to search for a most efficient way for a parallel program code.

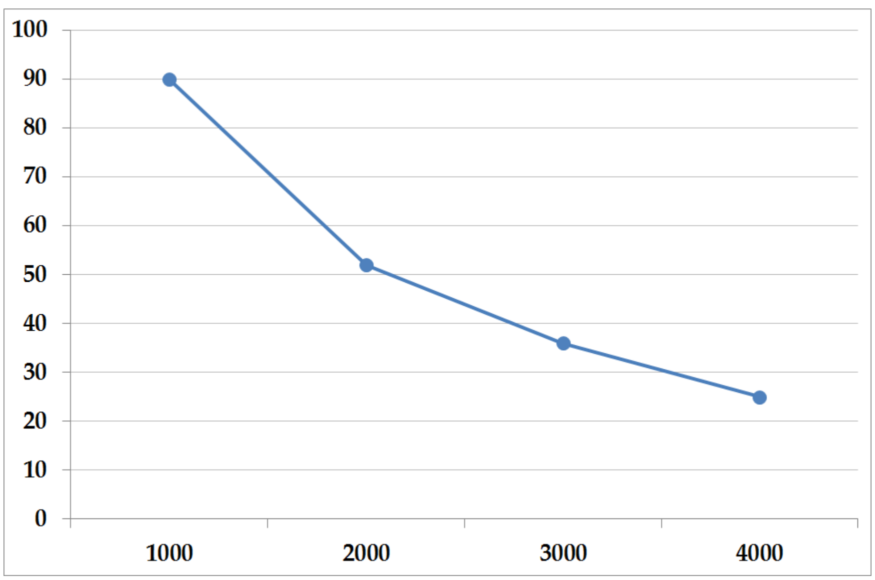

Fig. 3. Time for calculating the model as a function of the number of processors (X axes– number of processors, Y axes – time in seconds)

5 Acknowledgement

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Pure Versus Hybrid Strategies: On Exploring the Limits of Adaptability

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Abstract: Pure strategy advocates argue that competitive advantage is a function of efficiency and focus. Hybrid strategy advocates, in contrast, emphasize the importance of adaptability for achieving advantage. But despite previous literature, this is not a dichotomy, instead these strategies should be viewed as variations on a continuum with efficiency and focus on one end and flexibility on the other. By reframing hybrid strategies as deviations from pure strategy ideal types, we shift the focus from questioning *whether* firms should introduce variations to *when* and *to what extent* they should incorporate adaptability in their strategies. We argue that while such deviations increase the firm's adaptability, there is a *limit* to such adaptability. We develop an agent-based model to test these arguments. We introduce the concept of *adaptability frontier*, defined as the limits of the market space within which a firm remains competitive vis-à-vis the competition and conditions of resource fungibility.

Keywords: pure vs. hybrid, adaptability vs. efficiency, competition, organizational strategy

1 Introduction

Pure strategy advocates argue that competitive advantage is a function of efficiency and focus. Hybrid strategy advocates, in contrast, emphasize the importance of adaptability for achieving advantage. Do firms with pure strategies perform better than firms with hybrid strategies? Over three decades of strategy research has failed to establish conclusively the superiority of one strategy over the other, a surprising finding for a question that has been termed by some as "the central hypothesis of the dominant paradigm of competitive strategy" (Campbell-Hunt, 2000, p.149). Some studies have found support for the effectiveness of pure strategies (Dess & Davis, 1984; Kim & Lim, 1988; Kumar, Subramanian & Yauger, 1997), others have found that hybrid strategies perform better than pure strategies (Spanos, Zaralis & Lioukas, 2004; Miller & Friesen, 1986; Phillips et al., 1983; White, 1986; Campbell-Hunt, 2000). Still others have found that hybrid strategies perform no worse than some pure strategies (Thornhill & White, 2007). The indeterminacy of this stream of work indicates the need for a fresh approach to answering this important question.

In this study, we revisit this debate between hybrid and pure strategies by reframing the central question of interest. Rather than viewing pure and hybrid strategies as mutually exclusive options, we argue that they should be viewed as organizational choices along a continuum, with efficiency and focus on one end and complete flexibility and variety on the other. Instead of asking whether pure or hybrid strategies are relatively more effective, we therefore ask the more germane question - how much can organizations deviate from their intended strategy without losing competitive advantage? Such a framing enables us to reconceptualize hybrid strategies, not as distinct monolithic strategies, but as *deviations* from pure strategies along a continuum. While such deviations increase the firm's adaptability to multiple niches, there is a limit to such adaptability. Our focus thus shifts to the more important issue of identi-

adfa, p. 1, 2011.

fying the *factors* that affects the limits of adaptability. We propose that *resource fungibility* and the *firm's competitive context* are two critical. Resource fungibility is the extent to which resources and capabilities developed for one purpose can be deployed for alternative purposes. We test these arguments using an agent-based model wherein we study firm performance for different strategies under varying conditions of resource fungibility and competitor contexts.

2 The Adaptability Frontier

We propose two factors that we argue have a significant effect on the limits of adaptability: the extent of resource fungibility, which affects the costs of adaptability, and the competitive context, which determines the extent to which those costs of adaptability matters. We draw on these factors to develop the concept of the adaptability frontier - the extent to which firms can incorporate adaptability in their strategy without losing competitive advantage.

2.1 Extent of Resource Fungibility

Resource fungibility captures the extent to which resources and capabilities developed for one purpose can be used for alternative purposes. Perfect adaptability would imply that resources are fungible across competitive positions and can be seamlessly deployed from one position to another. Poor resource fungibility, on the other hand, implies significant costs in deploying resources and capabilities developed for one purpose onto other alternative purposes. As we noted, the empirical evidence (Thornhill & White, 2007; Dess & Davis, 1984) as well as arguments in the literature (Karnani, 1984; Murray, 1988; Phillips et al., 1983) suggests that resources and capabilities are neither perfectly fungible nor completely rigid, indicating that the level of resource fungibility will affect the extent to which firms can incorporate flexibility in their offerings. Resource fungibility is a critical factor affecting the limits of adaptability of an organization because it drives the costs of incorporating flexibility and variation in the firm's offerings.

2.2 Competitive Context

We complement the internally focused arguments of the current literature by arguing that the *external environment,* in the form of the firm's competitive context, also plays a significant role in determining the extent to which firms can deviate from its intended strategy. The role of competition in determining the effect of organizational action has been a significant theme in the competitive dynamics literature (Chen & Macmillam, 1987; Ketchen, Snow & Hoover, 2004). The effectiveness of any action is determined by the competitive position of others in the market, as evidenced by examples of head-to-head competition such as the Netscape – Microsoft browser wars (Yoffie & Cusumano, 1999) and the more recent iPhone – Android competition. The outcomes of firms' actions in the marketplace, such as market entry, innovation and new product development, depend on the actions and competitive positions of *other* firms in that segment. We therefore propose that the limits to adaptability also depend on the relative position of other competitor firms in the market.

We argue that the limit of adaptability for a firm is, thus, a function not of only the internal costs of such adaptability but also the presence of competitors in the market niche into which the firm is trying to position itself. For every firm, there is a range of acceptable, value-enhancing variations that can be undertaken from which positive payoffs accrue. Beyond this range of adaptability, the firm is outperformed by its competitors and variations that the firm undertakes to move into this space results in adverse performance. Resource fungibility will no doubt influence this range of adaptability but so will the competitive position of others in the market space. These two factors together help determine the firm's adaptability frontier.

The concept of an adaptability frontier is important for several reasons. First, it enables us to explain the inconsistent and ambiguous empirical evidence in this literature. Second, the adaptability frontier provides an actionable way to understand and respond to competitive dynamics in industry, controlling for resource fungibility. Third, it enables us to focus on the relevant question: how much variability can firms introduce into their strategies? We describe the agent-based simulation model developed to answer this question in the next section.

3 The Agent-Based Model

3.1 Context and Approach

We constructed an agent-based model to operationalize and demonstrate the above arguments. Effective ABM models capture the essence of the phenomenon of interest in the most parsimonious and least complex manner (Burton & Obel, 1995; Rand & Rust, 2011). Guided by this principle and consistent with the literature (Miles & Snow, 1978; White, 1986; Porter, 1980), we operationalized firm strategy using a parsimonious set of parameters: (i) internal resource profile, (ii) environmental characteristics and (iii) the nature of the products or services offered. Using these three sets of parameters, we delineated two pure strategies - the low cost defender (LCD) and differentiator (DF). We modeled the LCD as operating in a stable environment utilizing standardized processes and resources, providing the marketplace with a set of standardized products. Alternatively, the DF operates in a turbulent environment utilizing organic processes and high quality resources in order to provide products and services that are differentiated in terms of quality and complexity.

We choose for convenience to explain the model using the context of a "projects" metaphor to describe the firms and their services, i.e., the "firm" in the simulation executes a portfolio of projects. Based on knowledge drawn from software outsourcing firms, we established a set of model parameters that reflect qualitatively typical environments. Though the goal of this research is not to predict exact values, by using a specific context we are able to appropriately scale the parameter values to each other. Project-based firms are reflective of a number of different industries grounding the parameter settings and assisting with the validation of the model, while at the same time allowing the model findings to be generalized beyond one particular firm. The model assumes that new projects continuously enter the portfolio while completed projects exit. We assume no inventory and that revenue accrues to the firm on completion of the project. The central question of interest is to identify the extent to which each ideal-type firm can deviate on the standardization-complexity continuum from their espoused strategy without losing their competitive advantage.

3.2 Parameter Settings

As noted earlier, we operationalize firm strategy using three sets of parameters. To carry this out, we create firm agents and specify how the firm operates using these parameters. The first parameter, *Fraction-HQ-Resources*, is internally focused and captures heterogeneity in the firm's resources. We model each firm as possessing a fixed set of resources (25), with some fraction of these resources denoted as high quality (HQ) resources depending on the *Fraction-HQ-Resources* parameter. Examples of HQ resources include personnel with more experience and education or more sophisticated and capable technology. To reflect this increased competence, we set the productivity of HQ resources to be 25% greater than that of the standard resources on standardized projects (to be explained below). The firm can vary its resource profile by changing the proportion of HQ resources in its total resource set. In the simulation, the *Fraction-HQ-Resources* parameter varies from 10% (0.1) to 90% (0.9) in intervals of 20% (0.2). LCD firms would traditionally be conceived of having a lower value of this parameter (0.1) while DF firms would typically have a higher value (0.5). This parameter is set deterministically in each run of the simulation.

The second parameter, *Fraction-Complex-Projects*, reflects the mix of projects that the firm is willing to implement (*offerings*). The firm's portfolio of projects at any time comprise of two types – Standardized and Complex projects. Complex projects represent greater complexity and necessitate higher output quality; complex projects also generally require high-quality resources and consequently provide higher value to the firm. Firms can vary their project offerings by changing the proportion of complex projects in their portfolio. *Fraction-Complex-Projects* in the simulation varies from 0.1 (10%) to 0.9 (90%), in intervals of 0.2 (20%). LCD firms would traditionally be thought of as executing less complex projects (0.1) while DF firms execute a higher proportion of these projects (0.5). The specific type of each project in a simulation run is driven by a random draw from a uniform distribution followed by a condition set at the parameter level. For instance, for parameter settings of 0.5, projects created are randomly assigned as complex or standard with equal probability.

The third set of parameters operationalizes uncertainty in the task environment, which is a function of both organizational design and the environment (Miles & Snow, 1978). Standardization and efficiency necessitate a task environment that has little variance and volatility. LCD firms achieve this by either operating in stable markets or by buffering themselves from uncertainty in the environment (Thompson, 1967). In contrast, DF firms, with their focus on complexity, operate in environments that have significant volatility and variance, which is managed through their use of high quality resources. We model volatility and variance in two ways. First, on the input side, we model for volatility and variance using *Project-Size* and *New-Project-Entry-Rate*. We operationalize *Project-Size* in terms of anticipated resource needs for completion of the project and *New-Project-Entry-Rate* in terms of days between projects. In our model, both parameters follow a normal distribution[1] whose mean is the same for both pure strategies (LCD and DF) but whose variance is significantly higher for DF firms. Second, we model volatility and variance in the internal organizational processes though interruptions, which disrupt progress due to unforeseen factors such as changes in resource availability, change in customer specification and technical failures (Perlow, 1999). We model such random interruptions using two parameters – *Interruption-Rate* and *Interruption-Magnitude*. The effect of interruptions is modeled in person-days lost on the project. This is captured by the *Interruption-Magnitude* parameter and is set at 0.1 (*the proportion of incomplete work on the project is increased by 10% for the interrupted project*) across all runs. The *Interruption-Rate* represents the frequency of interruptions and consists of independent draws from a uniform distribution for each project on each day. DF projects stand a 5% chance of being interrupted while LCD projects are interrupted 1%.

Table 1: Pure Strategy Parameters and Settings

Parameters	**LCD Pure Strategy**	**DF Pure Strategy**	**Range of Parameters**
Task Environment			
Project-Size mean	180		Fixed
Project-Size sd	18	180	Fixed
New-Project-Entry-Rate mean	8		Fixed
New-Project-Entry-Rate sd	0	8	Fixed
Interruption-Rate, -Magnitude	0.01, 0.10	0.05, 0.10	Fixed
Resources			
Fraction-HQ-Resources	0.1	0.5	0.1, 0.3, 0.5, 0.7, 0.9
Project Complexity			
Fraction-Complex-Projects	0.1	0.5	0.1, 0.3, 0.5, 0.7, 0.9
Resource Fungibility			
Standard-Resource Penalty	0.7	0.7	0.7, 0.8, 0.9, 1.0

3.3 Modeling Pure Strategies

Table 1 details the underlying parameter specifications in general and the specific settings for the two baseline pure strategies. LCD firms are staffed almost

[1] Since New-Project-Entry is modeled naturally as a Poisson (waiting) process, the rounded draw from the normal distribution is used as the mean for a draw from a Poisson distribution. This allows us to have two different Poisson processes with similar means but different levels of variance over time.

completely by standard resources (*Fraction-HQ-Resources* = 0.1), focus on executing mostly standardized projects (*Fraction-Complex-Projects* = 0.1), that are of largely similar size (*Project-Size* mean = 180, sd = 18), with steady rate of inflow (*New-Project-Entry-Rate* mean = 8, sd = 0). The *Interruption-Rate* is set at 0.01, reflecting low volatility and disruption to the project portfolio.

DF strategies employ a higher proportion of high quality resources (*Fraction-HQ-Resources* = 0.5), which are required to execute a higher proportion of complex projects (*Fraction-Complex-Projects* = 0.5), that are significantly different in size (*Project-Size* mean = 180, sd = 180), with significant variance in the inflow (*New-Project-Entry-Rate* mean = 8, sd = 8). Finally, *Interruption-Rate* is set at 0.05, reflecting a more volatile internal environment.

3.4 Modeling Hybrid Strategies

We model *hybrid* strategies as deviations from pure strategies along two parameters: *Fraction-HQ-Resources* and *Fraction-Complex-Projects*. The set of hybrid strategies are created by varying one parameter at a time while keeping all other parameters fixed. For instance, a *LCD (Complex Projects=0.3)* is a hybrid firm that deviates from the LCD pure strategy by seeking to execute a higher proportion of complex projects but with the same set of resources in a similar task environment as the LCD pure strategy firm. Similarly, a *LCD (HQ Resources = 0.3)* hybrid firm is similar to a LCD pure strategy in all respects, except that it seeks to compete with a higher fraction of HQ resources. In this instance, the hybrid firm seeks to execute the same proportion of standardized projects in a similar task environment as the LCD pure strategy firm but with a higher proportion of high quality resources. Using this framework, we have four[2] parameter settings that the two key parameters (*Fraction-Complex-Projects* and *Fraction-HQ Resources*) can take, leading to 8 hybrid strategies related to each pure strategy (4 x 2 parameters). This approach leads to a total of 18 strategies in the simulation (2 pure strategies + 8 LCD hybrids + 8 DF hybrids), providing a broad range of strategic positions to examine precisely the extent to which firms can vary in their strategy effectively.

3.5 Modeling Resource Fungibility

We argued earlier that resource fungibility is critical in determining the success of various firm strategies. We model resource fungibility in two ways. First, we model resource fungibility of *standard* resources when they were deployed on *complex* projects under different of levels of productivity (0.7, 0.8, 0.9, 1) settings. A 0.7 setting indicates that there is a cost in deploying *standard* resources on *complex* projects since in this setting, *standard* resources only provide 70% of the productivity they provide on standardized projects when deployed on *complex* projects. In contrast, a 1.0 setting indicates perfect fungibility, where there is no cost to deploying these *standard* resources on *complex* projects. We refer to this as the *Standard-Resource-Penalty* parameter. Second, we model *HQ resources* as being more productive (125%) on *standardized* projects than *standard* resources, and they work at full productivity (100%) on *complex* projects. Throughout this paper we leave *Standard-Resource-Penalty* parameter at 0.7, which means that *standard* resource agents are 70% as effective as *HQ* resource agents on *complex* projects.

To further capture fungibility, we also consider variations in the cost of resources. We vary the *unit cost* of *HQ* resources relative to the *standard* resources from the same cost (i.e., the cost of the *HQ* resource to the firm is the same as the cost of a standard resource) to 50% costlier (in steps of 10%). This captures the notion that even if resources exhibited the same productivity with respect to project completion, their cost to the organization is likely not the same, with HQ resources being more costly to acquire in the market. Thus, we test for the effect of resource fungibil-

[2] There are five parameter settings for each of these parameters - 0.1, 0.3, 0.5, 0.7, and 0.9, but since pure strategies take on of these parameter settings each, that leaves 4 hybrid strategies for each pure strategy for each parameter.

ity under a range of conditions on the extent to which firms can be flexible and effective in their offerings.

3.6 Model Execution

We ran several simulations for each of the different strategies under different conditions of resource fungibility. In this section, we discuss the model's execution. In all runs of the simulation, the firm agent starts with five project agents and 25 resource agents (employees). The properties of these project agents (*starting conditions*) are drawn stochastically based on the parameters defined above for each strategy. We use a simple prioritized resource agent allocation algorithm wherein complex projects get priority in terms of being allocated superior resource agents. They are assigned resource agents at twice the resource requirements of standard projects. In addition, projects nearer to completion get priority over newer projects. Using these simple rules, the resource allocation method matches the priority-ordered queue of projects with the full set of resource agents, ordered by resource agent quality. This resource allocation algorithm is only invoked on a time-step when there is a new project entering the portfolio, when an existing project is completed or when an interruption occurs. These three events represent changes to the composition and prioritization of projects in the portfolio and therefore, trigger the resource allocation process.

Based on the *New-Project-Entry-Rate* parameter[3], a new project (complex or standard) may be created. When this happens, the firm reallocates all resource agents across the projects (existing and new projects) using the resource allocation heuristic described above. In addition, the model simulates interruptions on project execution. In each time-step, every project in the firm's portfolio is checked to see if it has been "interrupted", based on the interruption parameters for that run. If so, the interruption penalty (*Interruption-Magnitude* = 0.10) is added to the project, thereby delaying its completion. Over the course of the simulation, the firm's resource agents complete work on each project per time-step, based on resource agent productivity settings in Table 1b and each project is checked for completion. Upon completion of a project, the resource allocation algorithm is re-executed to reallocate the released resources to the revised portfolio of projects and the performance metrics on the completed project are recorded. Each run of the simulation represents 500 time-steps of activity on the portfolio of projects. Since the model has been parameterized such that a time-step is roughly one day, 500 time-steps represents roughly two years of work. In robustness tests, the runs were extended to 800 and 1000 time-steps, with no change in the results. In each set of parameter settings, we ran the simulation 100 times, to generate a distribution of results observed in the given setting. In all runs, there are projects left incomplete at the time of the termination of the run; these do not result in any revenues and we also capture the data on the incomplete projects to validate our theory.

4 Testing for Face Validity of the Model

An important step in simulation models is to examine the computational model created in order to verify and validate that they adhere reasonably to the real-world phenomenon and underlying theoretical logics. We conducted verification (comparison of the implemented model to a conceptual model) of the model through comprehensive documentation, programmatic testing and test cases, available upon request from the authors. In addition to verification, it is also necessary to validate the model, i.e., compare the implemented model to the real world. As discussed in Section 6.1, the model parameters were chosen to maintain face validity at both the micro- and macro-level with real project-based firms, specifically in the software outsourcing context. Now we validate the outputs of our model on the basis of expert agreement (stylized facts) about how firms should operate in different conditions (Rand & Rust, 2011).

[3] If the number of current projects in the portfolio equals the number of resources, no new projects are added.

In a series of validation tests (available from the authors upon request), firms with LCD strategy complete on average more projects (63.64) than the DF firm (41.31). In addition, LCD firms complete a larger proportion of standard projects compared to DF firms. We simulated the DF firm as operating in a more volatile and turbulent task environment which should result in higher schedule slippage and lower utilization of resources. As expected, DF firms report higher slippage levels (1.27) and generate lesser billable effort (9115.4) relative to the LCD firms (0.99, 11796.39). The exact numbers are not important here since we are only exploring qualitative patterns of behavior, but our model is thus relationally valid in recreating the essential elements of the two pure strategies.

We find that the results are in concordance with expectations for hybrid strategies as well. Increasing the proportion of HQ resources within the LCD pure strategy (*LCD HQ resource hybrids*), all else being equal, will result in more completed projects, greater resource utilization and lower schedule slippages. Without any change in the other strategy parameters, the positive benefits from increasing resource quality will however tend to plateau off beyond a certain level. We observe these effects in the simulation results when the proportion of HQ resources goes beyond the 0.5 setting. LCD (Complex) hybrids, on the other hand, should experience an adverse effect on performance since these firms attempt to execute a higher proportion of complex projects, with no change in the quality of its resources. The simulation results reflect this trend; the total number of projects completed, schedule slippage and resource utilization all systematically decrease as the proportion of complex projects increase.

We observe similar results when we examine DF hybrids. Changing the proportion of resource quality systematically affects simulation outcomes. When firms try to execute the same proportion of complex projects with fewer HQ resources (DF HQ Resource = 0.1 or 0.3) in the same complex and volatile task environment, they perform much worse on schedule slippage, resource utilization and project completion rate relative to the DF pure strategy. However, when we consider the DF (HQ Resource = 0.7) and DF (HQ Resource = 0.9) hybrids, we find, as expected, the opposite effect since these hybrids have more HQ resources. With respect to the DF (Complex) hybrids, the results are again consistent with expectations. As the proportion of complex projects increases, performance degrades but not radically. However, as the proportion of complex projects decreases, performance improves. These findings are consistent with theoretical expectations and also provide strong support for the validity of the simulation model.

5 Analysis and Results

As noted before, firms in our model have three dimensions along which they can deviate from the pure strategy. We fix two of these parameters in the simulation for each run representing a specific strategy – proportion of HQ Resources and proportion of Complex Projects. We use the output from the simulation to examine the third dimension: how much flexibility and variation should firms incorporate in their offerings. Should they compete in the entire continuum from standard to highly complex projects or should they focus on a specific segment of the market in terms of project complexity? We address these questions through varying the competitive context faced by each firm, i.e., we juxtapose different strategies in the marketplace and examine their relative performance if they were to co-exist, thereby replicating the "thought experiment" setting described before.

5.1 Testing the Limits of Adaptability – Modeling the Competitive Context

In order to reasonably compare different firm strategies in the market concurrently, we need a measure of firm surplus. We first run a series of simulations for the different values of *Fraction-HQ-Resources* and *Fraction-Complex-Projects* described in Table 1. Using the results of these simulations and starting with the cost side, we first create a baseline by assuming that each time-step of resource effort by both standard and HQ resource costs one unit. Since we start with 25 resources and each run extends to 500 time-periods, the baseline cost for all firms, regardless of intended strategy, is 12500 units. We then vary the cost of high-quality resources from 1.1 times the standard resource to 1.5 times the standard resource cost (as mentioned above). In effect, we allow the cost premium of high quality resources to vary from 10% to 50% of the cost of a standard resource. The total cost incurred by a firm in these varying conditions depends on the proportion HQ resources it possesses (*Fraction-HQ-Resources*) and the cost premium for such resources. This cost faced by each firm during a run is therefore fixed, given the parameter settings for that run, is incurred whether the firm completes projects or not and hence reflects the cost of adaptability from resource fungibility

On the revenue side similarly, we create a baseline by assuming that both standard and complex projects results in revenues of one unit per completed effort. By assuming that the complex projects derive the same revenue as the standard projects, we simulate the logic that in terms of complexity, complex projects are not very different from standard projects. We then vary the revenue resulting from complex projects from 2 times that of the standard project (100% higher) to 4 times that of the standard project. That is, increasing revenue of complex projects relative to standard projects reflects the increasing quality and complexity in those projects. Therefore, a firm's total revenues are driven by three parameters – the proportion of standard projects *completed*, the proportion of complex projects *completed* and the measure of complexity of the complex (denoted by the revenue multiplier that applies in that given context). We refer to this third factor as the *complexity multiplier* because we assume that increasingly complex work will be associated with higher per-unit revenues. Therefore, as a firm's proportion of complex projects increases, it will likely draw higher per-unit revenues for its effort. Using the variations on the cost and revenue models described above, we create a variety of scenarios of surpluses (*revenues less costs*) for each firm strategy.

We can then compare these strategies to identify the extent to which the costs of resources (fungibility) and the presence of competition affect each firm's adaptability frontier. The model itself only has one firm functioning at a time, but what the model produces is a description of what revenue the firm can generate for a given set of conditions. We make the implicit assumption that if one firm can generate a higher revenue level in a given set of conditions, then they will necessarily outcompete another firm. Thus, the adaptability frontier shows areas where one strategy will always produce a higher level of revenue than another strategy.

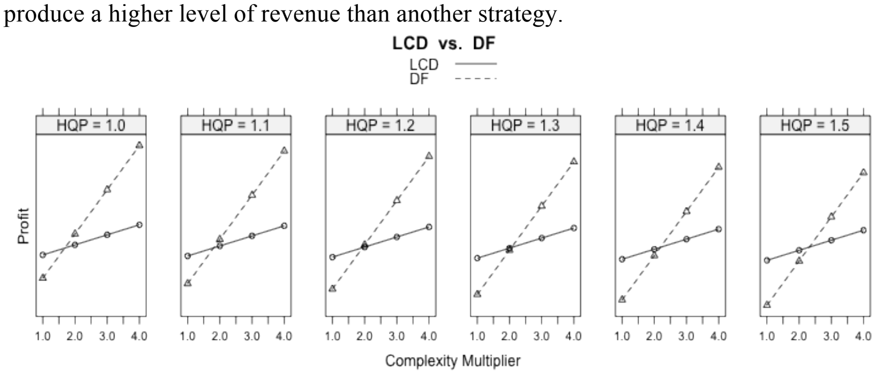

Figure 1a-f: Surplus Graphs of Pure LCD and DF Strategies: Complexity Multiplier on the Horizontal Scale

5.2 LCD Versus DF Strategies and the Adaptability Frontier

Figures 1a to 1f plots the surplus generated (as described earlier) at each level of complexity in the projects at different cost assumptions for the HQ resources for the two pure strategies LCD and DF. Figure 1a plots the curves when HQ resources cost the same as standard resources (HQ Premium = 1). Figures 1b through 1f represent the curves when the cost premium for HQ resources increases from 10% to 50% that of standard resources. The surplus (*profit*) from a set of simulation runs is on the y-axis while the x-axis represents the complexity multiplier (i.e., the revenue premium that complex projects provide over standard projects). When we examine the curve for LCDs in Figure 1a, the line has a positive slope as expected. Surplus for the LCD increases as the complexity multiplier increases. Thus, in a market with no competition, the LCD has complete flexibility to operate at any level of project complexity. Rationally therefore, the LCD should target highly complex projects in the absence of any competitors. But introducing the DF curve in Figure 1a sharply circumscribes the flexibility of the LCD. As shown in Figure 1a, the two curves intersect, with the DF having a higher surplus beyond the crossing point while the LCD has a higher surplus before the crossing point.

The presence of both these firms in the market thus sharply affects the extent of adaptability for both the firms. The LCD firm is better off executing mostly standardized projects, losing its competitiveness vis-à-vis the DF firm when it executes projects that are 60% more complex (higher quality) than standardized projects. Similarly, DF firms have an advantage in the highly complex, non-routinized, high quality segment of the market, but not so when they attempt to execute projects that are of lower complexity, ceding the market completely to the LCD firm below the crossing point in Figure 1a.

We find the same pattern repeated in Figures 1b to 1f, which depict the same curves under varying values of the HQ Premium, i.e., resource fungibility. The LCD firm continues to be competitive at the standardized end of the market while the DF retains its advantage at the complex end of the market. But in contrast to Figure 1a, the point at which the competitive advantage switches from LCD to DF shifts to the right as the cost of the higher quality resources increases. Increasing the HQ Premium affects the extent of adaptability for both pure strategy firms. For the DF firm, increasing costs of HQ resources systematically makes them less competitive in the less complex segment of the market, pushing them to compete in the more complex segment of the market. For the LCD firm, increasing HQ costs enables them to compete more successfully at a higher level of complexity than was possible when the cost differential was lower. We plot the individual crossing points from Figure 1a-1f to create a visualization of *an adaptability frontier* (Figure 1g), where the x-axis denotes the complexity multiplier of projects and the y-axis denotes the cost differential between standard and HQ resources. The area to the left of the curve represents the market space within which LCD is competitive while the shaded area to the right of the curve depicts the same for the DF firm. Areas dominated by one firm are areas where the other firm can not possibly generate as much revenue. As is evident, the extent of complexity which either firm can incorporate in their offerings depends both on the presence of the other firm *and* the cost of resources. Figures 1a-1g provide strong support for our thesis that the limit to a firm's adaptability is driven by resource fungibility *and* competition.

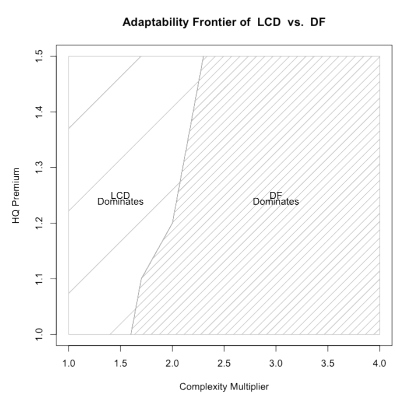

Figure 1g: Adaptability frontier of Pure LCD vs Pure DF Strategies – Comparison of Surplus in the Marketplace under Conditions of Resource Costs and Varying Complexity

5.3 Pure (LCD) Versus LCD Hybrid strategies and Adaptability Frontiers

We next turn to examine the question that initially motivated this study - is a pure strategy unambiguously better than a hybrid strategy? We first examine the limit of adaptability for the LCD in the presence of a related hybrid firm - LCD (HQ Resources = 0.30). Specifically, how does the adaptability for the LCD change in the presence of another firm that is similar in all respects but has a higher proportion of HQ resources? Figures 2a-2f depict the surplus curves and Figure 2g maps the adaptability frontier for these two firms. As is evident, the extent of adaptability of either firm is strongly affected by the relative cost of the HQ resources. The LCD (HQ Resources = 0.3) hybrid, competing with a higher proportion of HQ resources, is superior to the LCD across all segments of the market only when such increase in resource quality is accompanied by little or no increase in the cost of acquiring them. As the cost increases however, the LCD acquires significant competitive advantage vis-à-vis the hybrid across all segments of the market. The adaptability frontier in Figure 2g reflects this almost horizontal segmentation of the marketplace, where the hybrid has advantage only when there is little or no HQ Premium. The LCD firm, on the other hand, has competitive advantage and complete adaptability when this cost differential is significantly higher.

When we examine the curves Figures 3a-3g comparing the LCD with the other kind of hybrid LCD (Complex = 0.3) firm, we find that the adaptability frontier follows a different pattern. Figure 3g reveals a market that is segmented almost vertically, unlike that shown in Figure 2g. The LCD is superior to the hybrid at the standardized end of the market, while the hybrid (with a higher proportion of complex projects) is superior to the LCD and has considerable flexibility at the complex end of the market. These figures provide strong reinforcing evidence for our central argument - the limits of adaptability for firms depend not only on resource fungibility but also on the nature and type of competition in the market.

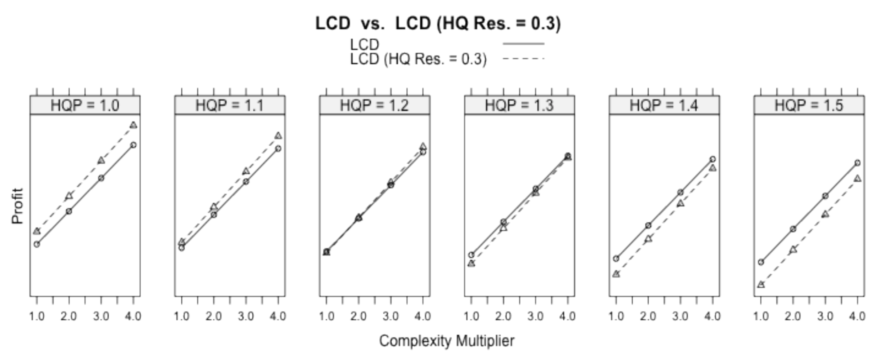

Figure 2a-f: Surplus Graphs of Pure LCD and LCD Hybrid (HQ Resources = 0.3) Strategy: Complexity Multiplier on the Horizontal Scale

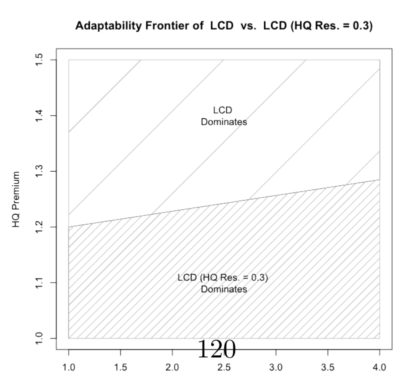

Figure 2g: Adaptability frontier of Pure LCD vs LCD Hybrid (HQ Res = 0.3) – Comparison of Surplus in the Marketplace under Conditions of Resource Costs and Varying Complexity.

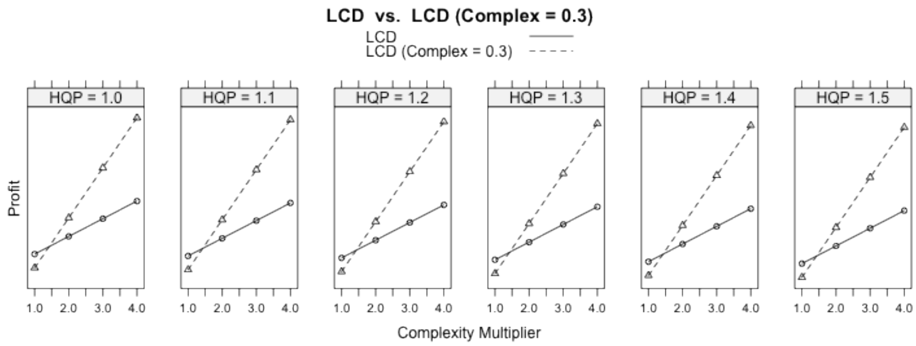

Figure 3a-f: Surplus Graphs of Pure LCD and LCD Hybrid (Complex = 0.3) Strategy: Complexity Multiplier on the Horizontal Scale.

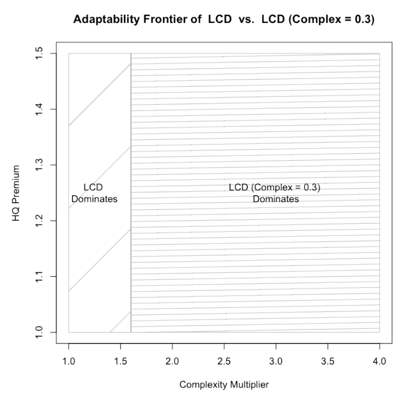

Figure 3g: Adaptability frontier of Pure LCD vs. LCD Hybrid (Complex = 0.3) – Comparison of Surplus in the Marketplace under Conditions of Resource Costs and Varying Complexity.

6 Discussion

In this study, we re-examined the debate regarding the relative efficacy of pure and hybrid firm strategies. While methodological issues may account for some of the inconsistent evidence in the literature, we argued that such inconsistencies were a function of a research perspective that viewed these strategies as mutually exclusive. Viewing them as choices along a continuum enables hybrid strategies to be framed as deviations from pure strategies. Such a change in perspective enabled us to reframe the research question to ask instead – how much can firms deviate from their intended strategy without losing competitive advantage? Such a reframing also recognizes that while such deviations from pure strategies enhance firm adaptability, there are limits to such adaptability. We argued that resource fungibility *and* the competitive context are critical factors affecting the limit of adaptability.

The limits of adaptability for any strategy depend, even in a relatively simple representation of pure and hybrid strategies, on both resource fungibility and the competitive context. Our analysis thus leads us to the concept of the *adaptability frontier,* which we define as the market space within which a focal firm retains competitive advantage. The size of this space determines the range of adaptability available, i.e., variations the firm can introduce in its product/service offerings, and is a function both of the internal costs of adaptability and the competitive position of others in the market space. Thus, we advocate for a middle ground that rejects the extremes of rigid focus *and* limitless flexibility by arguing that the optimal strategy is to pursue calibrated change, based on an understanding of the competition and an assessment of internal resources.

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WIZARDABSS: a Graphical Tool for Generating Social Simulation Scenarios

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Abstract. Agent Based Social Simulation (ABSS) has seen increased use as a computational approach to model social phenomena. In order to develop ABSS models, skills in software programming are often necessary. However, social scientists, usually, do not possess enough experience in coding. In this paper, we present WizardABSS, a computational tool that aims help social scientists to develop ABSS models, without needing of writing to a program. Using the proposed Wizard based system, the user goes through a ordered User Interfaces, which "ask" all information necessary to instantiate the desired model. After this process a computational simulation based on NetLogo is generated and is ready to be used. In order to validate WizardABSS we performed two experiments based on Schelling's Segregation Model and Epidemiology (epiDEM). Results show that WizardABSS generates computational model that resemble the original ones, with the technical difficulties.

1 Introduction

In most areas of Social Sciences (e.g. Economics, Sociology, Anthropology) "conducting experiments (in the real environment) is either impossible or undesirable"[8]. In this context, the use of computational models are growing as an alternative to test hypotheses, theories or make predictions about a social phenomenon. Agent-Based Social Simulation (ABSS) is one of these approaches. The idea is to develop computational models using heterogeneous agents (with its attributes and behaviors), within an environment, that can interact with each other. From this micro level interaction, macro level phenomena can emerge, as occurs in social phenomena [6].

In order to develop computational models (such as ABSS) coding is necessary. This is a barrier for the social scientists because formal training in programming is not an intrinsic skill related with the area [10]. Some approaches have been published in order to minimize this obstacle, trying to avoid the need for coding. Most of those aims to generate a computational model from Metal-Models [1][5][16]. Even facilitating the simulation build, these tools are not so easy to manipulate and still requires notions of software development.

The present work presents a tool that aims to build ABSS models based on Wizard user interface system, called WizardABSS. The general idea is to provide an set of graphical windows, which the user will be guided to provide basic information about the processes that will be simulated. WizardABSS aims to extract the necessary components to build the simulations, based on (*i*) environment (its attributes and actions) and (*ii*) agents (its attributes and actions). After this processes, the user can generate a computational model for NetLogo platform and simulate it.

This paper is organized as follow: Section 2 explains relevant published works related to this paper. Section 3 introduces the WizardABSS architecture and features. Section 4 presents experiments and discussions. Finally, Section 5 provides a brief conclusion and future works.

2 Background

2.1 Agent-Based Social Simulation

Agent Based Social Simulation (ABSS) is a relatively new area that emerged from the intersection of three scientific fields: agent-based computing, social sciences and computer simulations [3]. An ABSS is composed by three basic elements: (i) a set of agents (their attributes and behaviors), (ii) a set of agent's relationships and methods of interaction and (iii) an environment [12]. From the interaction of these elements at micro level behavior, macro level global patterns or regularities can emerge. Gilbert and Terna defines an emergent phenomenon if "it requires new categories to describe it which are not required to describe behavior of the underlying components (in this case, agents)"[9].

Several works have been published about application of ABSS. Schelling's Model of Segregation [19] is considered the first work in this field. In this model, agents are placed in an environment that represents a local district. Agents are segregated in two different ethnic groups. Agent's objective is to satisfy its happiness, it means be in a place that the total of neighbors of its own group is greater than a threshold (chosen by the modeler). In Economics, Jordan et. Al [11] have proposed apply ABSS to study a virtual society under a governmental social transfer. Pluchino et al [18] proposed an ABSS to study the behavior of pedestrians while moving in a museum. Pita and Neto [17] and Stroud et al [20] have discussed application of ABSS to diseases' spreading in a virtual society. Gilbert proposed an ABSS model aims explains the "Collectivities" culture [7].

Several works composed by methodologies, computational tools and techniques have been proposed in order to facilitate ABSS' development. NetLogo [21] is a very know tool that uses a simple programming language, called Logo. NetLogo is very suitable to develop simple ABSS models as well as a platform to teach agent based modeling. NetLogo has an active community, therefore is very common find documentation and computational models developed using it.

Repast [15] is a software suite that supports Java and Logo programming languages. One of the most interesting features of this suite is the integration with statistical (such R) and data mining tools (like WEKA). The Plausible Agent Matrix (PAX) [14] is a tool that aims to develop models based on levels (e.g. communication, infrastructure) in order to simplify the observation of the simulation. Using PAX you can easily active or deactivate on these levels to verify the impact of these operation in the simulation.

Even facilitating the development of ABSS models, these three tools require that the user programs his own model, by using one of the programming languages supported by the tool. Some authors have been proposed alternatives to coding. The idea is use Meta models to develop formal descriptions of the models. AgentUML [1] aims to develop a specific modeling language for agent-based development, using the Unified Modeling Language (UML). MAIA [5] is a frameworks that allows the development ABSS Meta models from a web interface. INGENIAS [16] is a methodology based on Model Driven Development composed by a toolkit that uses a graphical interface in order to generate an ABSS model.

2.2 Wizard

Wizards are graphical components that aims to help novice users to solve hard long tasks, such as install a new operating system. These graphical provides “task assistance by breaking a task into linear series of steps and presenting the steps to a person one at time” [4] Wizards have been used in previously works related to agent based modeling. Mitkas et al. [13] developed a framework to instantiate intelligent agents (so as its training). Tuchinda et al. [22] developed a methodology for build agents, based on a set of questions using a Wizard system. In these two work there are no mentions regarding the environment

3 WizardABSS

3.1 Proposed Model

This work proposes a novel tool that assists social scientists in order to reduce the dependence of a software developer experts during the simulation performance. Its means: avoiding the need for write code in order to generate a social simulation. To achieve this we propose WizardABSS, a friendly user tool based on Wizards interfaces that helps social scientists to build Social Simulation scenarios.

In traditional development, if a social scientists aims to develop an ABSS model first he needs to define a theoretical model (represented in step 1, Fig 1). Next step is the development of the computational model (represented in step 2, Fig 1) which can be achieved by computational tools such as NetLogo, Repast or Pax. As mentioned in Section 2 these tools requires knowledge about software development, which can be a constraint for the social scientists. WizardABSS appears as an alternative to develop computational models without coding. The output of WizardABSS is a generated computational model designed for a simulation platform (*e.g.* NetLogo, Repast or PAX) which is represented in step 3 of Fig 1. The last step (4) is the simulation of the generated model to study the social phenomena.

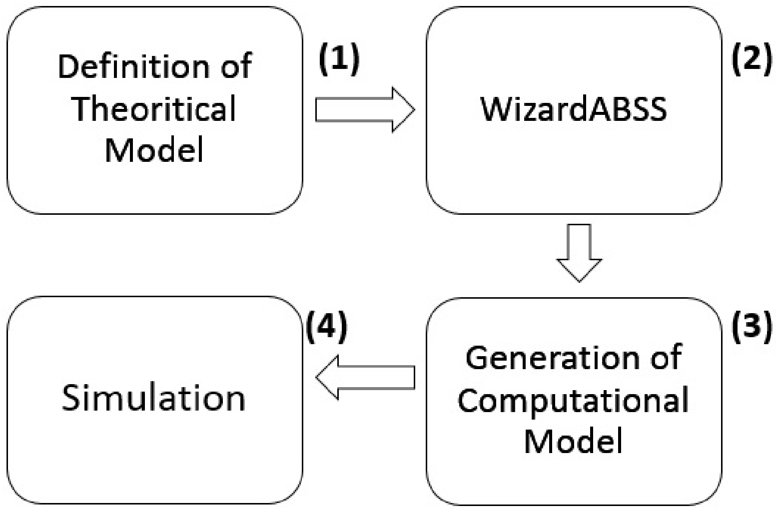

Fig. 1. Representation of the proposed development process for create a ABSS, adding a new step (2.1) represented by WizardABSS.

WizardABSS displays a sequence of user interface forms (UI) that "asks" questions regarding the model. Wizard requests the following data:

1. About the Environment
   (a) Environment Color definition: define the environment color. It can be defined for visualization; Colors definition are based on NetLogo standard (blue, black, yellow, green, etc.);
   (b) Environment attributes definition: define the environments' attributes, so as global simulation attributes. The user can define the type of the attribute (number, literal string or a Boolean) and initial values.
   (c) Environment attributes update: define how attributes (chosen in element 1.a) will be update during the simulation. WizardABSS has a list that contains several options for update (increases, decreases, change a value due a restriction) provided by the Components Library (described in Fig 2).
2. Agents
   (a) Quantity of agents: define the initial quantity of agents;
   (b) Agent's shape definition: define the shape of the agents. It is conformed to the NetLogo standard. This definition is basically for visualization;
   (c) Agent's color definition: define the initial agent's color. Colors are defined on NetLogo standard (blue, black, yellow, green, etc.);

(d) Agent's position definition: define the initial agent's position in the environment;
(e) Agent's attributes definition: define the agents' attributes. The user can define the type of the attribute (number, literal string or a Boolean) and initial values.
(f) Agent's actions definition: Define the possible actions that an agent will perform during the simulation. WizardABSS has a list that contains several possible actions: move, die, communicate, sell, buy, copulate, etc provided by the Components Library.
(g) Agent's attributes update: define process of attributes' update (chosen in element 2.e) during the simulation. WizardABSS has a list that contains several options for update: increases the attribute, decreases, count agents in a radius (based on attribute), etc provided by the Components Library.

All these questions are composed by elements that are often necessary to build a computational model. We have develop these steps based on the analysis of previously researches that explains the basics elements to model a social phenomenon (discussed in Section 2) and on the analysis of several ABSS computational models, which are available on NetLogo library and on the internet. While the user is answering the questions proposed by the WizardABSS, information are being stored in a database.

When the user goes through the UI and finish the process of information gathering is possible to generate a computational model based on the stored information, without writing any line of code, as represented in (step 2.2, Fig 1). The generated model is build using a simple code generator for the target platform. The code generator has several pre-built code snippets that are responsible for generate distinct parts of the model, such as creation of the agents, definition and updates of attributes, actions, etc. When the code snippets are linked with the information obtained by WizardABSS, the code generator can generate model's code. Code snippets were developed based on our experiments, observing models from several libraries and from ABSS' works. Fig 2 exemplify all the modules involved in our approach.

3.2 Computational architecture

Fig 3 shows a simplified WizardABSS' class diagram. WizardABSS core was developed using the Java Platform. There are three main packages: "User Interface", "Information Manager" and "Code Generator", developed in a modular architecture. Using the concept of modularity, these packages can be replaced (or updated) without huge impact on the software.

The "User Interface" package contains all the necessary classes to instantiate the graphical Wizard user interface. The main class "UiWizard" contains the implementation of Wizard main objectives (i.e. design graphics windows to input information). Using an inheritance process, "UiAgents" and "UiEnvironemnt"

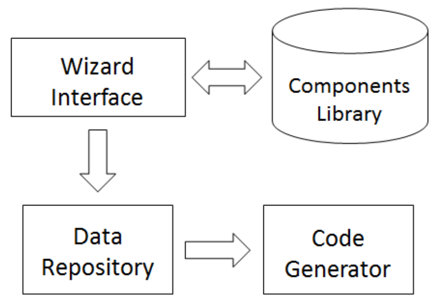

Fig. 2. A generic view of all process involved to create a ABSS model using WizardABSS.

can use UiWizard's base to implements its own definitions (as described in Section 3.1). All the classes in this package were developed using WindowBuilder, a tool for design Java user interfaces. The "Information Manager" package contains all the necessary classes to manage the model information added by the users on the UI.

"Code Generator" package contains the code to generate the computational model designed by the user, inputted in the "User Interface" classes and managed by classes on the Information Manager package. As described in the last Section, the code generator is composed by a set of code snippets. These code snippets are stored in Extended Markup Language (XML) because this language is easy to read, extensible and platform independent.

4 Experiments

In order to validate our approach we have performed two experiments: develop two ABSS models using WizardABSS to be simulated on NetLogo's platform. We have choose two models in the literature: (i) Schelling's Urban Segregation [19] and (ii)epiDEM (Epidemiology: Understanding Disease Dynamics and Emergence through Modeling)[2]. The motivation behind these models is because they are composed with characteristics that express all the basic aspects for a Social Simulation in a simple way, such as interaction between agents and environment, micro level behavior and macro level emergence processes. The main objective of the experiment is proof that the model generated by WizardABSS resembles the original one (*i.e.* has the same result as the original one), based on the analysis of specific variables on each one of the models.

4.1 Experimental setup 1: Schelling's Urban Segregation Model.

Using WizardABSS, we went through the UIs filling out the information required in the fields, based on the elements described in Section 3. For Schelling Urban Segregation Model, the answered questions were:

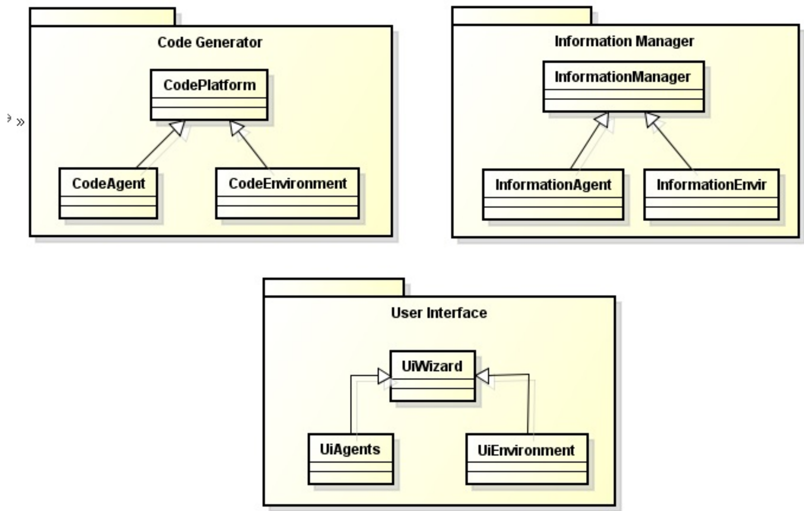

Fig. 3. WizardABSS's simplified class diagram.

1. Environment
   (a) Environment Color definition: black;
   (b) Environment attributes definition: one attribute - the similarity tax 80%;
   (c) Environment attributes update: Similarity tax is a constant, it does not requires update;
2. Agents
   (a) Quantity of agents: 1000 initial agents.;
   (b) Agent's shape definition: 500 agents using NetLogo default shape and 500 agents using x" shape;
   (c) Agent's color definition: 500 agents red and 500 agents green;
   (d) Agent's position definition: Randomly;
   (e) Agent's attributes definition: happy - a Boolean value, initial value "False" ;
   (f) Agent's actions definition: if an agent is not happy at its position then move to an empty position;
   (g) Agent's attributes update: if an agent feels happy at its position set "True".

After the process of information gathering by UI, we generated the model and simulated it in NetLogo. All experiments were performed 30 times each one, and we the observed variable was the percentage of happy agents at ticks (represents time in NetLogo) 0,50,100,150,200 and 250. We have plotted box plots to show how this variable behaves over the time. Fig 4 represents the box plots of the experiments performed in the original model and WizardABBS generated model.

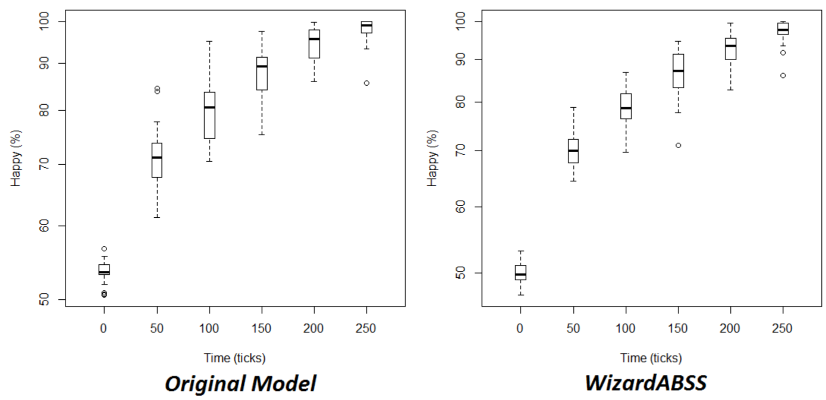

Fig. 4. Box plot of the performed experiment based on Schelling's Segregation, comparing the original model and WizardABSS generated model.

We have developed statistical tests in order to verify if the values of happiness in each model represents the same sample. We proposed the following null hypothesis:

$H_0 = (Happiness_{Original})^t - (Happiness_{WizardABSS})^t = 0$, which means that the value of Happiness in the original model ($Happiness_{Original}$) is the same of Happiness in the model generated by WizardABSS ($Happiness_{WizardABSS}$) at time t (tick in NetLogo context). Therefore, the model generated by WizardABSS resemble the original one at the observed time.

Table 1 represents comparison between these models in tick 0,50,100,150,200 and 250. First column shows time (ticks on NetLogo), second and third column shows the average and standard deviation of the happiness on the two models. The last column represents the result of the Wilcoxon test (using significance level = 95%) for H_0. In the Wilcoxon test column symbol "!=" represents that the null hypothesis can be refuted, so the values of happiness were derived from a different sample. Symbol "=" represents that null hypothesis cannot be refused, so the values of happiness were derived from the same sample.

Table 1. Average, standard deviation and Wilcoxon test comparing Original and WizardABSS generated models.

Ticks	Original Model	WizardABSS	Wilcoxon test
0	53.554 (1,15)	49.974 (1.314)	!=
50	71.075 (3,96)	70.227 (3.227)	=
100	80.142 (3,03)	79.133 (4.32)	=
150	88.019 (2,04)	86.752 (5.445)	=
200	94.57 (0,84)	92.431 (4.352)	=
250	98.09 (0,84)	97.238 (2.95)	=

Based on the observation of the results, we can argue that WizardABSS have generated a computational model, which resembles the objective of the original. Based on the Table 1, we can verify that only at "Tick 0", when the simulations starts, the WizardABSS generated model does not resemble the original. This can be explain due the agent's position initialization: as WizardABSS generates models using code generator that is composed by pre-defined code snippets, these code snippets are developed in a generic way, so we cannot guarantee the optimization of the initialization. Fig 5 represents the visualization of WizardABSS' Schelling generated model, at the beginning (tick 0) and at the end (tick 250). As expected, we can observe the segregation of two groups in some locals, as occurs on the original.

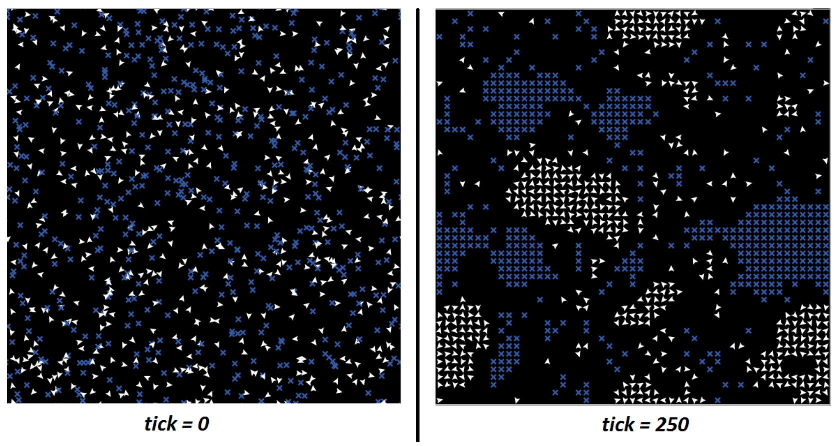

Fig. 5. Formation of segregated groups on the WizardABSS generated model.

4.2 Experimental setup 2: epiDEM (Epidemiology: Understanding Disease Dynamics and Emergence through Modeling)

epiDEM is a computational model available in NetLogo Library that simulates the spread of an infectious disease in a closed population[2]. Using WizardABSS, we went through the UIs filling out the information required in the fields, based on the elements described in Section 3. For epiDEM the information inputted were:

1. Environment
   (a) Environment Color definition: black;
   (b) Environment attributes definition: there are three global attributes: (i)infection chance(initial value was 60%), (ii)recovery-chance (initial value was 30%) and (iii)average recovery time (a random number between 1 and 150);

   (c) Environment attributes update: all attributes are constants, so update does not apply in this case.
2. Agents
   (a) Quantity of agents: 100 initial agents.
   (b) Agent's shape definition: Person shape;
   (c) Agent's color definition: all agents white;
   (d) Agent's position definition: Randomly;
   (e) Agent's attributes definition: three attributes (i) cured (initial value false), (ii) sick (around 5 % of initial agents were true, another ones false) and (iii) infection length (initial value 0);
   (f) Agent's actions definition: two actions: (i) move randomly (ii) infect =¿ there is a chance (based on infection chance attribute) of a sick agent infect a healthy agent and (iii) get cured =¿ sick agents could be cured, based on how long it was sick;
   (g) Agent's attributes update: the update process of attributes (i) if an agent got sick, set its color to red (ii) if an agent became cured set its color to green and (iii) if an agent is sick, increases its infection length;

In order to verify if the model generated by WizardABSS resembles the original one we performed experiments. We choose based our experiments on the R0 variable which stands for the number of secondary infections that arise as a result of introducing one infected person in a wholly susceptible population, over the course of the infected persons contagious period (*i.e.* while the person is infective, which, in this model, is from the beginning of infection until recovery).

We have developed statistical tests in order to verify if the values of R0 in each model are derived from the same sample. We proposed the following null hypothesis: $H_0 = R0_{Original} - R0_{WizardABSS} = 0$, which means that the value of R0 in the original model ($R0_{Original}$) is the same of R0 in the model generated by WizardABSS ($R0_{WizardABSS}$) at the end of the simulation. Therefore, the model generated by WizardABSS resemble the original one at the observed time. Fig 6 shows the box plots comparing the R0 between the original model and the WizardABSS generated model.

Here we present the results of the comparison between the original model and the model generated by WizardABSS. The value of R0's average and standard deviation for the original model were 4.134 (0.644). The value of R0's average and standard deviation for the model generated by WizardABSS were 4.293 (0.321). The p-value for H_0 was 0.387 which means that null hypothesis cannot be refused, so the values of R0 were derived from the same sample. Therefore, we can argue that the model generated by WizardABSS resemble the original one.

5 Conclusions

This work have presented WizardABSS, a new computational tool (WizardABSS) that aims to help social scientists in order to build ABSS without concerns about writing computing code. As a proof of concept we have applied

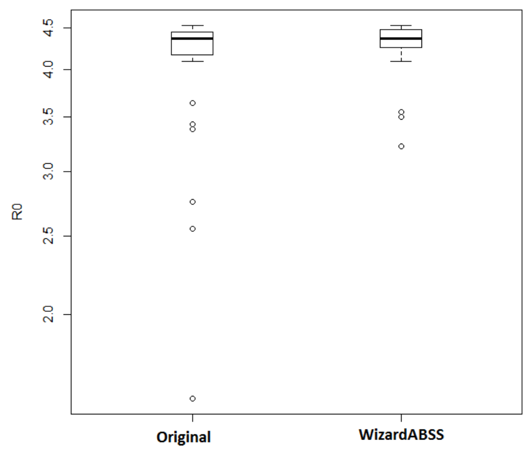

Fig. 6. Box plot of the performed experiment based on epiDEM original model and WizardABSS generated model

WizardABSS to implement two ABSS models: Schelling's Segregation Model and epiDEM. In both case, the generated model resembles the original ones. In order to implement more complex models the Components Library need to be improved with new elements. We believe this will be possible with the integration of the community with the tool. The Social Scientists will propose new behaviors for the simulations based on their needs which will be incorporated on the library. As future work, we intend test WizardABSS with others ABSS models, such as migrations, diseases spreading , etc. We also intend to increase the available code snippets related components regarding agents' actions. The generation of computational models for others platforms, such as Repast and PAX is a possible upgrade in the tool. We intend to publish WizardABSS for the community using a free license. The software will be available soon on the website of Social Computing Team (SCT) http://sct.ecomp.poli.br/ .

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Security & Stability Modeling

Agent-Based modeling of protests and violent confrontation: a micro-situational, multi-player, contextual rule-based approach

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Abstract. We propose an innovative Agent-Based model of street protests with multiple actors: police agents, three types of protesters ("hardcore", "hangers-on" and "passers-by"), and "media" agents that seek to witness and publish episodes and situations of violence. Agents have multiple goals and action selection is performed using a "personality" vector together with context rules that provide adaptation. Protesters turn active or violent according to the threshold rule proposed by Epstein, and police agents arrest violent protesters within their move range if they have sufficient backup. The model was applied to a scenario where policemen defend a government building from protesters and described several emergent crowd patterns in real protests, such as clustering of violent and active protesters and formation of a confrontation line moving back and forth with localized fights. Violent behavior was restricted to the initially more aggressive protesters and did not propagate to the bulk of the crowd.

Keywords: Agent-Based model, protests, violence, complexity, social simulation, crowd dynamics.

1 Introduction

Protest demonstrations are both a manifestation of social conflicts and an instrument of political participation through which citizens press governments for political change. History provides startling examples of regimes being overthrown by the "power of the crowds" [1]. Media coverage and widespread access to Social Networks (SN) and Information and Communication Technologies (ICT) have been used by governments, parties or activists [2] to plan, coordinate and show the course of events in real time to a global audience (e.g. in Brazil, Turkey, and Ukraine). Understanding and, if possible, predicting or controlling how the social context leads to large protests and how these in turn change the social context, is a significant problem in sociology, social psychology, and political science. This problem is very difficult due to the number and diversity of players, the complexity of the links and interactions, and the multiple scales of the phenomena. Fig. 1 shows our conceptual framework for the relationship between protests and the intensity of a social conflict.

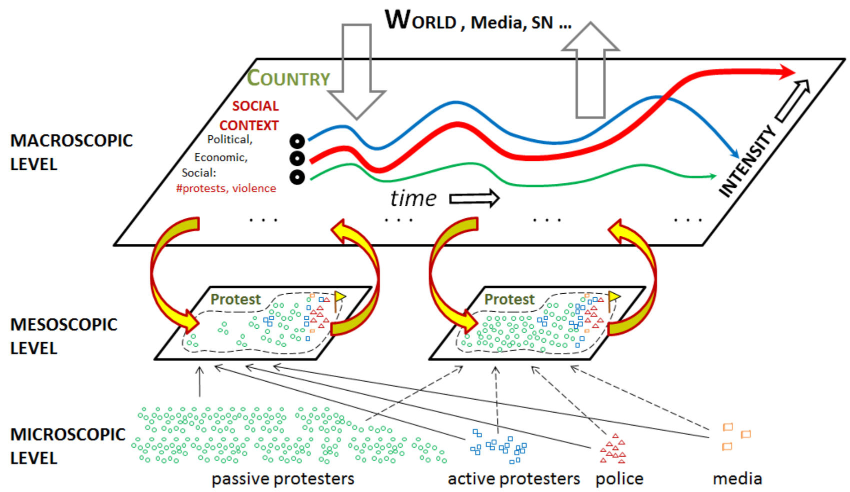

Fig. 1. Relation between protests and a social conflict viewed as a complex and path dependent process, with three distinct levels (macroscopic, mesoscopic and microscopic), types of relevant players (agents) and micro-macro and feedback (macro-micro) links.

In this paper, we present a new ABM of street protests with police agents (herein referred as "Cops"), protester and media agents, which is part of work in progress on the simulation of social conflict phenomena [3]. We consider three types of protesters, "hardcore", "hanger-on" and "passer-by" (using the terminology adopted in [4]), with different behaviors. All protesters can be in four states, "quiet", "active" (shouting, waving, etc.), "violent" (ripe to start a fight) and fighting with police agents. The spatial environment is a two dimensional grid that includes attraction points (sites that protesters try to occupy and police forces must protect), obstacles (walls or barriers) and entrances/exits (streets adjacent to the protest area). The purpose of the new model is to simulate the emergent patterns in protests and obtain quantitative measures of protest intensity, such as the number of violent confrontations and violent episodes covered by the media. These can be used to formulate the feedback links represented in Fig. 1. The research questions for which we seek answers are:

- How do the features of the protest space and the density, proportion and initial placement of each type of protester affect the crowd formation patterns (wandering, clustering and fighting) and protest intensity?
- How does violent confrontation arise? Once initiated, does it spread to the bulk of the crowd or remains confined to specific types and clusters of protesters?
- How does the presence of media agents affect the dynamics of protests?

The novel features of the model are the consideration of multiple types of agents and spatial features, using a simple but efficient agents' architecture that allows the representation of a rich variety of states, behaviors and micro-interactions. The combination of protester's state variables and measures of intensity (e.g. number of arrests and violent episodes registered by media agents) can also be used to formulate micro-macro links (such as legitimacy feedback).

The remainder of this paper is organized as follows. In section two, we present a summary of the theoretical background for the protest model. In section three we present a summary description of the model, which is complemented by a more detailed description according to the Overview, Design Concepts and Details (ODD) protocol [5] in Appendix A. Section four contains a description of the test cases and model parameters used in the simulations, together with results that show the model's capabilities and potential. Section five contains the discussion and in section six we present a summary of conclusions and prospects for the work in progress.

2 Theoretical background

In this section, we present the theoretical background of the present work using the scale of social conflict phenomena as guideline, according to the conceptual framework sketched in Fig. 1.

2.1 Macro-scale social conflict phenomena. Issues and models

Macro-scale conflict phenomena such as generalized uprisings of civil violence, insurgence or war involve a large part of the population (society). The concept of Relative Deprivation (RD) provides an explanation of the potential for social conflict within a society [6]. Indices of deprivation and social context variables derived from methods of objective analysis and extensive data bases [7], can be useful for parameterization of the individual agents.

Epstein introduced an ABM of rebellion against a central authority (Model I) or violence between two rival groups mediated by a central authority (Model II) with two types of agents, population and cops [8], [9]. Epstein's model successfully explains many features of civil violence processes at the macro-level, such as intermittent generalized bursts of violence, but has some drawbacks, like the crude representation of the "Cops" behavior and the agents' movement (see [3] for a review).

2.2 Meso-scale phenomena. Theories of crowd behavior

Theories and studies of collective behavior in crowds (temporary gatherings of a significant and potentially very large number of persons at one place at a specific time) are an important source of knowledge for the formulation and interpretation of the results of ABM of protests. Some of the key questions in the study of crowds are the formation of collective behavior, the classification (or taxonomy) of crowds, the effects of heterogeneity and the symbolic value of the places.

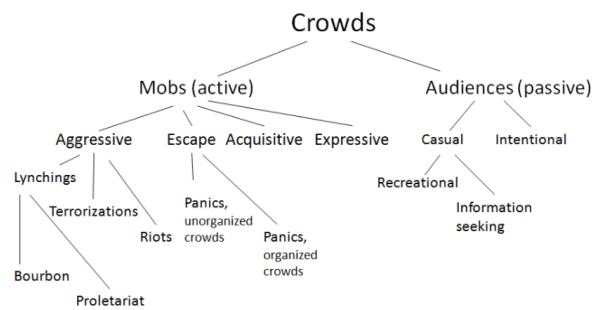

Fig. 2. Taxonomy of crowds, according to Brown [10].

Fig. 2 shows Brown's proposed taxonomy of crowds [10]. According to this scheme, protests can be classified as Expressive Mobs, which may turn to Aggressive if part of the crowd engages in violent confrontation, or Escape if there is a police charge. Also, part of the crowd may be passive and thus behave as an Audience. This taxonomy is relevant in the formulation of ABM for defining the relevant types of agents, their proportions and interactions, the environment representation (obstacles, attraction points, escape points) and other features (e.g. events), as done in [4], [11]. From this viewpoint, protests are indeed complex crowd events which do not usually fit in a single category. Moreover, the agents in a protest model must be endowed with different behaviors and several possible states depending on their percepts and internal state to describe the timing, location and size of violent hot spots.

2.3 Micro-scale processes. Theory and models

At the micro-level, it is necessary to describe how the agents move and how they will become "active" (waving, shouting, etc.) or "violent" (throwing objects or fighting), to model protest dynamics in a realistic way. Existing models of crowd dynamics provide theoretical background for modeling the agents' movement and micro-situational theories of violence provide guidelines for modeling the conditions for individuals to engage in violent confrontation and the spread of violence within a crowd.

The movement of pedestrians in crowds is an important topic in many contexts such as safety and architectural modeling, entertainment software, mathematics and physics, and has been studied using methods from fluid dynamics, cellular automata or particle dynamics [12]. The "Social Force Model" [13], [14] is an empirically based continuous space/continuous time description of the motion of pedestrians as self-propelled particles driven by three components that express individual motivations to: *i*) maintain a desired speed towards a wanted destination point; *ii*) keep clear from other pedestrians or obstacles; and *iii*) approach attractive features (such as other persons or displays). In discrete space/discrete time models with a large number of agents and one agent per cell, the agents' movement can be modeled by minimizing/maximizing the distance to attraction/repulsion points weighted by individual "relative motivations", because neither the repulsion forces (with shorter range than the typical cell size) nor the acceleration due to variations of attractive forces within the vision radius can be represented. This (discrete space and time) approach was used in the present work, due to its simplicity and advantage for handling large numbers of agents.

The situational action theory (SAT) [15] and the micro-sociological theory of violence [16], [17] provide guidelines for modeling violent confrontation in protests. According to SAT, acts of violence result from the interaction of a person's propensity and the exposure to situational factors conducive to violence. If the individual has propensity but the context is not conducive to violent action, violence will depend on the level of deterrence [15]. According to the micro-sociological theory, the key factor for the outbreak of violence is the emotion of confrontational tension/fear. For violence to occur there must be pathways around the barrier posed by this emotion. Two such pathways are: *i*) to find a weak victim to attack, and *ii*) the "forward panic" reaction in group confrontation when one side gains overwhelming local advantage [16]. In the context of ABM, the most relevant findings of this theory are: *i*) in protest demonstrations only a few agitators engage in violent behavior, except when the crowd is already divided into antagonistic groups; *ii*) "forward panic" is typical of violent confrontations if local conditions set the pathways around the tension/fear barrier (e.g. indiscriminate police beating during a charge, or the overbeating of isolated protesters or police agents by the opposing group).

ABM of micro-interactions in violent confrontations takes into account some of these theoretical findings. Jaeger, Popping and van de Sande [4] presented an ABM of fighting between two parties (e.g. hooligans supporting two different football teams) and considered three types of agents, "hardcore", "hangers-on" and "passers-by" with a (typically) small proportion of "hardcore" agents. In this model, aggressiveness is a function of the number of local supporters on the current and past cycles but is not linked to social context variables, and there are no authority agents. Durupınar [11] presented a sophisticated ABM for different types of crowds with psychological effects, including various types of protesters (characters) and police agents. This model describes the micro processes in a very realistic way, but is computationally demanding for simulating large crowds. Ilachinski [18] developed an ABM of land combat in which the agents have a "personality vector" whose components are weights that set orientation to multiple goals, together with a set of meta-rules that provide adaptation to the local context. The agents' action selection is done by minimizing a penalty function computed for all positions accessible to the agent. This method allows the efficient implementation of goal-driven behavior.

3 Model description

In this section we present and overview of the ABM developed in this work, considering the model entities, main design concepts and development issues. The model was developed in the NetLogo simulation system [19]. A more complete description based on the ODD protocol is presented in Annex A.

3.1 Model entities. Agents and scenario

In our NetLogo implementation, the protester, cop and media agents are implemented as subclasses of the turtle agent type using the breed primitive. The three different subtypes of protesters are implemented using a protester-own variable kind. “Hardcore” protesters try to cluster, occupy attraction points and engage cops, and have the highest propensity for turning “violent”. “Hanger-on” protesters correspond to the more susceptible protesters in the crowd, with moderate incentive to approach “violent” and “active” protesters; when “quiet” they try to keep a minimum distance from violent and active protesters, cops and attraction points, but assume an increasing aggressive behavior if they turn “active” or “violent”. “Passer-by” protesters try to avoid “violent” protesters, “active” protesters and cops, but in exceptional conditions they can turn “active” or even “violent”. All kinds of protesters have moderate incentive to approach “Media” agents within their vision field. “Cops” try to defend attraction points from violent protesters and keep close to other cops. If they have sufficient backup they engage and arrest violent protesters. “Media” agents try to locate fights and record (“take pictures”) violent events. The various spatial features are implemented using patches-own Boolean variables. The class diagram for our ABM is presented in Annex A.

3.2 Basic design concepts

In our model the agents are reactive, move in discrete time and space increments (one agent per grid patch), are activated once per cycle in random order, and have one move rule and one behave rule. The move rule has the same form for all agent types and subtypes, as described below. The behave rule is different for each type of agent according to the qualitative behaviors described in 3.1 and in Annex A. Upon activation, agents typically perform a three step scan-plan-behave sequence, by which *i*) they form their percept *P* (other agents and spatial features in sight); *ii*) determine their next position and state, and *iii*) update their position and state. Agents determine their future positions by minimizing a penalty function involving a “personality vector” that allows the definition of multiple goals in an efficient way. The state of the “Protester” agents (“quiet”, “active” or “violent”) is updated using the rule proposed by Epstein, which is compatible with the micro-situational theories of violence.

3.3 Goal-driven agent movement

In the plan procedure, agents determine the center of the empty patch within their move range that minimizes a penalty function of the form $V_{\mathrm{A}}(x,y,I,P) = \boldsymbol{\omega}_{A,c}/\|\boldsymbol{\omega}_{A,c}\|_1 \cdot (\mathbf{S}(x,y) - \mathbf{S}(x_0,y_0))$, where *I* is the agent’s internal state, *P* is the percept, (x_0,y_0) is the current position of agent *A*, $\boldsymbol{\omega}_{A,c}$ is a “personality vector” whose components are weights that determine the agent’s tendency to approach or avoid visible (perceived) features and $\mathbf{S}_A$ is a vector whose components are the sum of distances from point (x,y) to each visible feature element. Table 1 shows the correspondence between the weights in the personality vector and the feature elements that influence the agent's movement. The weights range from +5 (strong attraction) to –5 (strong repulsion).

Table 1. Meaning of the components (weights) of the "personality vector".

Component (weight)	ω_0	ω_1	ω_2	ω_3	ω_4	ω_5	ω_6	ω_7
Feature	"violent" protester	"active" protester	"quiet" protester	"Cop" agent	"Media" agent	Flag patch	Obstacle patch	Exit patch

Each agent has a pre-defined "default personality vector" $\boldsymbol{\omega}_{0,A}$ that determines its goal-directed movement, and a set of context-rules for changing the components of $\boldsymbol{\omega}_{0,A}$ according to the agent's internal state and perceived features. For instance, "Hardcore" protesters try to pursue cops when they have local superiority but avoid them in the reverse case. The context-dependent personality vector $\boldsymbol{\omega}_{A,c}$ is then used to minimize the penalty function. Annex A contains a full description of the default personality and context rules for all agent types and subtypes. In the behave procedure, agents move to the optimal position with a probability p (set to 0.9) and to a random empty cell within their move range with probability $(1-p)$. This represents the agents' faults while assessing the local situation and adds realism to the simulations.

3.4 Behavior rules. Transition to "Active" and "Violent" behavior

Each type of agent has a different behavior rule (see 3.1 and Annex A). For "Protester" agents it is necessary to model the transitions from "quiet" to "active" and "violent" states and vice-versa, which are critical for describing emergent patterns of violent confrontation. In our model, these transitions are described using a variant of Epstein's threshold rule $G - N > T$, where $G = H \cdot (1 - L)$ is the level of grievance, $N = R{\cdot}P$ is the net risk perception, T (constant exogenous variable) is a threshold, H is the (endogenous) perceived hardship, $L \in [0,1]$ is the "perceived government legitimacy", R is the (endogenous) risk aversion, and P is and estimated arrest probability which is our case depends on the ratio between the numbers of "cops" and "active" plus "violent" protesters within the agent's vision field. This rule is consistent with the SAT and micro-sociological theories: predisposition can be modeled by the values of G and R, the situational and deterrence elements by the form of P, and the "barrier" by the threshold T. Annex A provides the implementation details.

3.5 Development issues

The use of a personality vector allows a simple and efficient implementation of goal orientation, for it avoids the combinatorial explosion problem that would arise from simple **if <context> then <action>** rule-based formulations. The relative importance of the goals is determined by the weights and measures associated with the perceived features, not by the order by which simple rules are applied. However, it should be noted that although the "default personality vector" encodes an important part of the agent's behavior, it is the context rules that provide adaptation and autonomous decision (fundamental attributes of agency). Furthermore, the context rules effectively connect the move and behave rules.

4 Results

We performed a set of simulations to test the model, for a case in which protesters try to reach the entrance of a government building and are opposed by a police force. This situation is typical of protests near the Parliament in Lisbon, Portugal, which is familiar to the authors. The scenario was defined by a 150*m* × 37*m* grid (closed boundaries). The access to an existing space in front of the main entrance of the Parliament where police forces usually stand (a wide stone staircase 25 *m* wide) was defined by flagging a rectangle of cells near the top boundary. The defensive perimeter was defined by means of two sets of obstacle cells on each side of the central staircase, each with a width of 48 *m*. The protest area was defined as a strip 30 *m* wide in front of the staircase and obstacles, with an entrance on the right and an exit on the left. Table 2 summarizes the initial proportions of agents, type of placement and perceived government legitimacy used in the simulations.

Table 2. Initial numbers of "Cops", "Hardcore", "Hanger-on" and "Passer-by" protesters, value of perceived government legitimacy (L), and initial placement (random or non-random).

Run:	# cops	# hardcore	# hanger-on	# passer-by	L	Initial placement	Comments
AR1	125	100	800	300	0.82	selective	Adopted reference condition
AR2	125	100	800	300	0.82	random	Random initial placement
AR3	125	100	300	800	0.82	selective	Invert proportions of hanger-on/passer-by protesters
AR4	65	50	400	150	0.82	selective	Lower density (1/2 reference)
AR5	125	100	800	300	0.79	selective	Lower perceived legitimacy

We introduced four "Media" agents (standing for the four Portuguese TV Channels). The "Cops" were placed on the "Parliament staircase" and their base personality as $\boldsymbol{\omega}_0$ = (2 ½ ½ 5 0 5 ½ 0) so that cops would spread more uniformly in the defensive area and also react to approaching "active" and "quiet" protesters. In the selective initial placement, the four "Media" agents are stationed between the "Cops" and "Protesters", with "Hardcore" in the front, then "Hangers-on" and finally "Passers-by", all facing the police force and the "Parliament". Fig. 3 shows three snapshots of the simulated protest space for simulations AR1 (top), AR2 (middle) and AR3 (bottom). These snapshots were chosen because they were representative of the emergent patterns obtained with the model (AR1), and of the variations resulting from: *i*) initial blocking by "active" and "quiet" protesters due to random placement (AR2), and ii) the reverse effect, due to the reversing of proportions of "Hanger-on" and "Passer-by" protesters. Lower density (AR4) had the same effect (initial blocking) as random placement.

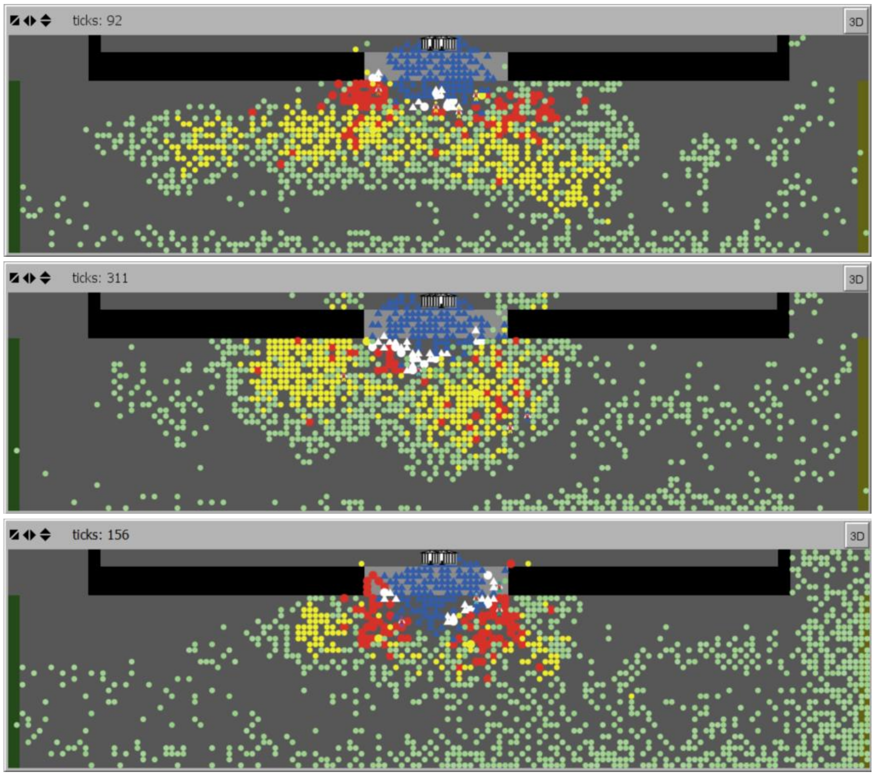

Fig. 3. Snapshots of the simulation space obtained in simulations AR1 (top), AR2 (middle) and AR3 (bottom). "Cops" are represented by blue triangles, "Hardcore" protesters by large circles (size = 2), the remaining protesters by small circles (size = 1) and "Media" agents by little human figures. Fighting agents are represented in white, "violent" protesters in red, "active" protesters in yellow and "quiet" protesters in green. Obstacles are represented in black, flagged cells in gray, entrances in dark yellow and exits in dark green.

In Fig. 3 it can be observed that the model reproduced several crowd patterns observed in real protests, such as clustering of "violent" and "active" protesters, the formation of a confrontation line moving back and forth along which fights and occasional arrests occur. "Media" agents attracted nearby protesters (inducing local clustering) and moved to find "hot spots". Many "quiet" ("Hanger-on") protesters also clustered near the confrontation zone, whereas "Passers-by" remained "quiet" and walked from entrance to exit in wandering paths, avoiding the confrontation zone. Different initial placement and variations in the proportion of "Hanger-on" and "Passer-by" protesters had impact on the capability of the policemen to simultaneously protect the perimeter and engage and arrest "violent" protesters. Fig. 4 shows the time variation of some quantitative measures of violence intensity, for simulation AR5. 99 "Hardcore" and 39 "Hanger-on" turned "violent", showing that in this case there was some contagion of "active" protesters to "violent" state. Fights occurred in bursts (with a peak of 11 protesters fighting, the largest number in the simulation set) once “violent” agents reached contact with the “Cops”. The number of arrests increased steadily, with about two “Media” records for each arrest.

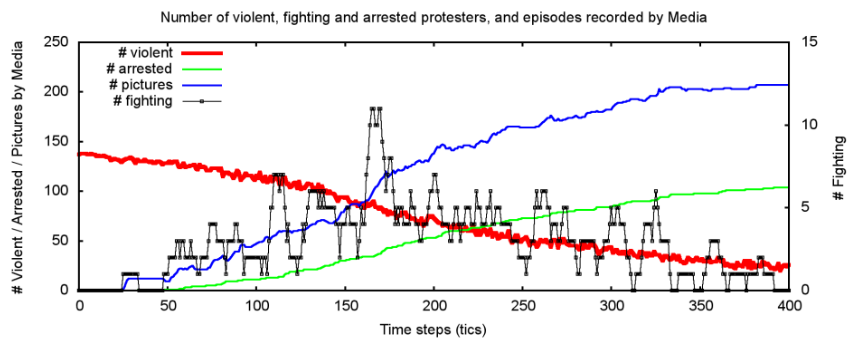

Fig. 4. Time history of the number of fighting (right vertical axis) and violent protesters, number of arrests and number of pictures taken by “Media” agents (left vertical axis), for simulation AR5.

5 Discussion

In all simulations the model reproduced in a realistic way several crowd patterns observed in real protests in this type of scenario, such as clustering of “violent”, “active” and “passive” protesters, wandering of “Passers-by”, formation of a confrontation line with localized fights and arrests, and “Media” agents attracting nearby protesters, moving near the “hot spots” and registering fight events. However, some results were somewhat unrealistic, such as some “quiet” and “active” protesters breaching the defensive perimeter due to “Cops” interacting weakly with these agents. The typical time variation of the crowd behavior was as follows. Transition to violent behavior occurred in the following sequence: *i*) “violent” protesters started clustering; *ii*) after clustering, they approached the “Cops” by breaching through the “active” and “quiet” protesters they found in between; and *iii*) they invested towards the policemen and tried to occupy the flagged area and began fighting with the “Cops”. The contact between “violent” protesters and “Cops” generally took the form of two wedges of “violent” protesters investing towards the police force from the flanks, not in the centerline of the staircase. This collective pattern behavior is often observed in real protests.

It is interesting to discuss how different conditions affected the outcome of the simulations, in terms of how well the police force copes with the tasks of protecting the perimeter and engaging protesters. The reference simulation (AR1) led to higher numbers of arrests (76 at t = 300) and “Media” pictures (76 at t = 300) than in the simulations with initial random placement and higher proportion of “Passers-by”, but also to a higher number protesters trespassing the defensive perimeter. In simulation AR3 there is less blocking by passive ones, and the police force appears to have difficulty in controlling the larger clusters of “violent” protesters (Fig. 3). In this case, the number of arrests was lower (54 at t = 300), but the number of protesters breaching the perimeter was also much smaller. Although the modeling of the police agents needs to be improved, the model already gives some hints on the tactical advantages and disadvantages for both sides in this “game”. For “violent” protesters, it is advantageous to invest from the flanks, have more confrontation spots (e.g. side accesses to the protest area that are usually less protected), attract support from “Actives” that may elude the “Cops” and trespass the defensive perimeter while the “Cops” are fighting, and avoid passive “Hanger-on” protesters blocking direct confrontation. For the “Cops”, it is advantageous to shorten the length of the confrontation zone, have a smaller number of fronts and avoid arrests that temporarily limit their mobility and give the “Media” opportunity to exploit the situation.

6 Conclusions and future developments

In this work an ABM of street protest dynamics was presented that includes multiple players (“Hardcore”, “Hanger-on” and “Passer-by” protesters, police agents, and “Media” agents). Agents can have multiple goals encoded in a “personality vector” plus a set of context rules that provide adaptation, and protesters can be “quiet”, “active” or “violent”. The model was applied to a typical protest situation in which a police force defends the entrance of a government building that protesters seek to occupy, and reproduced many features of real protests, such as clustering of “violent” and “active” protesters, the formation of a confrontation line moving back and forth, occasional fights and arrests and “Media” agents inducing local clustering and seeking the “hot spots”. It was found that with the transition rules and agents’ attributes used in the model, violent behavior was confined to the “Hardcore” and at most a small proportion of “Hanger-on” protesters, but did not propagate to the bulk of the crowd. The inclusion of multiple players with purposeful movement and multiple states allowed a more complete and realistic representation of micro-interactions than is found in previous models of civil violence, clustering and fighting.

Although the model represented well emergent crowd patterns found in real protests, it needs improvement in some aspects, such as: *i*) more advanced modeling of the police agents, with “Command”, “Defensive” and “Offensive” types; *ii*) additional context rules for “active” and “quiet” protesters when they are near police agents; *iii*) variable velocity (by subdividing the grid and using a variable move range), *iv*) legitimacy feedback mechanisms associated with the measures of intensity; and *v*) parameterization of the agents’ attributes using data collected in real protests. These developments are being considered as part of an ongoing work on ABM simulation of social conflict phenomena.

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Annex A – ODD Description of the Agent-Based Model of Protest and Violent Confrontation.

A.1 Purpose

The purpose of the model is the simulation of the interaction between protesters, police forces and media agents in street protests, to understand emergent crowd patterns such as clustering of protesting or violent individuals, fighting and transition to violence, the influence of passive actors, and the effect of media coverage on the protest dynamics**.** The model allows the representation of spatial features such as attraction zones (symbolic sites within the protest space), obstacles (physical obstructions) and entrances/exits (adjacent streets and open spaces).

The key ideas and innovative features of the model are: *i*) consideration of three types of actors ("Protester", "Cop" and "Media") and three different kinds of protester personality and behavior ("Hardcore", "Hanger-on" and "Passer-by"), for a more complete and realistic modeling of their micro interaction modes (movement and state transitions) than in currently available ABM; *ii*) introduction of media coverage effects, which change the micro behavior and help describing the feedback links between protests and the social context; *iii*) use of a "personality vector" and context rules (as proposed in [1] for land combat) for programming the agents' action selection, taking into account theoretical results of crowd dynamics [2], and qualitative analysis of protest videos for setting the weights and context rules; *iv*) modeling the protesters' state changes ("quiet"→ "active" and "active"→ "violent") using the Epstein's threshold rule (as in [3], [4]) with more stringent conditions for the transition to "violent" state; *v*) arresting of protesters is not instantaneous but requires a fighting arrest delay and local superiority of the cops.

A.2 Entities, state variables, and scales

The model was implemented in NetLogo and consists of the following entities: Observer (World, global variables), agents and patches (space variables). Figure A.1 shows the class diagram for the model.

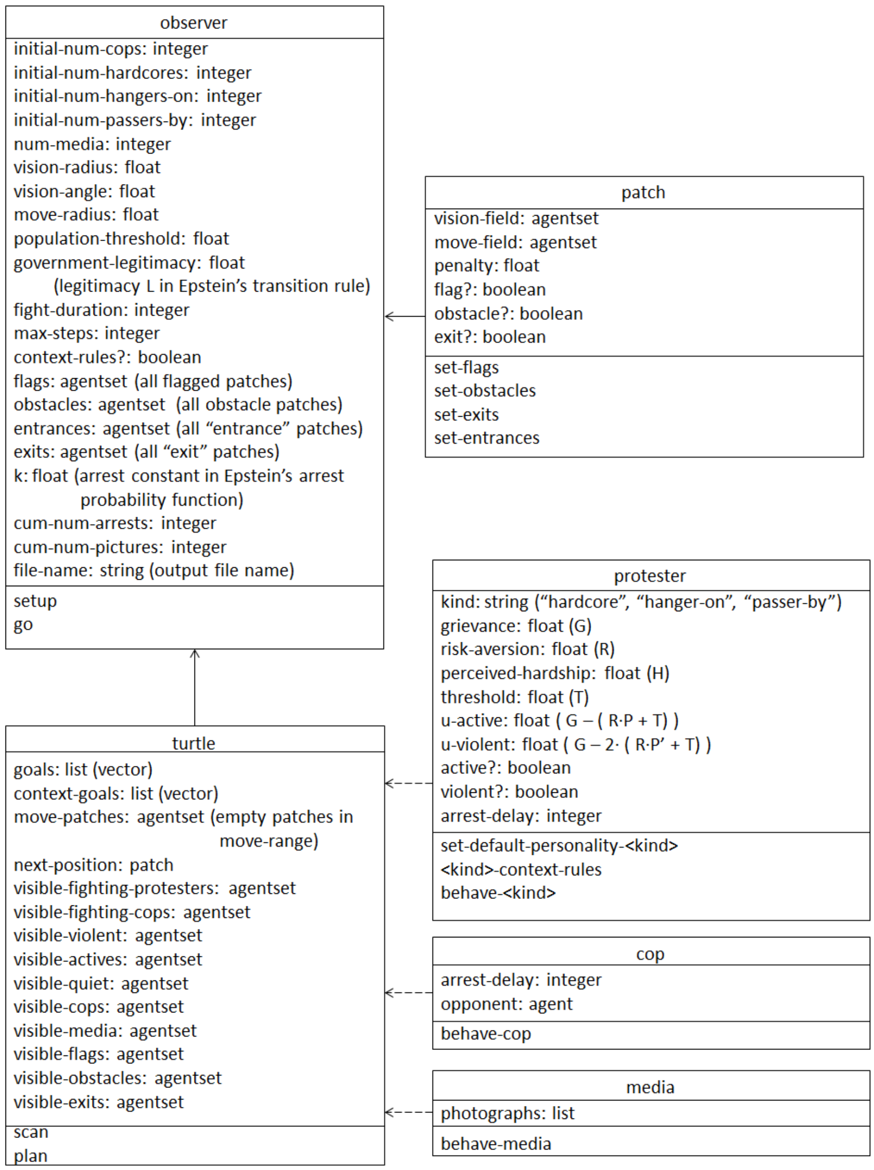

Fig. A.1 Class diagram of the ABM of protest dynamics.

Agents: There are three types of agents, "Protesters", "Cops" and "Media". "Protester" agents can be of three subtypes (kinds): "Hardcore", "Hanger-on" and "Passer-by", each with a different behavior. "Hardcore" agents form the small proportion of protesters with highest propensity for violence, whereas "Hangers-on" form the proportion of more or less "susceptible" protesters and "Passers-by" correspond to curious participants that try to avoid hotspots. Cops must protect specific sites within the protest space (for instance, the access to a government building) and keep near other cops, to avoid gaps or situations of dangerous local inferiority. "Media" agents try to approach hotspots and avoid uninteresting zones.

Table A.1 summarizes the qualitative behavior of all agent types and subtypes. From this table, the strengths and limitations of the model can be clearly understood. The implementation of the agents' qualitative behavior is done using a "personality vector" and context rules as described in sections A.4 and A.7.

Table A.1. Qualitative behaviour of agent types and subtypes considered in the model.

Type/subtype	**Description**
Protester/ hardcore	• Easily turn to "violent" state • Try to occupy the attraction points and engage cops • Cluster with "violent"/ "active" protesters to avoid being outnumbered by cops • Neutral to obstacles and entrance/exit points
Protester/ hanger-on	• Moderate incentive to approach attraction points and entrance/exit points • Low incentive to avoid obstacles • Low incentive to approach "violent" or "active" protesters and cops • Can turn "active" or even "violent" depending on their internal characteristics (hardship, risk aversion, threshold) and on the local context
Protester/ passer-by	• Low incentive to avoid "violent" or "active" protesters and cops when "quiet", which reverses when "active" or "violent" • Other behavioral characteristics as for hangers-on • Usually remain passive, because they avoid clustering with "active" or "violent" protesters
Cop	• Try to defend attraction points from "violent" protesters and keep close to other cops, to avoid being outnumbered by "violent" protesters • Try to escape from "violent" protesters when outnumbered and alone • Moderate to high incentive to pursue "violent" protesters, when in local superiority • Engage and arrest "violent" protesters in their move range, when in local superiority and with sufficient backup
Media	• Try to locate "hot spots" and record ("take pictures") of violent episodes (fights between violent protesters and cops) • Moderate incentive to approach attraction points and entrance/exit points • Moderate incentive to avoid "uninteresting" zones with many "quiet" protesters

Environment: The spatial environment consists of a 2D grid (to represent a protest space with physical boundaries) of patches (sites). The patches can be marked as "flag" to represent attraction points that protesters try to occupy and police agents must defend, "obstacle" to represent obstructions (walls, barriers), and "exit" to represent open boundary sections (adjacent streets) of the protest area.

Spatial and temporal scales: The patch size, or space occupied by one agent, has dimensions $1m \times 1m$. The time scale is $1s$, giving a constant speed of 1 ms^{-1}. The user-defined global variable arrest-delay represents the number of seconds in a fight between protesters and police agents before an arrest is made.

A.3 Process overview and scheduling

The model is based on discrete space and time representation, with a fixed time cycle and a 2D discrete grid of patches. Obstacle patches cannot be occupied by agents. The remaining patches can be occupied by only one agent at a time. The model is implemented in two procedures, setup and go, with the following operation sequences:

setup:

This procedure clears all variables from previous simulation; resets cycle counter; builds the environment (protest space); builds the agents list; and initializes the cumulative number of arrests and the cumulative number of "pictures" taken by "Media" agents in protest and plots the protest space (environment features and agents).

go (main cycle):

This procedure implements the main cycle of the ABM via the following actions: *i*) tests for termination (if ticks > max-steps the simulation halts); *ii*) resets the number of arrests and number of "pictures" taken by "Media" agents for the current cycle; *iii*) activates all agents not involved in fights (arrest-delay = 0) in random order, which perform the sequence scan – plan – behave; *iv*) activates all agents involved in fights (arrest-delay > 0), decrements their arrest-delay variable by one, and if the decremented value is zero, the agent is a "Protester" and the number of adjacent "Cops" exceeds twice the number of adjacent "violent" protesters, the agent is removed from the protest space (arrested); otherwise it is free to restart the scan – plan – behave sequence; *v*) updates the cumulative numbers of arrests and "pictures" taken by "Media" agents; and *vi*) updates the display of the protest space.

The scan procedure allows the agents to get information on the agents ("violent", "active" and "quiet" protesters, "Cops", and "Media") and spatial features (flagged cells, obstacles and exits). In the plan procedure, agents decide where to move next (or stand in the same patch) and, in the case of "Protester" agents, update the auxiliary variables used to set their next state ("quiet", "active" or "violent"). In the behave procedure, agents move to the next position and perform an action: *i*) "Protesters" update their state; *ii*) "Cops" try to engage violent protesters within their move range; and *iii*) "Media" agents try to take pictures of violent confrontations).The scan, plan and behave procedures as well as the auxiliary reporter procedures used in the model will be described in the Submodels section below.

A.4 Design concepts

A.4.1 Basic principles

The model is based on the following general concepts:

- All agents are reactive, goal driven and rule-based, move in discrete time an space increments (at most one agent per grid patch), and can have multiple goals that change according to the local context. This is consistent with the hypothesis that in protests, as in other crowd phenomena, people move and act according to simple motivations and rules, without sophisticated deliberation. Also, this approach permits simulations with large numbers of agents while retaining many important aspects of the multi-player micro-interactions in real protests;
- Agents' have one **move** rule and one **behave** rule.
- The **move** rule consists of moving to the patch within the move range that minimizes a penalty function with probability $p = 0.9$ and to a random patch within the move range with probability $p = 0.1$. The penalty function involves weights that represent approach/avoid motivations to other agents or space features and of the relative proximity of such features. The weights of the move rule depend on a "personality vector" and on context rules, as proposed in [1] for land combat. This is consistent with simplifying the attraction forces and a neglecting the short-range repulsion forces in the social force model of crowd simulation [2] in the framework of our discrete time/discrete space representation. Random movement simulates errors in the agents' estimates, as described in A.4.9.
- The **behave** rule is different for each type of agent: "Protesters" determine their state ("quiet", "active", "violent") according to Epstein's threshold rule, "Cops" try to protect the flag cells (defensive perimeter, or objective) and arrest violent agents within their move range, "Media" try to locate and record violent episodes;
- The **move** and **behave** rules are connected to the agent's overall goals. For instance:
    - Clustering of "violent" protesters facilitates not only their remaining in this state but also their advance towards attraction points and cop formations;
    - Cops remaining close to each other except when outnumbered by "violent" protesters and alone maximizes both the effectiveness of their protective action and the chances of arresting "violent" protesters.

The implementation of these rules is done by calls to NetLogo procedures upon agents' activation, as described in section A.7.

A.4.2 Emergence

The model is expected to represent the following emergent patterns: clusters of "violent" and "active" protesters, localized fights between protesters and police, police forces either defending the perimeter or engaging violent protesters according to the local context, passers-by giving clearance to fights an active clusters, Media agents moving around the "hot spots". Model output includes the time-history of the number of quiet, active and violent protesters, as well as the number of arrests and violent fighting episodes registered by media agents.

A.4.3 Adaptation
Agents adapt their goals depending on their precepts and internal state in the previous time cycle, but have no internal representation of previous percepts or states, and thus have no evolutionary or learning capabilities.

A.4.4 Objectives
The agents' goals are programmed in their default "personality vector" and in the context rules, which are different for the various agent types and subtypes. The individual's success is determined by the values of the penalty function, which determines the next position. In the case of "Hardcore" protesters, the move rule also maximizes their chances of advancing towards the attraction points and engaging police agents without being arrested.

A.4.5 Learning
Agents have no learning capabilities.

A.4.6 Prediction
As described in A.4.4 and A.4.5.

A.4.7 Sensing
Agents' planning and decision is based on the percept constructed in the scan procedure. This percept is local for the other agents, obstacles and possible positions (empty patches within the move range) and global for attraction points and exits. This is consistent with the assumption that other agents and obstacles exert influence only when they are visible, but attraction points and exits are permanent features of the protest space known to all agents anywhere within the protest space. The local percept is constructed using NetLogo's in-cone primitive with range vision-radius (global variable in the interface tab, varying between 2 and 20 *m*) and vision angle 180° to detect all visible agents (turtles) and applying the appropriate logical conditions to identify: *i*) the visible "violent", "active" and "quiet" protesters; *ii*) the visible cops; *iii*) the visible "Media" agents; and *iv*) the visible obstacles. Attraction points and exits are identified as patches with [flag?] or [exit?], respectively. Sensory information is used to find the quantities (sum of distances) and context-adjusted goal-directing weights (via the context rules) in the penalty function (see section A.7 below).

A.4.8 Interaction
Agents interact in the following ways:

- Approach/avoid specific types of agents or agents in a certain state as determined by the positive or negative components of the "default" personality vector and the context rules, leading to clustering/dispersing patterns;

- Induce state changes, which may result from clustering (facilitates transition to active and violent behavior, mostly for "Hardcore" protesters but also for the other two protester profiles) or dispersion;
- Engage in fights between "violent" protesters and cops. This is modeled by immobilizing the fighting cops and protester (two cops for one potential detainee) during an arrest-delay period, thereby simulating the cost to the police force of doing one arrest and creating opportunities for "Media" agents to move towards hotspots and record violent episodes.

A.4.9 Stochasticity

Pseudo-random variables are used in NetLogo primitives, e.g. for setting the initial positions for all agents and the endogenous context variables (hardship and risk aversion) for protester agents, for activating the agents, and for selecting the next position when the penalty function has more than one local minimum within the agent's move range. Epstein's rule for protesters state changes involves an estimated arrest probability, but state transitions are based on a deterministic formula. The model has other features that induce stochasticity and complex behavior due to sensitivity to initial conditions, such as:

- Multiplicity of goals, personalities and context rules among the agents;
- Variations of the orientation of the vision cone, which lead to other agents and features to enter and leave the vision field from cycle to cycle;
- The agents' next position is the center of the patch within their move radius that minimizes a penalty function (see section A.7) with a probability p = 0.9, and the center of a random patch with probability p = 0.1. This simulates random errors in the agents' estimates of the optimal movement and increases the realism of the simulations.

A.4.10 Collectives

Collectives of agents form as emergent patterns resulting from clustering due to their "personality vector" and the effect of context rules:

- Cops aggregate in tight formations over attraction points (flagged cells);
- "violent" protesters also cluster and form patterns that advance towards attraction points and defending cop formations;
- Confronting cop and "violent" protester clusters tend to form lines (phalanxes) thus avoiding involvement and preventing the other side from acquiring overwhelming local superiority (consistent with the micro-sociological theory of violence)
- "Passer-by" protesters tend to avoid clusters of "violent" and "active" protesters thus forming gaps in the protest space.

These features are observable in many videos of street protests.

A.4.11 Observation

No empirical data were used for parameterization of the agent's attributes, but information about hardship factors and perceived legitimacy in protest events in Portugal is being collected, using a specific questionnaire. This information may allow the formulation of more realistic distributions of the protesters' attributes.

Videos of protest events in different parts of the world were analyzed to perform qualitative validation of the patterns of movement and violent confrontation obtained in the simulations.

A.5 Initialization

Table A.2 describes the global variables, their initial default values and ranges (for global variables defined in sliders in NetLogo's interface tab).

Table A.2. Default values and ranges of the global variables for model initialization

Variable name	Description	Default value	Range
min-pxcor	minimum x-coordinate for patches	0	–
max-pxcor	maximum x-coordinate for patches	149	–
min-pycor	minimum y-coordinate for patches	0	–
max-pycor	maximum y-coordinate for patches	37	–
initial-num-cops	initial number of cops	125	[5,250]
initial-num-hardcores	initial number of hardcore protesters	100	[0,100]
initial-num-hangers-on	initial number of hanger-on protesters	800	[0,800]
initial-num-passers-by	initial number of passers-by protesters	300	[10,800]
num-media	number of "Media" agents	4	[0,5]
max-steps	maximum number of time steps	1200	[0,3600]
vision-radius	agents' vision radius	10	[2,20]
vision-angle	agents' vision angle	180	[90,185]
move-radius	agents' moving radius	1	[1,3]
population-threshold*	threshold for state transition	0.1	[0.0,1.0]
government-legitimacy*	government legitimacy	0.82	[0.0,1.0]
k*	arrest constant	2.3	–

*the meaning of these variables is explained in section A.7

The initial positioning of the agents is programmed by hand according to the scenario to be simulated. The setup of the agents' personality vector, context rules and state transition formulae for protesters (which involve the last three variables in Table A.2) is described in section A.7.

A.6 Input data

The present version of the model does not use empirical data or external files/sources for the parameterization of the agents' attributes. However, work is in progress to formulate the parameterization of the protester attributes that determine the state transitions according to data obtained in real protests using questionnaires.

A.7 Submodels

This section contains a description of the submodels (NetLogo procedures) used in the two main procedures (setup and go) described in section A.3. We start by presenting the basic architecture common to all agents, followed by a description of the implementation of goal-driven agent movement and state transitions. We also include a list of auxiliary procedures used by the setup and go procedures to implement the agents' move and behave rules.

A.7.1 Agent architecture

We formally define the agents as a 5-tuple

$$\text{Agent} = < P, I, \ A, in, out >, \tag{1}$$

where *in* is the input, *P* is the percept, *I* is the agent's internal state, *A* is the action and *out* is the output or change of the environment due to the agent's action. Fig. A.2 illustrates the implementation for the case of a "Protester" agent.

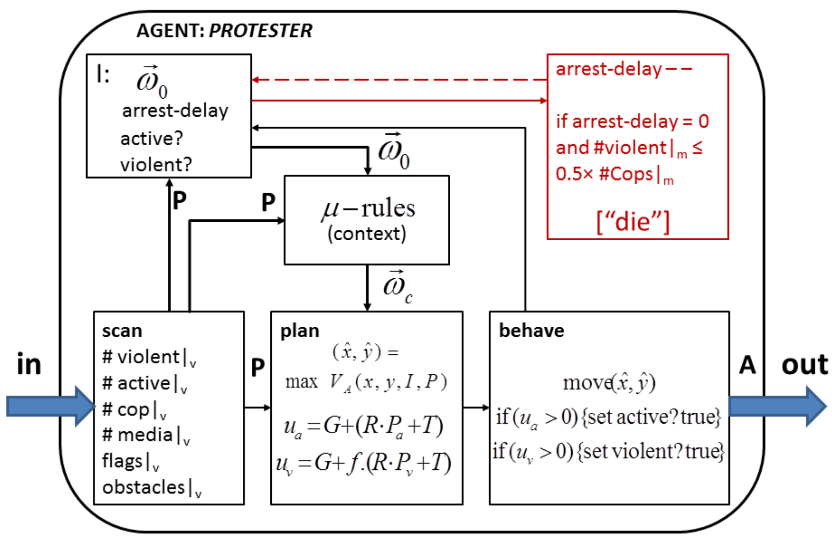

Fig. A.2. Agent architecture diagram for the "Protester" agent type. In this diagram $|_v$ is the neighborhood within the vision cone of the agent, $|_m$ is the move range, u_a and u_v are auxiliary functions that are positive when the agent is "active" or "violent" (respectively), V is the penalty function and $(\hat{x}, \hat{y})$ is the position (patch center) that minimizes this function. "Cop" and "Media" agents have a similar architecture.

The agent's internal state consists of a "default personality" vector $\boldsymbol{\omega}_{A,0}$ of weights $\boldsymbol{\omega}_{A,i}$ which define the agent's goal orientations; two variables that indicate whether or not the agent is "quiet", "protesting" or "violent"; and an arrest-delay that identifies the agent as engaged in fighting with "Cops" and counts the number of cycles remaining before arrest. If the agent is fighting, the arrest-delay is decremented. If the decremented arrest-delay is zero and the number of "Cops" adjacent to the protesters is equal or exceeds twice the number of adjacent “violent” protesters, the agent is arrested and disappears from the simulation space; if this condition is not verified (not enough local superiority of the “Cops”), the fight is broken and the agent becomes free. Otherwise, the agent scans the environment, resulting in a percept P with the relevant context features.

The **plan** procedure combines the “default personality” with the meta-rules that may be activated by P. The result is a context-adjusted vector $\boldsymbol{\omega}_{A,c}$ used to find the next position (analogous to the method in [1]) and compute the values of the auxiliary functions that define the agent’s state according to a variant of Epstein’s threshold-based transition rule [3], [4]. Finally, the **behave** procedure moves the agent and updates its state.

A.7.2 Goal-driven agent movement

Agents move to the position (patch center of an empty patch) within their move radius that minimizes the penalty function

$$V_A(x,y,I,P)=\frac{\boldsymbol{\omega}_{A,c}(I,P)}{\left\|\boldsymbol{\omega}_{A,c}(I,P)\right\|_1}\bullet\left(\mathbf{S}(x,y)-\mathbf{S}(x_0,y_0)\right) \qquad \textbf{(2)}$$

where $\boldsymbol{\omega}_{A,c}(I,P)$ is the context-adjusted personality vector,

$$\mathbf{S}(x,y)=\sum_{F_i\in P}\left(\sum_{j=1}^{N_{Fi}} D_{(x,y)}F_{i,j}\right) \qquad \textbf{(3)}$$

is the sum of distances from element j (say, one violent protester) belonging to a feature F_i (say, the agent set of visible violent protesters) in percept P to the point (x,y), and (x_0,y_0) is the current position of agent A.

The goals have absolute value between 5 (very high) and 0 (neutral). Table A.3 shows the default personality weights which sets the default goal-driven behavior for all agent types and subtypes. From this table, the default behavior of the agents can be inferred. For instance, Cops have a strong attraction towards other cops and flags and moderate attraction to violent agents, but have low attraction towards active protesters and are indifferent to all other features.

Table A.3. Default personality weights for all agent types and subtypes. A positive sign means attraction and a negative sign means repulsion.

Agent type/ subtype	violent ω_0	active ω_1	quiet ω_2	cops ω_3	media ω_4	flag ω_5	obstacle ω_6	exit ω_7
hardcore	+ 5	+ 2	0	+ 4	+ 3	+ 5	–1	0
hanger-on	+ 1	+ 1	0	+ 1	+ 3	+ 1	– 1	+ 1
passer-by	– 1	– 1	0	– 1	+ 3	0	– 1	+ 1
cop	+ 2	+ 1	0	+ 5	0	+ 5	0	0
media	+ 3	+ 1	– 1	+ 3	+ 2	+ 2	– 1	0

Depending on the internal state I and percept P, the default weights may be changed according to the local context by application of meta-rules, which are different for different type and subtype of agent. Table A.4 summarizes the context rules for each agent type and subtype.

Table A.4. Context rules for all agent types and subtypes.

Agent type/subtype	Context rule	Meaning	Condition*
hardcore	CLUSTER	Get support before confronting cops	Visible flags and $N_{viol} < ½ N_{cops}$
	PURSUE	Pursue cops when in advantage	$N_{active} + N_{viol} \geq 2 N_{cops}$
	AVOID	Avoid cops when outnumbered	$N_{active} + N_{viol} < ½ N_{cops}$
hanger-on	KEEP CLEAR	Keep clear for other agents when "quiet"	Keep 2.5 *m* clearance from "quiet" and 5 *m* clearance from "violent" protesters and "Cops"
	CLUSTER	Approach other "actives" when "active"	active? = true
	TURN VIOLENT	Assume "Hardcore" personality when "violent"	violent? = true
passer-by	KEEP CLEAR	Keep clear for other agents when "quiet"	Keep 2.5 *m* clearance from "quiet" and 5 *m* clearance from "violent" protesters and "Cops"
	CLUSTER	Approach other "actives" when "active"	active? = true
	TURN VIOLENT	Assume "Hardcore" personality when "violent"	violent? = true
cop	ON-STATION	Increase attention towards nearby agents when in position (flagged cell)	[flag?] of patch-here = true
	PURSUIT	Pursue "violent" protesters	$N_{violent} \leq ½ N_{cops}$
	RETREAT/AVOID	Avoid "violent" protesters when outnumbered and alone	$0 \leq N_{cops} \leq ½ N_{violent}$
	SUPPORT	Help comrades in "hot spots"	$0 \leq N_{cops}\|_m \leq ½ N_{violent}\|_m$
media	MINIMUM CLEARANCE	Keep good distance for "taking pictures"	Distance to nearest "violent" protester or "Cop" ≤ 3 *m*

We used the following guidelines for implementation of context rules:

- Start with the two types of agents with strongest interaction (in this case, "Hardcore" Protesters and "Cops") and successively add other agent types;
- Set and adjust the components of the "default personality vector" to define the intended goal-orientation for each agent type;
- Successively introduce and test the context rules and observe if they provide the intended behavior adaptation with respect to the default behavior;
- When implementing the context rules, it is necessary to pay attention to the following points: *i*) context rules should be as independent as possible from each other; *ii*) when two or more rules are dependent it is necessary to check carefully if they do not cancel each other or produce unrealistic effects; *iii*) effective context rules "focus the agent's attention" by setting the default weights of less relevant features to zero and increasing the absolute value of the weights associated with the (context-dependent) important features.

A.7.3 Transition to "Active" and "Violent" behavior

In Epstein's civil violence model [3], [4] transition from "quiet" to "active" (rebellious) behavior is determined by the rule $G - N > T$, where $G = H \cdot (1 - L)$ is the level of grievance, $N = R \cdot P$ is the net risk perception, T (constant exogenous variable) is a threshold, $H \sim U(0,1)$ is the (endogenous) perceived hardship, $L \in [0,1]$ is the "perceived government legitimacy", $R \sim U(0,1)$ is the (endogenous) risk aversion, and P is the estimated arrest probability $P = 1 - \exp(-k\lfloor C/(A+1)\rfloor_v)$ in which k is a constant and C and A are the number of "active" citizens and cops within the vision radius v. Although it was proposed for a macro-scale ABM, this rule is consistent with the main tenets of the SAT and micro-sociological theories: predisposition can be modeled by the values of G and R, the situational and deterrence elements by the form of P, and the "barrier" by the threshold T. In our model, a Protester's transition from "quiet" to "active" and "violent" is determined by the following rules:

$$\text{if } G - (R \cdot P_a + T) > 0, \text{ turn to "active"} \tag{4}$$

$$\text{if } G - 2\,(R \cdot P_v + T) > 0, \text{ turn to "violent"} \tag{5}$$

where $P_a = 1 - \exp(-k\lfloor C/(A+V+1)\rfloor_v)$, $P_v = 1 - \exp(-k\lfloor 2\cdot C/(A+V+1)\rfloor_v)$ and V is the number of active Protesters within the vision cone. The factor two is in Eq. (4) is arbitrary and accounts for the increased risk and need for local support in the transition to violence. Finding a more correct value for this parameter requires empirical analysis of real protest events.

A.7.3 <u>List of auxiliary procedures</u>

The submodels described above, as well as some straightforward routines for defining the flag, obstacle and exit configurations of the protest space were implemented as NetLogo procedures and reporter procedures. Table A.5 contains a description of those auxiliary routines, and completes this section.

Table A.5. List of auxiliary NetLogo procedures used by the setup and go procedures.

Calling procedure	Submodel	Description
setup	set-flags	sets flag? = true and color = gray for flagged cells
	set-obstacles	sets obstacle? = true and color = black for obstacle cells
	set-exits	sets exit? = true and color = green – 3 for exit cells
	set-default-personality-<agent>*	sets the agents' default "personality" vector
go	scan	gets the entities (agents and environmental features) necessary for agents' planning using NetLogo's in-cone primitive
	plan	computes the value of the penalty function for all patches in move field, and the variables used for updating the agent's state in the case of "Protester" agents.
	<agent>-context-rules*	reports the context-dependent "personality vector" that results from changing the components of the default "personality" vector according to the percept received from the scan procedure. There are different procedures for each type and subtype of agent, which implement different rules.
	sum-distance [agentset]*	reports the sum of distances agent to perceived entities (agents of environmental features) in the agentset argument
	arrest-probability-active*	reports the estimated arrest probability of turning "active" for "Protester" agents
	arrest-probability-violent*	reports the estimated arrest probability of turning "violent" for "Protester" agents
	behave	makes agents move and act according to plan. There are different behave-<agent> procedures for each type of agent
	display-<agent>	displays agents (in either 2D or 3D NetLogo display)

*procedure of the reporter type.

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From Anarchy to Monopoly: How Competition and Protection Shaped Mafia's Behavior

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Abstract. Mafia-like organizations are characterized by their extortive activities that impact societies and economies in different modes and magnitudes. This renders the understanding of how these organizations evolved an objective of both scientific and application-oriented interests. We propose an agent-based simulation model – the *Extortion Racket System* model – aimed at understanding the factors and processes explaining the successful settlement of the Sicilian Mafia in Southern Italy, which may more generally account for the transition from an anarchical situation of uncoordinated extortion to a monopolistic social order. Our results show that in situations of anarchy, these organizations do not last long. This indicates that a monopolistic situation shall be preferred over anarchical ones. Competition is a necessary and sufficient condition for the emergence of a monopolistic situation. However, when combined with protection, the resulting monopolistic regime becomes even more preferable for societies in which extortion activities are endemic.

1 Introduction

Mafia-like organizations are remarkably prosperous organizations originating in Southern Italy at the end of the XIX century, if not earlier, and now widely spread all over the world. They are highly dynamic and organized criminal groups that impact societies and economies in different modes and magnitudes [5, 8].

The origins of the Mafia, however, are not yet well understood, mainly due to the lack of information, which is in part a consequence of their secret nature. Currently, an explanation largely supported among scholars proposes three main factors for its origins, (i) the *land reforms*, (ii) the *property rights* and (iii) the *weak State* institutions. These factors were present in the Sicilian transition from feudalism to pre-capitalism and in the typical market structure of the region in the XIX century [2–4, 10].

Following to this view, the Mafia phenomenon developed when the State was weakly represented in the Sicilian region and widespread criminals were freer to engage in repeated raids against properties and production, thereby creating a chaotic or anarchical situation all over Sicily [1].

Those criminal activities mainly consisted in the imposition of a predatory *taxation* on landowners, i.e., the extortion racket. The victims were forced to pay under the threat of harmful retaliation. Only if they did pay, they suffer no harm. Extortive activities were *uncoordinated* and the victims were exposed to the predatory requests of many *competing roving bandits* [7]. This situation induced landowners to hire reputable violent criminals to control banditry and protect their land and production [1].

This need for *protection*[3] increased the practice of *protection racketeering*, which is defined as "an institutionalized practice whereby tribute is collected on behalf of a criminal group that, in exchange, claims to offer (...) protection" [13, p. 140]. The activity of protection racketeering has been identified as the Mafia's typical activity [4, 5, 9], which led Gambetta [4] to define it as "The Business of Private Protection."

Schelling [9] noted, however, that protection racket activities cannot tolerate co-existing extorters as possible victims are less likely to pay more than one extorter per time. Successful racketeering seems to require a *monopolistic regime*[4]. Monopoly, in contrast to an anarchical situation of uncoordinated extortion, creates a sort of social order through which, once individuals accept to pay one extorter, they "do not need to worry about theft by others" [7].

Consequently, it becomes crucial to understand what are the factors leading to the achievement of monopolistic situations and what are the benefits that they may provide over anarchical ones. Another important issue is exploring what factors may lead to monopolistic situations that are more desirable for the societies in which extortion activities are endemic.

In our view, the understanding of how mafia-like organizations may have evolved from uncoordinated groups of *roving bandits* into real *governments of the underworld* is an objective of both scientific and application-oriented interests. On the one hand, it aims at contributing to the general study of the bases and origins of social order [7, 11]; on the other, it aims at understanding what makes the settlement of these organizations successful.

Hence, the present study proposes an agent-based simulation model – the *Extortion Racket System* (ERS) model – aimed at understanding the factors and processes explaining the successful settlement of the Sicilian Mafia, which may more generally account for the transition from an anarchical situation of uncoordinated extortion (i.e., widespread banditry) to a monopolistic social order. The model will test the effects of the transition from a primitive and anarchical form of extortion to a monopolistic government of the underworld, both on the racketeering system and on the whole population.

The model involves the interplay between two types of agents – Extorters and Targets – and reproduces a situation in which rival extortive systems exist

[3] There are different types of protection that extorters may provide to their victims, for a recent analysis of Mafia protection, see also [12]. In this work, we refer only to protection against other extortionists who would tax the same targets.

[4] By monopoly, we refer to the presence on the territory of only one criminal organization practicing protection racketeering.

and compete with one another. The extorters' goal is to extort the targets in their domain and to expand such domain by competing with other extorters, thereby providing a sort of *unintended* protection to their targets. Alternatively, the extorters may reproduce a *intended* protection, in which they provide a more active shelter to their targets.

In particular, the ERS model aims to test the following research questions:

1. How to explain the transition from an anarchical and uncoordinated extortive situation to a monopolistic one? What are the minimal factors that suffice to bring about a monopolistic regime?
2. What is the effect of either regime, anarchical and monopolistic, on the targets?
3. What is the effect of either regime on the extorters? In particular, what is the effect of the monopolistic regime on the profile of the surviving extorters?

We hypothesize that (1) a monopolistic regime is required for an ERS to be successfully and steadily settled; (2) a monopolistic regime is preferred by the targets over an anarchical one; (3) the competition among extorters plays a key role in the transition from an anarchical and uncoordinated extortive situation to a monopolistic one; and (4) the protection enables the selection, among those competing, of the relatively most sustainable extortive system to become the monopolist.

The paper will unfold as follows. In Section 2, we describe the ERS model aimed to check the research questions we posed above. Next, we discuss the results we have obtained so far in Section 3. Finally, we provide some conclusions as well as some ideas for future work in Section 4.

2 Model Description

This simulation model represents a world populated by *extorters* ($E = \{e_1, \ldots, e_n\}$, where n is the total number of extorters in the model ($n = |E|$)) and possible *targets* ($T = \{t_1, \ldots, t_m\}$, where m is the total number of targets in the model ($m = |T|$)) of extortion.

The extorters interact among themselves and with the targets. The extorters' basic activity is to extort targets and their goals are: (1) to receive extortion payment from as many targets as possible, and (2) to maintain and expand their domains as much as possible.

Each extorter behaves according to its own extortive policy that remains unchanged over time. Each policy can be seen as an extorter's profile and consists in the combination of two traits: *extortion level* (i.e., the amount of the targets' endowment requested as extortion money) and *punishment severity* (i.e., the amount of punishment effectively inflicted by the extorter on the target that did not pay the extortion request). Punishment is costly both to the target receiving it and to the extorter inflicting it.

We characterize an extorter as an agent having the following set of attributes:

- *Wealth* – Accumulated extortion received.

- *Domain* – List of targets to extort.
- *Enlargement Probability* – Probability of incorporating a new (randomly selected) target in the extorter's domain.
- *Protection Provision* – Flag indicating whether the extorter tries or not to protect its targets from other extorters.
- *Extortion Level* – Percentage of the target's income demanded as extortion.
- *Punishment Severity* – Percentage of the target's income inflicted as punishment.
- *Cost of Fighting* – Percentage of the extorter's wealth inflicted as cost on the opponent extorter.
- *Cost of Punishing* – Percentage of the punishment inflicted paid as cost by the extorter.

Targets are entrepreneurs that operate businesses (e.g., supermarkets, building companies, retail shops), which generate regular earnings. Their aim is to minimize the amount of earnings spent in paying extortion and in receiving punishment. Targets are agents with the following set of attributes:

- *Wealth* – Accumulated income.
- *Income* – Earning received at each round.

Each target keeps a record of the punishments and successful protections received from each of the extorters it interacted with. This piece of information is used by the target for ranking the extorters whenever it cannot afford paying all extortion requests. Initially, the targets have an estimation of the information, which they update whenever having direct interactions with the extorters.

In the initialization stage of the simulation, the same number of targets is assigned to each extorter and referred as their domain. This assignment procedure is aimed at reproducing an anarchical situation, characterized by all targets initially having more than one extorter demanding payment, and all extorters initially having the same number of targets to extort. The underlying idea is that prior to the Mafia consolidation, as evidence shows, there was no clear territorial separation among groups. Extorters needed to keep, defend, and expand their domains by competing with other extorters for the same limited set of targets.

Each extorter's profile, consisting of the extortion level and punishment severity, is also defined in the initialization stage. The extortion level is randomly selected by applying a uniform distribution from 0% to 100%; also punishment severity is randomly selected on a uniform distribution, but the possibilities are limited between the extortion level value assigned to the extorter and 100%. For instance, if the extortion level randomly assigned to an extorter is 60%, then the punishment severity will be randomly selected from 60% to 100%.

Once completed the initialization stage, extorters and targets interact for several rounds, following the steps illustrated in Figure 1.

Each round begins with the targets receiving their incomes that result from regular business activities. This income varies among targets representing different businesses' type and size. In stage 1, each extorter has a given probability (extorter's attribute *Enlargement Probability*) to increase its domain by one new

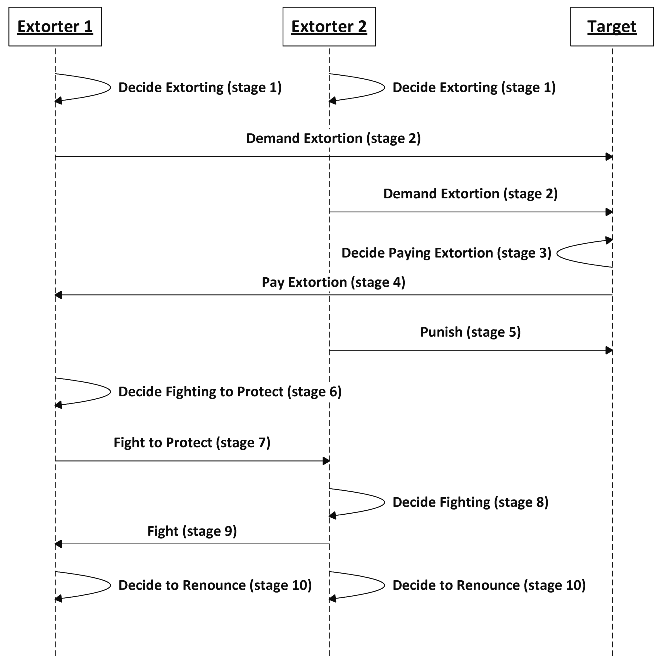


Fig. 1: Sequence diagram of the agents' interaction.

target. Once defined its new domain, extorters define how much to extort from each target (*Decide Extorting*, see Figure 1), which corresponds to the target's income multiplied by the extorter's extortion level. Then in stage 2, extorters make their extortive request to their targets (*Demand Extortion*, see Figure 1).

In the third stage (*Decide Paying Extortion*, see Figure 1), each target checks whether they can afford paying all the demanded extortions (i.e., they check whether their income is greater than or equal to the sum of all the extortions received). If so, it proceeds straight to stage 4; otherwise, the target is forced to establish a preferential order among extorters. In order to rank them, the target assigns to each extorter a *convenience value* calculated according to Equation 1.

$$C_i = Ext_i + \left(\left(\sum_{j=1, i \neq j}^{n} Pun_j \times probPun_j \right) \times probProt_i \right) \tag{1}$$

where, i and $j \in E$. C_i is the *convenience value* assigned to extorter i. Ext_i is the amount demanded as extortion by extorter i. Pun_j is the punishment inflicted by extorter j in case it does not receive the extortion payment. $probPun_j$ is the probability of the target being punished by extorter j in case of non-payment of extortion, which is calculated based on the outcomes of previous interactions of this target with the same extorter j, considering those interactions in which the target has not paid the extorter j. $probProt_i$ is the probability of the target being protected by extorter i in case the latter is paid, which is calculated based on the outcomes of previous interactions with the same extorter i in which the latter successfully protected the target from extortions.

This convenience value is based on a simple algorithm aimed at minimizing the target's losses when selecting which extorters to pay. It combines the extortion demanded by the evaluated extorter and the potential protection service that the extorter may provide against other extorters. Based on the extorters' convenience value, the target sorts the extorters list in ascending order. It means that the target prefers to pay the lowest extortion and to receive the lowest punishment by all the unpaid extorters.

Then in stage 4, the target pays all or as many extorters it can afford to pay (*Pay Extortion*, see Figure 1), starting from the top to the bottom of its ranking extorters convenience's list.

In stage 5, those extorters that did not receive payment decide whether to punish or not the targets that have not paid extortion (*Punish*, see Figure 1). The inflicted punishment reduces the target's wealth, but also imposes a cost on the punisher (extorter's attribute *Cost of Punishing*). Once punished, the target updates the extorters' punishment probability ($probPun_j$, see Equation 1).

Stages 6 and 7 depend on whether the *Provider Protection* extorter's attribute is enabled. If so, the extorter goes through these stages; otherwise, it proceeds to stage 8, which means that the extorter does not intentionally provide protection to its targets.

In stage 6, extorters with the Provider Protection attribute enabled that received extortion payment (henceforth *protectors*) face a new decision, namely whether or not to fight against other extorters that tried to extort the same target (henceforth *opponents*) (*Decide Fighting to Protect*, see Figure 1). Fighting, which reproduces what we call protection, results in a reduced probability that one's targets will receive others' extortion demands in the future, and in a reduced risk that they will pay any of these. The protector decides to fight only weaker or equally strong opponents, according to Equation 2.

$$\frac{wealth_p}{\sum\limits_{x\in\{p,o\}} wealth_x} + \frac{numTarget_p}{\sum\limits_{x\in\{p,o\}} numTarget_x} \geq \frac{wealth_o}{\sum\limits_{x\in\{p,o\}} wealth_x} + \frac{numTarget_o}{\sum\limits_{x\in\{p,o\}} numTarget_x} \quad (2)$$

where, $wealth_p$ and $numTarget_p$ are respectively the wealth and the number of targets of the protector extorter. $wealth_o$ and $numTarget_o$ are respectively the wealth and the number of targets of the opponent extorter.

If the protector decides to fight (*Fight to Protect*, see Figure 1), then in stage 7 both extorters suffer a reduction in their wealth (extorter's attribute *Cost of Fighting*) according to the Lanchester's N-Square rule [6]. This rule states that when fighting, both extorters (protector and opponent) lose wealth, but each extorter loses wealth proportionate to the adversary's wealth. This means that the wealthier extorter has a greater impact on the less wealthy one, and there is no winner in such situation as both lose. The incentive for the protector to fight against its opponents is that of increasing the wealth difference between itself (stronger) and the opponent (weaker). This increased difference may then force the latter to give up the target or die (i.e., successful protection). The emergent effect of protection is that of building a reputation of reliable protector.

In stage 8, unpaid extorters decide whether or not to fight against opponents (*Decide Fighting*, see Figure 1). This fighting decision is also based on Equation 2 in which the extorter decides to fight only weaker or equally strong opponents. The incentive for fighting is a resulting larger wealth difference from opponents, to the point that these might possibly quit the market. The long-term emergent effect is instead a reduced number of competitors, and finally a monopolistic situation in which both the targets and the extorters are better off than they are in an anarchical and uncoordinated regime. In stage 9, if the extorter decides to fight (*Fight*, see Figure 1) the cost of fighting is calculated also on the basis of the Lanchester's N-Square rule.

Finally, in stage 10 each extorter decides whether or not to renounce (*Decide to Renounce*, see Figure 1) the targets it unsuccessfully tried to extort. Renouncing means that the extorter will remove the targets from its domain. Three conditions must be satisfied for renouncing a target: (1) the extorter did not receive payment from the target; (2) the extorter was attacked by a protector of that target; and (3) the extorter did not attack anyone to protect that target.

If the extorter succeeds in leading others to renounce a target (i.e., in protecting it), the target will keep track of this information and will update the protection probability concerning that extorter. This piece of information will obviously affect the target's ranking of future extorters (see Equation 1).

At the end of each round, the extorter dies if its wealth is not higher than 0 or if it has no targets to extort. In the former case, its targets will be redistributed to the extorters that fought for them. The target dies if its wealth is not higher than 0.

3 Results and Discussion

This section describes a simulation experiment aimed at answering the posed research questions and check the validity of our hypotheses presented in Section 1. The simulation experiment includes three treatments:

1. *No-Competition* – Extorters do not compete among themselves, meaning that they do not fight. Extorters demand extortion to the target and punish those that do not pay.
2. *Competition & No-Protection* – Extorters that receive extortion do not protect (extorter's *Protection Provision* attribute disabled) their extorted target from other extorters. Extorters that are not paid, first punish the targets that did not pay, and then decide whether to fight or not in order to increase the probability of expanding their domain.
3. *Competition & Protection* – Extorters that are paid may fight in order to protect their extorted targets (extorter's *Protection Provision* attribute enabled) and increase their chance of being paid in the future. Extorters that are not paid decide whether to fight or not in order to increase the probability of expanding their domain.

These treatments vary by just one feature. The *no-competition* treatment differs from the other two because extorters do not compete among themselves. By contrast, the *competition & no-protection* and *competition & protection* treatments differ as to the provision of the protection service to the targets. In the former treatment, extorters do not provide explicit protection service to the targets: paid extorters do not fight against other possible extorters; in the latter treatment, the paid extorters have the option to provide protection to their targets.

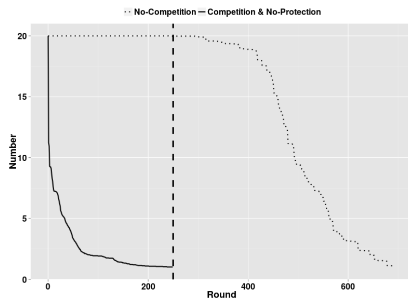
For each treatment, the simulation model was run 50 times with different random seeds and targets, but with the same set of extorters' profile randomly chosen once at the begin of the experiment. Each simulation was run with 20 extorters and 2000 targets. Each extorter attributes are set as: *wealth* = 1000, the *enlargement probability* = 10%, the *cost of fighting* = 3%, the *cost of punishing* = 33.3%. Each target attributes are set as: *wealth* = 1000, *income* = value between 300 and 1000 varying its value each round from 90% to 110%.

The analyses of the treatments are based on a set of output metrics, whose values are calculated as the average of the results of the 50 simulation runs carried on for each treatment. The output metrics are: *Number of Extorters* – The number of extorters active on the simulation; *Number of Targets* – The number of targets active on the simulation; *Speed to Monopoly* – The number of rounds to achieve monopoly; *Extortion Burden* – Proportion of the targets' income spent on paying extortion; *Punishment due to unsuccessful extortion* – Proportion of unpaid demanded extortions that triggered punishment; *Losses due to punishment* – Proportion of the targets' income lost because of punishment.

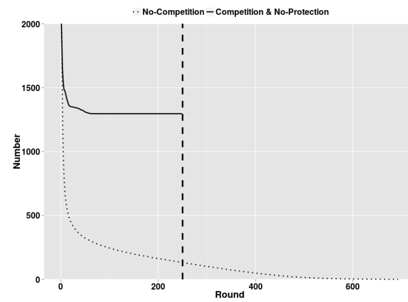
Here is a summary of the main results. Figures 2a – 2d show the graphics of the dynamics of the *no-competition* (dotted line) and *competition & no-protection* (solid line) treatments.

Due to the lack of competition among extorters in the *no-competition* treatment, targets face an anarchical situation in which they are exposed to requests from all possible extorters, causing their death, and consequently that of all extorters approximately at round 700.

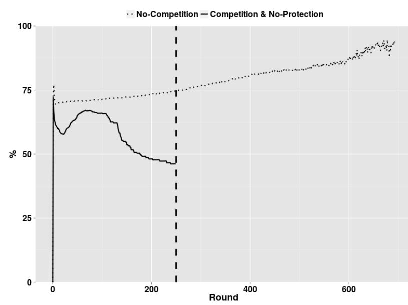
In this treatment, targets' death is ignited at the beginning of the simulation as each target receives on average four extortive requests (this number is specific for this experimental settings and it may vary according to the ratio between targets and extorters). Thus targets that cannot bear to pay all of these demanded extortions are punished, and consequently many of them die, as the steep decrease in the number of targets of Figure 2b shows (from 2000 to around 500 targets in the initial rounds). In the subsequent rounds, the proportion of targets' income used to pay extortion increases (see Figure 2c), and the targets become incrementally unable to pay all of the extortive requests; this in turn inflates the number of punishments (see Figure 2d), and consequently the number of targets' deaths. As the number of targets diminishes, some extorters see their domains shrinking until they get to zero, what also causes their death. The situation evolves by the remaining extorters enlarging their domains, what slowly leads to the death of all the other targets and subsequently of the extorters.



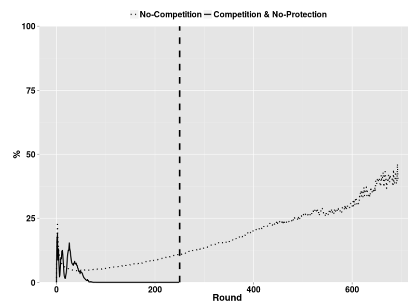
(a) Number of Extorters.



(b) Number of Targets.



(c) Proportion of target's income spent on paying extortion.

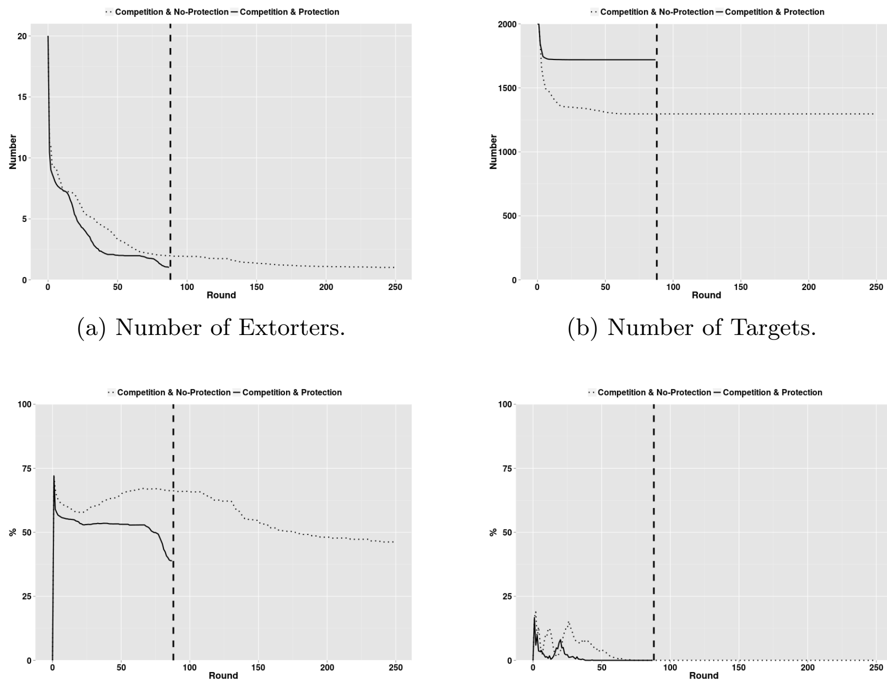


(d) Proportion of extortions demanded that resulted in punishment.

Fig. 2: Dynamics of *no-competition* (dotted line) and *competition & no-protection* (solid line) treatments. The vertical dashed line indicates the moment in which a monopolistic regime is achieved in one of the treatments. By this, we mean a situation in which there is only one active extorter in the environment. The x-axis unit is the number of simulation rounds.

The *no-competition* treatment represents a situation of predatory extortion, in which the extorters do not create any long-term relationship with their victims. They attempt to extort them, without caring about their survival. Moreover, they use violence as deterrence. Our results show that anarchical situations of non-regulated extortions are not sustainable in the long-term since they are characterized by predatory extortions and high levels of punishments, resulting in the rapid death of all targets and consequently of all extorters.

Instead, competition allows the situation to evolve from an anarchic violent situation to a regime of one stationary bandit (see the *competition & no-protection* treatment in Figure 2a) who monopolizes the taxation (i.e., extortion), thus allowing for the emergence of a more acceptable situation for the targets. In it, only a portion of their income is stolen through extortion (see Figure 2c) and they do not have to worry about the theft of others [7]. In this sense, competition



(a) Number of Extorters.

(b) Number of Targets.

(c) Proportion of target's income spent on paying extortion.

(d) Proportion of extortions demanded that resulted in punishment.

Fig. 3: Dynamics of *competition & no-protection* (dotted line) and *competition & protection* (solid line) treatments. The vertical dashed line indicates the moment in which a monopolistic regime is achieved in one of the treatments. By this, we mean a situation in which there is only one active extorter in the environment. The x-axis unit is the number of simulation rounds.

acts as a sort of weak or soft protection, in which targets, though victimized by one bandit, are at least freed from all others.

Competition is an important factor of protection in two ways: (1) it brings about a monopolistic regime, which is more tolerable for targets than anarchy; (2) it leads to the selection of the most successful competitor, which turns to be the most likely to be paid, or, ultimately, to the extorter that makes the most acceptable requests. Competition among extorters seems a sufficient condition for a basic form of social order to settle.

Let us now compare the *competition & no-protection* treatment's results with the *competition & protection* ones.

Figure 3a depicts the evolution of the number of extorters in the *competition & no-protection* (dotted line) and *competition & protection* (solid line) treatments. In both, the situation evolves from an anarchical into a monopolistic situation, determined by the survival of only one active extorter. In the former treatment, however, the monopolistic regime is reached in a shorter period of time, occurring approximately at round 90, while in the latter treatment, the same regime needs around 250 rounds to emerge. This time difference derives mostly from the fact that the activity of protection provision raises significantly the initial number of fights between extorters in comparison to the *competition & no-protection* treatment and consequently the number of extorters' death.

Protection has further positive effects on targets as it results in a reduced, respectively, frequency and severity of punishment inflicted on the targets that refused to pay. It therefore makes the number of surviving targets increase (see Figure 3b), and leads to an increasing amount of resources targets are left with, after they have paid extortions (see Figure 3c). Additionally, Figure 3c also shows that after the monopoly has been achieved, the level of extortion requested is lower with protection than without. This seems to indicate that protection makes the extortion burden more tolerable for targets, and the power of successful extorters more stable.

4 Conclusion and Future Work

The ERS model is aimed at understanding how social order may emerge from anarchical situation of uncoordinated extortion (i.e., widespread banditry). It focuses on the factors and processes that may lead from an anarchical and chaotic situation to a monopolistic social order. In particular, it is aimed at answering some research questions by testing the following 4 hypotheses: (1) a monopolistic regime is required for an ERS to be successfully and steadily settled; (2) a monopolistic regime is preferred by the targets over an anarchical one; (3) the competition among extorters plays a key role in the transition from an anarchical and uncoordinated extortive situation to a monopolistic one; and (4) the protection enables the selection, among those competing, of the relatively most sustainable extortive system to become the monopolist.

Our results show that in situations of anarchy, ERSs do not last long: they dissolve soon because they cannot sustain the rebellion and consequent death of their targets (Hypothesis 1). Moreover, the level of extortion paid by the targets is always lower whenever a monopoly of any type is achieved. This results in a situation in which both the monopolistic extorter and the targets are better off: targets do not need to worry about the thefts of other extorters, they are left with a certain capital after paying the extortion, thereby increasing future income that the extorter can benefit from. Monopolistic situation shall then be preferred over anarchical ones, as claimed by Olson [7, p. 568] (Hypothesis 2).

Moreover, results show that competition is a necessary and sufficient condition for the emergence of a monopolistic situation (Hypothesis 3). However, when competition is combined with protection, the resulting monopolistic regime presents features that make it preferable for the targets than the one emerging from competition alone. The protection of the subjects against other possible extorters favors the rapid emergence of a government of the underworld in which a peaceful order is provided (since less punishment has to be used to convince targets to pay) and more resources are left to the targets (Hypothesis 4).

In future work, we intend to perform further sensitive analyses using a design of experiments approach. Moreover, we intend to enable agents to improve their performance by dynamically adapting their extortive demands and punishment severity (i.e., their profile). Additionally, we may enable them to form coalitions instead of only competing among themselves enabling the representation and analysis of different types of mafia-like organizations, such as *'Ndrangheta* and *Camorra*. We also may enable the entry of new extorters that may challenge the dominance of a monopolist in order to validate the dominant resistance against new comers.

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Opinion & Attitude Modeling

Bounded Confidence model with fixed uncertainties and extremists: the opinions can keep fluctuating indefinitely

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Abstract. The bounded confidence model and its variants applied to moderate and extremist agents exhibit three types of attractors: central clusters, double extreme and single extreme clusters. These attractors are observed when the models include a dynamics on the uncertainties tending to decrease the moderate uncertainties when interacting with extremists. We show here that a new stationary state appears when the uncertainties are fixed, for large uncertainties of the moderates. In this stationary state, the opinions of moderate agents keep fluctuating without clustering, altogether forming a stable density which shape changes significantly when the parameters vary.

1 Introduction

Understanding how extremist minorities can influence moderate majorities is a major issue in social sciences. In social psychology for instance, Moscovici brought substantial advance in this understanding with famous experiments about the influence of minorities in small groups [17]. It is more generally an issue in the history of the last century with the emergence of totalitarian states or in the more recent period with terrorist attacks perpetrated by religious foundamentalists.

Computer simulations can provide some insight on this issue, particularly on large populations on which it is impossible to perform experiments. This approach requires expressing clearly some hypotheses on the rules of interactions modifying agents opinions and then to explore the consequences of these hypotheses on the collective behaviour of interacting agents. Several models are available and already addressed the issue of extreme opinion propagation or minority influence.

For instance, with the model based on Dynamic Social Impact Theory of Latane [18], minorities can maintain themselves, but only on the borders of the social structure; thus they can be seen as extremists. Moreover, in this model, the opinion of these minorities cannot diffuse in the population.

In this model and several others [1,11,21], the opinion can only take two values (e.g. A or B) (see [3] for a review of opinion dynamics models). The general mechanism is based on a function of the opinion in the local neighbourhood that determines if agents switch their opinion or not. Binary opinions are simple and fit to decision-making issues, but it is impossible to state if opinion A is more extreme than opinion B.

Other models include more possible values for the opinion and we consider here one of the most popular continuous opinion models: the bounded confidence model [12,14,6,22]. Its principles are very close to the theory of social comparison [10] and to social judgment theory [20]. The agents are characterised by an initial opinion (generally supposed between -1 and 1) and a threshold that can be interpreted as an uncertainty around this opinion. The dynamics in the version of [6] picks random pairs of agents that influence each other by slightly moving their opinions towards each other, but only if the distance between their opinions is lower than the uncertainty.

With variants of this model, [4,5] study the impact of extremists on moderate agents. The extremists are initialised with extreme opinions (+1 or -1) and all share the same small uncertainty, whereas the moderates are initialised with an opinion uniformly drawn between -1 and +1 and the same larger uncertainty. Moreover, in these models, both opinions and uncertainties are modified during interactions. The extremists tend to reduce the uncertainty of the moderates during interactions. By construction of the model, the extremists are more influential and less likely to change their opinions and uncertainties.

Depending on the initial number of extremists and the initial uncertainty of the moderates, three convergence types appear: central clusters, double extreme clusters, single extreme cluster. Recently [16] claimed to have found a different attractor map in the parameter space, but [7] show that the difference is due to a different criterion for stopping the simulations. The single extreme cluster was somehow unexpected and subject of specific studies [8]. [15] also studied populations with heterogenous uncertainties with different settings than extremists and moderates.

This paper studies the extremist effect using the original BC model with fixed uncertainties. As far as we know, such a study is not reported in the litterature. Moreover, [13] reports persisting high levels of uncertainty in some experimental groups, therefore this model can match observed situations.

Our main result is that the model with fixed uncertainties exhibits a stationary state that has not been observed in models with changing uncertainties. In this stationary state, the opinions of the moderate agents keep fluctuating with different amplitudes depending on the parameters (uncertainty, proportion of extremists) whereas the opinion density distribution remains stable.

We study this stationary state in more details with a large number of agents (10 millions) and a model of evolving density, corresponding to the limit case of an infinity of agents. The density distribution shows several patterns, depending on the uncertainty of moderates, the proportion of extremists and sometimes the intensity of the interactions.

In the next section, we describe the model and the rules determining the convergence types. Section 3 presents the map of steady states in the parameter space and gives more details about the new stationary state. The final section is devoted to a discussion of this result.

2 The model and steady state definition

2.1 The bounded confidence model (BC) with extremist and fixed uncertainties

Following the model of [4], in a population of N agents, we consider two types of agents, the moderates and the extremists. The moderate agents share the same uncertainty u and the extremists the uncertainty u_e (a positive real number). We take here a very small value of u_e compared to u (typically $u_e \leq u/100$). The opinions of the moderate agents are uniformly drawn between -1 and +1. The proportion of extremists in the population is denoted p_e and half of them is initialised with opinion +1 and the other half with opinion -1.

The dynamics of the opinions is the BC model in its version of [6] and the uncertainties remain constant, which is the major difference with [5,4].

At each time step, $\frac{N}{2}$ random pairs interact. A randomly drawn agent i with opinion x_i, an uncertainty u_i meets with a randomly drawn agent j with opinion x_j and uncertainty u_j. Their opinions are modified according the following rule:

$$\begin{cases} \text{if } |x_i - x_j| < u_i \text{ then } x_i := x_i + \mu(x_j - x_i) \\ \text{if } |x_i - x_j| < u_j \text{ then } x_j := x_j + \mu(x_i - x_j) \end{cases} \tag{1}$$

In this equation, μ is a parameter of the model that rules the intensity of the influence (generally $0 < \mu \leq 0.5$).

2.2 Indicators and rules defining convergence types

We use the same rules as in [4] for defining the convergence types, that we are recalling in this section. We consider that the model reaches convergence when the sum of all agent opinion variations is lower than 0.001. The indicators are based on the generalised number of clusters and the average absolute value of moderate opinions. We define the generalized number of clusters in a population involving k opinion clusters x_i, each with a proportion r_i of agents as:

$$c = \frac{1}{\sum_{i=1}^{k} r_i^2} \tag{2}$$

It corresponds to a smooth number of clusters obtained following the method defined in [9]. A cluster of opinions contains opinions which are different from each other from a maximum value equal to ϵ.

We also define the average of the absolute value of the moderate opinions, noted X, which indicates how extreme the population is:

$$X = \frac{\sum_{i=1}^{N} |x_i|}{N} \tag{3}$$

Finally, we combine these two indicators in order to characterize the convergence type :

- $X < 0.75$ and $c < 1.33$: convergence to a single moderate cluster, represented in “ligth blue” on Figure 1;
- $X > 0.75$, $c > 1.66$ and $c < 2.33$: convergence to two extreme clusters, represented in “green” on Figure 1;
- $X > 0.75$ and $c < 1.66$: convergence to a single extreme cluster, represented in “orange” on Figure 1;
- $c > 2.33$: convergence to several clusters, represented in “brown” on Figure 1;
- no convergence after 2000 time steps (the opinions keep fluctuating), represented in “dark blue” on Figure 1;

3 Experiments and map of stationary states

We perform an experimental design with a population of 400 individuals and $\mu = 0.5$ for the BC model. The parameters varying in the experiments are: $p_e \in [0; 1]$(the proportion of extremists) and $u \in [0.02; 2]$ (the uncertainty of moderates). We kept the ratio between moderate and extremist uncertainties at the value of 100. The map of convergence types is reported in Figure 1. Figure 2 shows examples of the usual patterns already identified in the litterature.

The regions of central and double extreme attractors are similar to the ones found with the BC model with changing uncertainties. However, two main differences appear:

- the single extreme attractor appears in a different parameter zone (in orange on Figure 1) and in this zone the single extreme convergence is systematic, whereas with the model with changing uncertainties, there is a probability to get also a central convergence;
- in a large parameter zone (high values of u) the opinions do not stabilise. Even if we increase the number of time steps, the moderate opinions do not cluster and keep fluctuating. With the model with changing uncertainties, the model converges to a single extreme or a moderate cluster for the same values of p_e and u. Simulations with 10 millions agents (see Figure 3) show that the distribution of the agents reaches a steady state. The stable distribution shows several maxima at opinions $-0.5; -0.25; 0.25; 0.5$.

We now analyse these differences in more details.

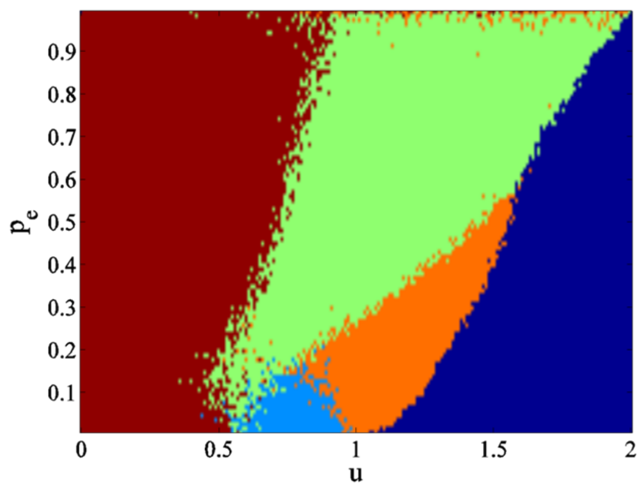
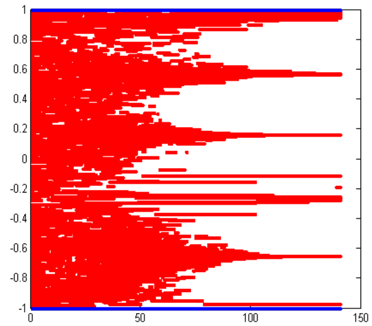


Fig. 1. Map of attractor types for 400 agents. Attractor type: light blue: a single moderate cluster; green: double extreme clusters; orange: a single extreme cluster; brown: several moderate clusters; dark blue: no clustering (opinions keep fluctuating).

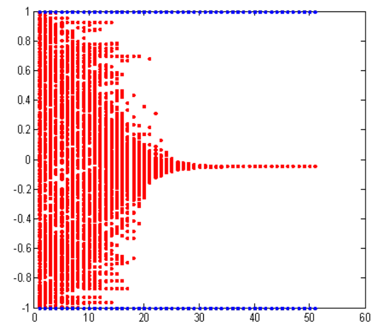
Systematic single extreme in a restricted parameter zone

The single extreme convergence zone takes place for u around 1 and $p_e < 0.2$ (in orange on Figure 1). The process of single extreme convergence is similar to the one identified in previous research [8]: in a first step a central cluster of opinions emerges. Then because the uncertainty is close to 1, when the distribution is narrow and not perfectly at the centre, there are significantly more agents that interact with only one extreme (positive or negative). Hence small fluctuations in this central cluster necessarily lead to the drift to this extreme (see Figure 2).

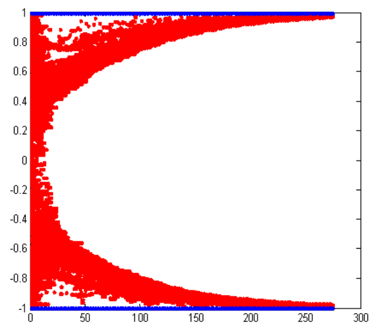
With the model with changing uncertainties, the single extreme convergence takes place for similar low proportion of extremists but also for initial uncertainties of the moderates much larger than 1. Indeed, the dynamics of uncertainties decreases these larger uncertainties progressively when the moderates are in the central cluster because of the influence of extremists, until these uncertainties reach a value close to 1 that leads to the unstability. However, the uncertainty may sometimes decrease below 1 before a significant drift towards one or the other extreme, leading to a central convergence (see [8]). This decrease below 1 does not take place when the uncertainties are fixed hence the unstability of the central cluster systematically leads to a single convergence when the uncertainty of the moderates is adequate.



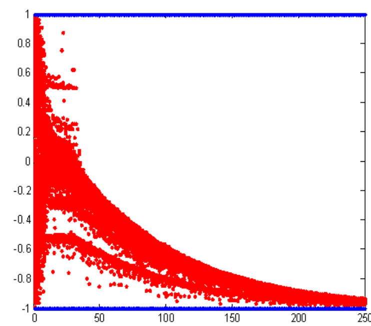
$p_e = 0.05$, $u = 0.25$, central clusters



$p_e = 0.05$, $u = 0.75$, single central cluster



$p_e = 0.05$, $u = 0.5$, double extreme



$p_e = 0.05$, $u = 1$, single extreme.

Fig. 2. Examples of opinion trajectories for different usual convergence types. The vertical axis is the opinion value and the horizontal axis is the number of iterations, the opinions of the 400 agents are represented at each time step. p_e is the proportion of extremists, u is the uncertainty of the moderates.

Moderate opinions keep fluctuating for large values of uncertainty

When the opinions keep fluctuating, it seems particularly interesting to study a density distribution model derived from the agent model, and representing the case of an infinite number of agents. This type of model makes the different phenomena more apparent because the initial uniform distribution can be perfect and eliminate the random irregularities of the agent based model. The model includes an array of n values ρ_i representing the probability that agents have an opinion x located in an interval of size $1/n$ and centred on i/n:

$$\rho_i = P\left(\frac{2i-1}{2n} \leq x \leq \frac{2i+1}{2n}\right) \tag{4}$$

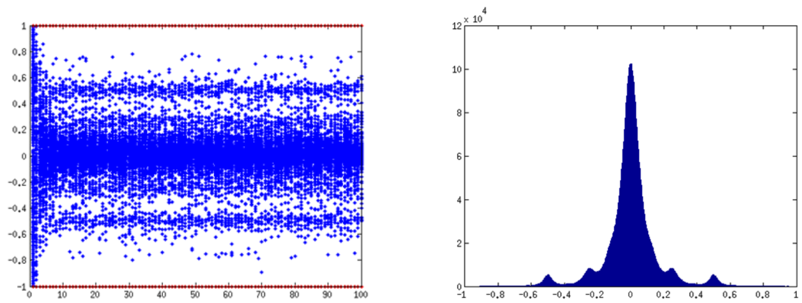


Fig. 3. Example of no clustering of moderates. u=1.8, p_e = 0.05 and μ = 0.5. The moderate opinions keep fluctuating. Left panel: time trajectories of the opinions. Right panel: convergence density for the model with 10 Millions agents.

Initially, the density distribution of the moderate opinions is uniform, and for all i, $\rho_i = \frac{1-p_e}{n}$. The extreme values of the distribution are given a density $p_e/2$ of extremists. Then we classically compute the flows between the cells of the density because of the interactions and update iteratively (see for instance [8] for details).

On Figure 4 we can check that the convergence density provides a good approximation of the one derived from the agent model with a large population. Therefore, we can use the density model to study the properties of this stationary state.

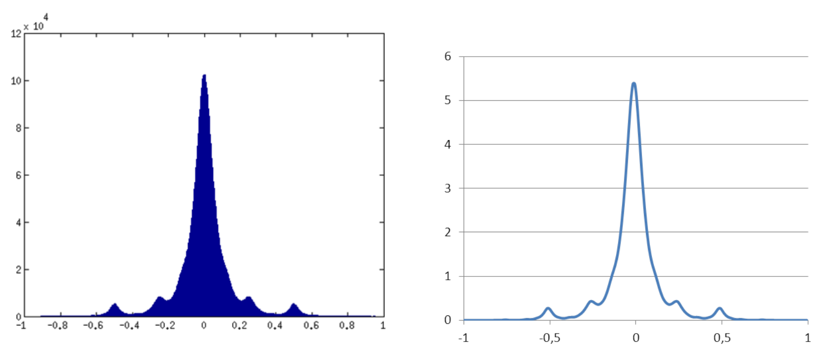


Fig. 4. Moderate uncertainty u=1.8 and proportion of extremists p_e = 0.05, intensity μ = 0.5. Left panel: histogram of number of agents for the model with 10 Millions agents. Right panel: convergence density with the density distribution model.

The patterns of convergence distribution are the result of two opposite tendencies:

- while the opinions can be attracted by both extremes, the extremist influence make them fluctuate strongly in both directions;
- the interactions between the moderates is averaging and tends to form a central peak of density, keeping the opinions in a zone where they can be attracted by both extremes.

These opposite tendencies reach an equilibrium leading to a stable density of opinions. However, the opinions keep and fluctuating the stable density is the result of averaging the presence of always changing agents.

Moreover, the model is ergodic: the positions of a single agent over a large number of time steps describe the same distribution as the positions of a large number of agents after convergence, as shown on Figure 5. This implies that the initial conditions are much less important. Many very different initial distributions of the moderates lead to the same stationary distribution.

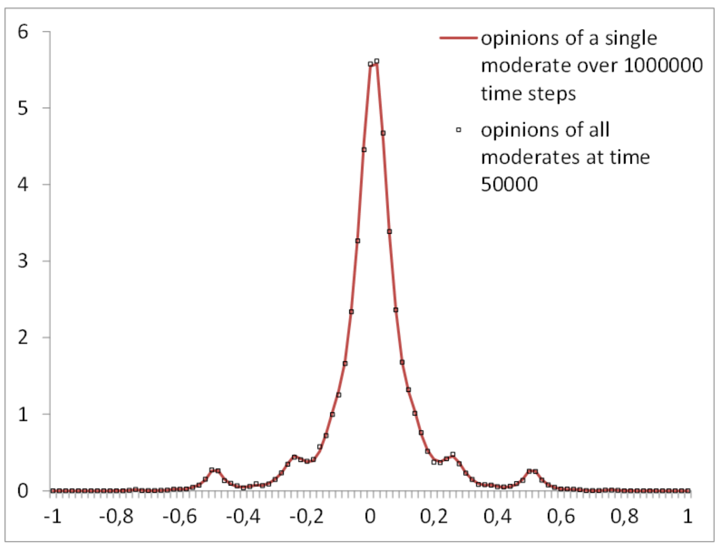


Fig. 5. Ergodicity of the model. Comparing the density of opinions of a single agent over 1 Million time steps with the density of opinions of 1 Million agents at time step 50000 for $u = 1.8$, $p_e = 0.05$, $\mu = 0.5$.

Depending on the values of the parameters we get very different patterns of distribution at convergence (see Figure 6):

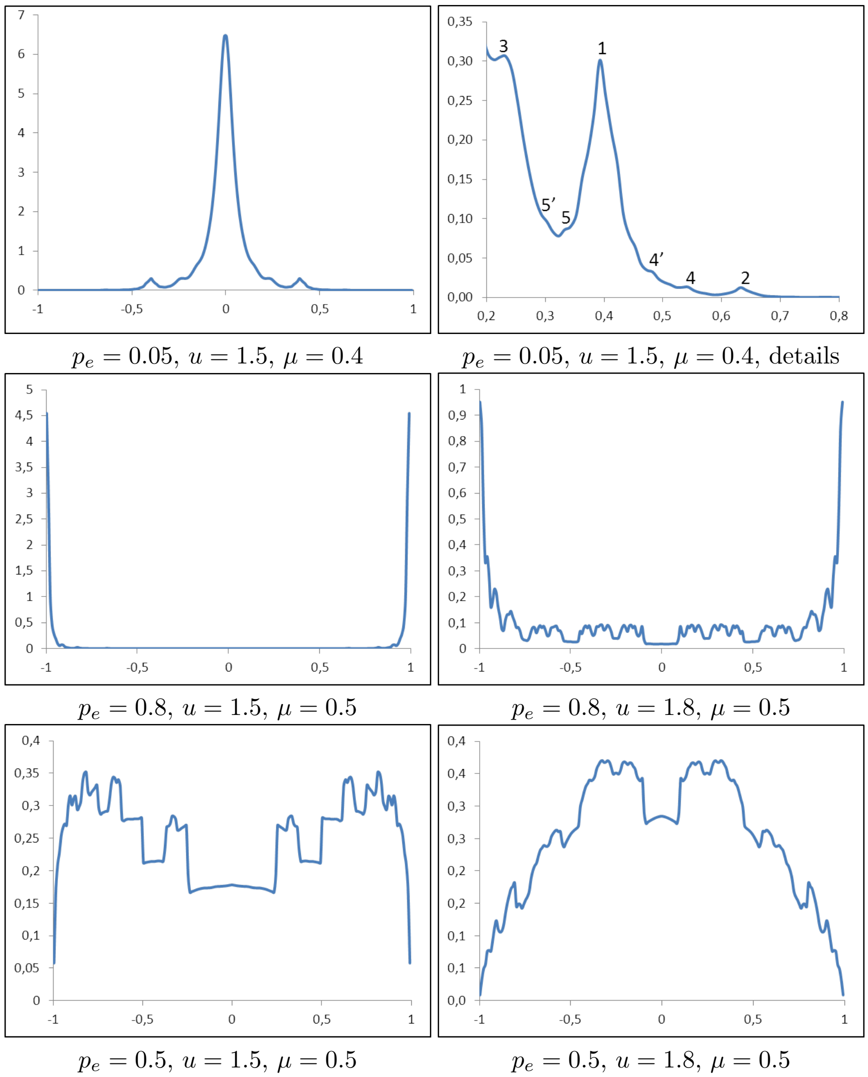
- When the proportion of extremists p_e is low, there is a central peak of density because the interactions between moderate agents tend to average their

opinions. However, the uncertainty of moderates is large enough for the opinions located close to 0 to be attracted regularly by extremists of both sides. This creates secondary peaks at a distance μ of the central peak, and then the interaction of this secondary peak with the extremists creates a smaller peaks at distance $\mu + (1 - \mu) * \mu$ of the central peak, and so on. For instance on Figure 6 on the first line, for $\mu = 0.4$, we can observe several peaks of the distribution on the right panel. Peak 1 at $x_1 = \mu = 0.4$, is the result of interactions $i(C, E)$ between central peak C and extremists E. Peak 2, at $x_2 = x_1 + (1 - x_1) * \mu = 0.64$, is the result of interactions $i(1, E)$ between peak 1 and extremists. Peak 3, at $x_3 = x_1 - \mu x_1 = 0.24$ is the result of $i(1, C)$, peak 4, at $x_4 = x_2 - \mu(x_2 - x_1) = 0.544$, is the result of $i(2, 1)$, peak 4', at $x_{4'} = x_1 + \mu(x_2 - x_1) = 0.496$, is the result of $i(1, 2)$ Peak 5, at $x_5 = x_1 - \mu(x_1 - x_3) = 0.336$ is the result of $i(1, 3)$, peak 5', at $x_{5'} = x_3 + \mu(x_1 - x_3) = 0.3046$ is the result of $i(1, 3)$;
- When the proportion of extremists p_e is high (for instance 0.8), then the attraction of extremists prevents the central peak to appear, and the distribution tends to be higher close to the extremists. When the uncertainty of moderates u is high, the probability of moderate opinions tends to be higher because the moderates attract each other for larger differences of opinions (see second row of Figure 6);
- Intermediate patterns take place for intermediate values of the parameters (see third line of Figure 6). Note the depression of the distribution at the centre and the complex geometry of local maxima and minima of variable sizes which are due to the local equilibrium between the attraction by extremists towards the extremes and towards the centre by moderates.

To summarise, the moderate opinion distribution tends to a central cluster when the proportion of extremists p_e is low and tends to a double extreme when p_e is high (higher than 0.5). Moreover, a high uncertainty tends to increase the centrality of the distribution. These results are in line with the ones obtained previously with changing uncertainty models but it appears that the fixed uncertainties prevent the single extreme convergence for high uncertainties of the moderates. Moreover, the absence of clustering is a really new feature. With the complex geometry of some densities, for instance for intermediate values of p_e, this new type of moderate opinions evolution shows a rich variety.

4 Discussion and conclusion

Theoretically, the possibility of stable density distributions of opinions with continuously changing agents had already been identified [2], especially when the interactions are not symmetric. However, in the currently published studies of standard variants of the BC model, only the models introducing directly some noise in the interactions exhibit such distributions [19]. In all the other studies, the model converges to a set of clusters in which all opinions are the same and stable. Therefore, the stationary state of the opinion density that we observe in



$p_e = 0.05$, $u = 1.5$, $\mu = 0.4$

$p_e = 0.05$, $u = 1.5$, $\mu = 0.4$, details

$p_e = 0.8$, $u = 1.5$, $\mu = 0.5$

$p_e = 0.8$, $u = 1.8$, $\mu = 0.5$

$p_e = 0.5$, $u = 1.5$, $\mu = 0.5$

$p_e = 0.5$, $u = 1.8$, $\mu = 0.5$

Fig. 6. Patterns of moderates opinion density at convergence for high values of u and different values of p_e and μ. For small p_e, the distribution tends to be concentred in the centre, while for large p_e, it is close to a double extreme clustering. The larger the uncertainty of moderates u, the more central is the distribution.

the model with fixed uncertainties is new. Moreover, the variety of the distribution patterns is particularly striking compared with the constancy of the set of clusters obtained with the changing uncertainties models.

The qualitative explanation of this difference is nevertheless rather straightforward. When moderates uncertainties are fixed and large, the moderates are submitted to the influence of both extremes and of the other moderates. They continuously fluctuate under these influences. This leads to ergodic dynamics (see Figure 5) which is a particularly new feature for the BC models. Indeed, the opinions of the agents take all the possible values of the distribution over time with a frequency that is proportional to the density at this opinion. The immediate consequence is that a large variety of initial distributions of the moderates opinions lead to the same stationary distribution (we tried with various non uniform distributions). This feature is interesting because the uniform distribution can be considered as a strong hypothesis for the initial condition.

Considering now the possible interpretation of this model in social processes, one can think of situations where hesitating agents are discussing with two very convinced groups with opposite opinions. This can reflect to some extent frequent political situations where two parties of convinced militants try to convince a majority of moderates. The hypothesis the moderates easily change their opinion after discussing with an extremist (or a militant) of one side and easily change it again when discussing with an extremist of the other side or with an other uncertain agent. The model predicts a very high volatility of the moderate opinions (change very frequently their opinion) when the proportion of extremists is high (say around 0.5), which could be related to “swing voters”. Moreover, the more the moderates are uncertain the more likely they are not to choose one side and remain neutral. According to the model, the global state of the opinion could appear stable from usual polls whereas many individual changes take place, and compensate each other.

The results remain quite theoretical and should be interpreted with caution, especially because each agent interacts with any other. They deserve complementary investigations, considering for example various social networks constraining the interactions.

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In the Leviathan Model, the average opinion is higher when vanity is weaker with lower valued agents

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Abstract. In the Leviathan model, agents form opinions about each other. During dyadic meetings, they directly influence each other, or talk about peers through gossip. Speakers highly valued by their listeners are more influential. Moreover, they are subject to a vanity process; if an agent feels undervalued, then he decreases his opinion about the despising agent and on the contrary he increases his opinion about a compliment-giver agent. This model produces several different patterns depending on the parameter values, but the average opinion is always negative whatever the emerging pattern. As a consequence, the gossips tend to be mostly negative. Since this is not in complete accordance with the social–psychology literature indicating that both mostly negative and positive gossip can be observed, we investigate the changes to operate to obtain also mostly positive gossips. We found that when the vanity process is less triggered by agents held in low esteem, the average opinion significantly increases. We check that with this modification, the model still yields the same patterns.

1 Introduction

The recently proposed Leviathan model [1] considers individuals forming and maintaining opinions about each other, including themselves through processes of opinion propagation and vanity. The opinion propagation includes a part which can be interpreted as gossiping. From its simple virtual dynamics of individual interaction emerges a collection of patterns such as “dominance”, “equality”, “hierarchy”, “elite” or “crisis”. One striking emerging effect is that in these patterns, the average opinion is always negative [1]. As a consequence, gossiping is mainly negative. At first, this sounds in accordance with the observations that gossip is more often negative [2]. But a recent study surveying a group of working nurses in a hospital shows the opposite [3]: negative gossip is quite rare in this group.

This paper aims at modifying the Leviathan model in order to get a more positive average opinion and consequently more positive gossips. With this aim, we tested two modifications of the vanity process, which, in the original model, applies with all interlocutors:

- Vanity is weaker with lower agents: An agent is subject to weaker vanity when discussing with an agent that he considers lower than himself;

- Vanity is weaker with higher agents: An agent is subject to weaker vanity when discussing with an agent that he considers higher than himself.

We found that when the vanity is weaker with lower agents, the average opinion tends to be significantly more positive. Moreover, the same patterns as in the original model are observed. Two of them show a highly positive opinion on average. However one pattern has probably been modified in deep by the change vanity process.

The paper is organised as follows. We start by a description of the dynamics and the emerging properties of the model. We describe the impact of vanity process modifications on the number of positive opinions and on the patterns. We then propose some theoretical explanations of the main result. Finally, we discuss our result and identify some complementary studies to make.

2 The model and the experimental design

The agent dynamics of the Leviathan model, inspired by Hobbes [4] and more recent studies from social-psychologists [5-10] [11] is presented in the next subsection. The following subsection describes the different patterns emerging from the interactions [1].

2.1 The Leviathan model: The agent dynamics

We consider a set of N agents, each agent i is characterised by her list of opinions about the other agents and about herself: $(a_{i,j})_{1 \leq i,j \leq N}$. We assume $a_{i,j}$ lies between -1 and +1 , or it is undefined (equal to nil) if the agent i never met j and nobody has talked to i about j yet. At initialisation, we suppose that the agents never met, therefore all their opinions are undefined. When opinions change, we always keep them between -1 and +1, by truncating them to -1 if their value is below -1 after the interaction, or to +1 if their value is above +1. The individuals interact in uniformly and randomly drawn pairs (i, j) and at each encounter, we apply two processes: the opinion propagation and vanity. We follow the people's interactions considering a time range called iteration. We assume one iteration, i.e. one time step $t \rightarrow t + 1$, is $N/2$ random pair interactions (each individual interacts N times on average during one iteration).

We now describe the processes with more details.

2.1.1 Opinion propagation with highly valued agents being more influential

The strength of the propagation of opinion is ruled by a parameter ρ multiplied by a coefficient $p_{i,j}$. This function implements the hypothesis that if i has a high opinion of j, then j is more influential on i. It is a logistic function (with parameter σ) of the difference between the opinion of i about j ($a_{i,j}$) and the opinion i about herself ($a_{i,i}$). If $a_{i,j}$ = nil (j is unknown to i), we assume that i has no opinion because he has not met or hear about j. At the first meeting, we suppose that the a priori about j is neutral and we set $a_{i,j} \leftarrow 0$. Let us also observe that, at the initialisation, an agent has no opinion about herself thus we also set $a_{i,i} \leftarrow 0$ at the first discussion. Then we compute the propagation function $p_{i,j}$, which rules the intensity of the opinion propagation from j to i :

$$p_{ij} = \frac{1}{1+\exp\left(-\left(\left(a_{ij} - a_{ii}\right)/\sigma\right)\right)}$$

$p_{i,j}$ tends to 1 when $a_{i,j}$ - $a_{i,i}$ is close to 2 (i values j higher than herself), and tends to 0 when it is close to -2 (i values j lower than herself). When σ is small, p_{ij} rapidly changes from 0 to 1. When σ is large, this change is progressive.

This propagation coefficient of influence is computed to determine the influence a speaker has onto a listener about the opinion the listener has of oneself, of the speaker and of their peers.

2.1.2 Vanity and opinion influence between protagonists due to direct contact

Let us assume that agents i and j have been drawn. During their first meeting, agent i and agent j don't know each other and their opinions are nil. Then, they instantaneously become 0 which is the neutral opinion. This initiates the meeting dynamics between i and j.

Then, i and j talk about themselves: i talks about herself and j, while j talks about herself and i. This direct exchange called face-to-face implies influence of each of them on what they think about themselves and the other, and a vanity process applied only by the listener to the talker.

This vanity process expresses that agents tend to reward the agents that value them more positively than they value themselves and to punish the ones that value them more negatively than they value themselves. The vanity equation considering the reaction of i to what j says about i has the following form:

$$v_{ij} = \omega(a_{ji} - a_{ii} + \mathrm{Random}(-\delta, +\delta))$$

This vanity is added to the influence i received from j regarding what she thinks about j to compute the updated opinion of i about j: a_{ij}.The agent i compares her self-opinion a_{ii} to the opinion j tells about her a_{ji}. If the perceived opinion of the other *(j)* is higher than her self-opinion, i increases her opinion of j (reward). Else i decreases her opinion of j (punishment). This particular reaction of i aims to increase or decrease the future influence of j in order to protect or enhance herself. The parameter ω rules the importance of the vanity process.

The influence of j on the opinion i has on i and j is controlled by the propagation coefficient $p_{i,j}$ (see 2.1.1) and a parameter ρ.

The modification of i's opinion of i is assumed as simply depending on the difference between the opinion of i about herself and the opinion of j about i. The modification of i's opinion of j is assumed on the difference between the opinion of i about j and the opinion of j about j (influence) and on the vanity v_{ij}.

Moreover, an agent i has no direct access to the opinions of another one (j) and can misunderstand her. To take into account this difficulty, we consider the perception of the agent i as the value a_{jz} more or less a uniform noise drawn between $-\delta$ and $+\delta$ (δ is a model parameter). This random addition then corresponds to a systematic error the agents make regarding the others' opinions. That can be seen as a noise that distorts the perception that i has about j 's opinions. The parameter δ rules the amplitude of this noise.

During the interaction, the procedures face-to-face(i,j) and face-to-face(j,i) are successively applied. The face-to-face can be formally described in pseudo-codes as follows (example given for face-to-face(i,j):

Face-to-face(i,j)

if $a_{ii} = nil$, $a_{ii} \leftarrow 0$

if $a_{ij} = nil$, $a_{ij} \leftarrow 0$

$$a_{ii} \leftarrow a_{ii} + \rho p_{ij}(a_{ji} - a_{ii} + \text{Random}(-\delta,+\delta))$$

$$a_{ij} \leftarrow a_{ij} + \rho p_{ij}(a_{jj} - a_{ij} + \text{Random}(-\delta,+\delta)) + v_{ij}$$

The gossip follows the face-to-face.

2.1.3 Gossip: individuals discuss about those they know

During an encounter, we have seen that agent j propagates to i her opinions about herself (j) and about i. It also propagates to i her opinions about k agents randomly chosen among her acquaintances through gossip (or about all her acquaintances if there are fewer than k).

The agent i modifies her opinion about the individual z that j talked using the same "influence mechanism" than the one used in the face-to-face. She applies the propagation coefficient $p_{i,j}$ multiplied by the influence parameter ρ to the difference between what j told about z and what she thinks of z.. More formally, the process can be written in pseudo-code as follows:

Gossip(i, j)

Repeat k times:

Choose randomly z taking into account $a_{jz} \neq$ nil, $z \neq j$

If $a_{iz} = nil$, $a_{iz} \leftarrow 0$

$$a_{iz} \leftarrow a_{iz} + \rho p_{ij}(a_{jz} - a_{iz} + \text{Random}(-\delta,+\delta))$$

2.1.3 Summary

Finally, the model has 6 parameters:

- N, the number of individuals;
- σ, the reverse of the sigmoidal slope of the propagation coefficient;

- k, the number of acquaintances an individual talked about during a meeting – they are randomly chosen among her acquaintances;
- δ, maximum intensity of the noise when someone is alluded to;
- ω, the coefficient of the vanity process;
- ρ, the parameter controlling the intensity of the coefficient of the influence.

The following algorithm describes one iteration: $N/2$ random pairs of individuals are drawn, with reinsertion, and we suppose that each individual influences the other during the encounter. The update is synchronous: every opinion changes occurring during a meeting are computed on the same value of opinions taken at the beginning of a pair meeting.

```
Repeat N/2 times:
    Choose randomly a couple (i,j)
    Save the opinions which are going to change in temporary variables to ensure
the update during the i and j meeting is synchronous
    Face-to-face(i,j)
    Face-to-face(j,i)
    Gossip(i,j)
    Gossip(j,i)
```

2.2 The Leviathan model: Emerging properties

This section aims to remind what we know from emerging properties of the Leviathan model. We have already said a bias to negativity of the whole population emerges from the agent dynamics: the average opinion is negative, sometimes very strongly [1]. This is due to a difference between the opinion an agent has of herself and the average opinion of this agent in the population. This difference is driven by the noise during the conservation and the assymetrical property of the influence (the agents are more influenced by the ones they value high than by the others). It corresponds to a bias of oneself for herself which is called positivity bias [12]. In other words, everyone thinks themselves better on average than the others. Such a bias can be amplified by the vanity for example, leading to a negative average opinion as an emerging process. Indeed the difference for agents between their opinion of themselves and the average opinion of them in the population leads them to be always desappointed in the interactions. Then, because of the vanity process, they continuously punish their interlocutors by decreasing their opinion of them. Such a punishment leads to a negative average opinion for the whole population. This is typically what occur in the crisis or the equality patterns we present now.

Indeed the dynamics not also reproduces biases but shows a striking variety of patterns representing structures of opinions. This variety can be described by five main patterns and several of them often take place in a single simulation. This section describes them shortly.

In a first set of patterns, when the opinion propagation is strong (high value of ρ), the agents tend to all have the same opinion about each agent (the differences are due to the randomness). If we call, for sake of simplicity, reputation[1] the average opinion about an agent, the distribution of reputations gives a good description of these patterns. There are generally more negative than positive reputations. For some patterns the number of reputations decreases progressively when getting more positive, giving the idea of a hierarchy. For other patterns, there is a single or a couple of agents that have a strongly positive reputation, while all the others have a very negative one. Agents with a positive reputation can be identified as leaders. These consensual leaders characterise two patterns emerging from the dynamics: (1) the absolute dominance or (2) a multiple-leaders hierarchy. There is one pattern without leaders: (3) the "crisis" in which each agent has a very negative opinion of all the others and of herself.

The second set of patterns emerges when vanity is strong. In these patterns there is no consensus about each agent who can be highly valued by some agents and lowly valued by others; we identified two main patterns "equality" and "elite". In (4) equality, each agent has a positive opinion about herself; she is connected by strong positive mutual opinions with a small set of agents and has very negative opinions about all the others. All agents have a similar number of positive (and negative) links. The (5) elite pattern shows two categories of agents: the elite and second category agents. The elite agents have a positive self-opinion and are strongly supported by a friend, but they have a very negative opinion of all the other elite agents and of all the second category agents. The second category agents have a very negative self-opinion, they have a very negative opinion of all the other second category agents and their opinion about the elite agents is moderately positive.

3 Modifying vanity for getting more positive opinions

This section describes our study. It begins by presenting our hypothesis and the experimental design allowing the study by simulations. A following subsection relates to the relevance of our hypothesis regarding the cause of the sign of gossiping while a next one investigates how the change in vanity impacts the emerging structures of opinions. A last subsection gives some explanations about our results.

3.1 Hypothesis and experimental design

In the original model, the vanity process does not depend on the relative value of the interlocutors; a flattery or an offense coming from a highly valued agent has the same effect as if it came from a lowly valued agent. It was choice for simplicity because it seems that the difference of value can weaken or strengthen the vanity, depending on the circumstances. We know the coupling of such a function to the influ-

[1] Reputations is understood in this paper as a consensus, inspired by the Emler's definition of reputation [13]: "consensus among knowledge informations as to the attributes of targets". We do not claim modelling "reputations" and other more relevant studies are more relevant for this issue than ours.

ence function with a sigmoidal coefficient based on the level of esteem for the talker implies a strong tendency of people to have a negative opinion of others.

We investigate the behaviour of the model with different variants of the vanity: the first one corresponds to the original model (same vanity process whatever the value difference); in the second one, vanity is weaker when discussing with lower valued agents; and in the third one vanity is weaker when discussing with higher valued agents :

- Constant vanity (CV) means that the vanity is applied to everyone with the same strength (as in the original model) ;
- Weaker vanity for lower valued (WLV) means that the strength of the vanity is weaker when discussing with lower valued agents; this is obtained by multiplying the vanity equation by the sigmoid function p_{ij} ;
- Weaker vanity for higher valued (WHV) means that vanity is weaker when discussing with higher valued agents; this is obtained by multiplying the vanity equation by the function $1 - p_{ij}$.

We now present the experimental design as well as how some values are measured and aggregated to build indicators of the dynamics.

The model includes 6 parameters and it is difficult to make an exhaustive study in the complete parameter space. In addition to the study of coefficient ϖ, we decided to study with more attention the influence of parameters k and σ because they have been poorly studied previously. We also decided to vary the noise δ, but not as much as k and σ. Also ρ varies poorly since it has been tested in details in [1]. In particular, we know from this first study that in the plane defined by parameters ρ and ϖ the transitions between patterns take place on right lines of origin (0,0). We fix N, the number of agents to 40, in order to make tractable results of our study and ϖ=1. We vary the other parameters as follows:

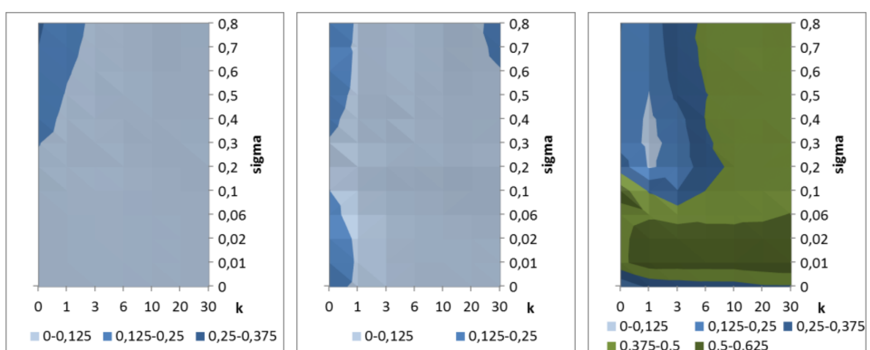
- k , the number of acquaintances about which the pair of agents discuss in the opinion influence takes the values 1, 2 , 3, 4, 5, 10, 15, 20, 25 and 30;
- δ, the intensity of noise disturbing the evaluation of other's opinions takes two different values: 0.1 and 0.3;
- σ, ruling the slope of the logistic function determining the propagation coefficients takes the values 0, 0.01, 0.02, 0.06, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8;
- ρ, ruling the intensity of the opinion propagation coefficient takes three values: 0.05, 0.5, 1;

For each set of parameter values, we run the model for 201 000 iterations (one iteration corresponding to $N/2$ random pair interactions), and we repeat this for 30 replicas. From iteration 30 000 to 200 000 every 10000 iterations, we measure a group of values allowing us to make conclusions about the impact of on the vanity variants on the average opinion and on the patterns. The measured values over times of 30 replicas are averaged to form one indicator. The indicators are presented in more details in in the next sections.

3.1 Average proportion of positive opinions

To study how modifications of vanity impact the number of positive gossip corresponding to positive opinions, we consider the average proportion of positive opinions over the 30 replicas for each set of parameters. Figure 1 shows this indicator averaged over the tested values of δ and ρ, for the various values of k and σ and the three variants of vanity process, on the left for constant vanity, in the middle for weaker vanity with higher valued agents (WHV), on the right weaker for lower valued agents (WLV). From these figures, we notice that for WLV the proportion of positive values is much higher than for the other variants and for some values of k and σ, the positive opinions represent more than 50 % (thus a majority) of the opinions while for other vanity variants, they always represent a minority (less than 25 %). Indeed we see onto the two left graphs that the average rate is mainly from 0 to 0.125 (in very light blue), or at most from 0.125 to 0.25 (in light blue) for low values of k and/or high values of σ. Differently, on the right graph (weaker vanity with lower valued) we observe the average rate of positive opinions is often between 0.37 to 0.5 (light green), especially for large values of k and σ, and goes up to [0.5,0.625] for low values of σ (in dark green). The results averaged over every other tested parameter values do not change the conclusion we can draw: for the weaker vanity with lower valued, the number of positive opinions is significantly higher.

These experiments suggest that the weaker vanity with lower valued produces populations where positive opinions are a majority or a minority while they are always a minority when vanity is constant or weaker with higher valued agents. The next section is dedicated to the impact of the changes of the vanity process on the patterns.



Constant vanity	Weaker vanity with higher valued	Weaker vanity with lower valued

Fig. 1. Average proportion of positive opinions (over time and replicas) for the three variants of the vanity process. On abscissa are values of the number of acquaintances gossiped about k and on ordinate are the tested values for the sigmoid parameter σ. The meaning of the colours is given at the bottom of each graph under the abscissa

3.2 Impact of vanity modifications on patterns of opinions

We consider a new indicator: the average over all the agents of the difference between their maximum and their minimum opinions. We call this measure "dispersion of opinions". It varies from 0 to 2. Figure 2a on the left shows that the opinion dispersion is smaller for large ρ (ie propagation strength) whatever the vanity variant and higher for small value of ρ=0.05. A large noise, such as δ=0.3, tends to increase the dispersion but the effect of ρ remains, especially for weaker vanity with lower valued agents (in green). This confirms it still exists two different areas that we can distinguish by the level of consensus about each agent and then probably our two different sets of patterns (see 2.2 for more details).

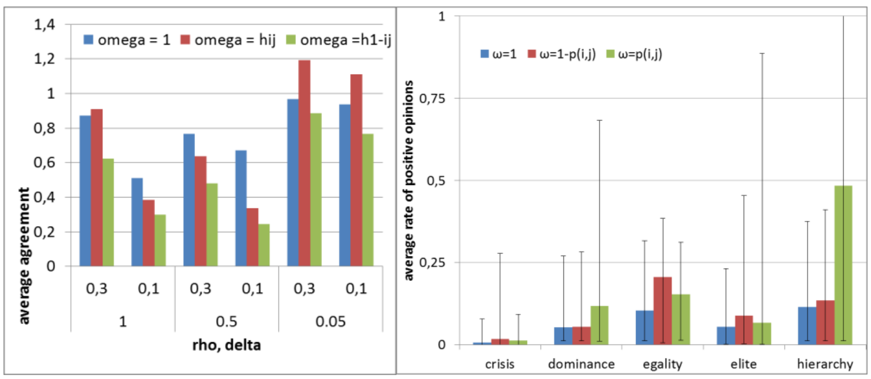


Fig. 2. a on the left, average opinion dispersion with on abscissa, from the bottom to the top, three values of ρ (1, 0.5, 0.05) and two values of δ (0.1 and 0.3). The level of agreement is still mainly driven by the propagation coefficient ρ: to this regards, the three various behave very similarly – **b on the right,** average percentage of positive opinion for the various vanity variants and the different patterns (the error bars represent the minimum and maximum variations)

We applied the diagnosis presented in [1] to define if already identified emerging patterns of opinions are still observable with the new vanity variants. Figure 2b on the right presents the average part of positive opinions of the diagnosed patterns. Firstly we observe that the five patterns are still diagnosed whatever vanity variant. Secondly this is clear the "hierarchy" is more positive for weaker vanity with lower valued agents and shows strong variations in its proportion of positive opinions. The other structures remain almost unchanged by the vanity variant but "elite" and "dominance", show strong variations of the proportions of positive opinions for the variant WLV, which would require more investigation. However, this is out of the scope of this paper.

3.3 An explanation of the impact of the various forms of vanity

In order to get an intuition about the effect of the various forms of vanity, we consider the simple case $\sigma = 0$ (the sigmoid function p_{ij} is then either 0 or 1) for which we can clearly identify who is going to be punished or rewarded, and k=0. Then, at the first meeting when everyone has an opinion valued at 0, the following table n°1 describes what occur and how the value of a_{ij} changes due to the vanity (d is a positive number comprised between 0 and δ) ; we suppose that the opinion of i about j is 0, and of i about himself is also 0.

Table n°1. Evolution in the face-to-face of the opinion of i about j (a_{ij}) for various forms of vanity and σ = 0, k=0; d is a positive number comprised between 0 and δ

Vanity heuristic	$a_{ij}=0;\ a_{jj}=$	$a_{ii}=0; a_{ji}=$	p_{ij}	ϖ =	$a_{ij}(t+1)$
h1	-d1	-d2	0	1	-d2
		d2	0	1	d2
	d1	-d2	1	1	(d1-d2)
		d2	1	1	(d1+d2)
h1-ij	-d1	-d2	0	1	-d2
		d2	0	1	d2
	d1	-d2	1	0	d1
		d2	1	0	d1
hij	-d1	-d2	0	0	0
		d2	0	0	0
	d1	-d2	1	1	(d1-d2)
		d2	1	1	(d1+d2)

These observations point out why weaker vanity with lower valued agents causes agents to see each other more positively than the other variants of vanity. In any case, the lowest opinion of i of j is higher for this variant since it is (d1-d2) while it is –d2 for the other variants.

Overall, at the very beginning, dispersion of opinions is smaller. More generally, the constant vanity process leads to cycles of mutual opinion increase or decrease that are stopped only by the limits of opinion values (+1 or -1) in the original model. When vanity is weaker with lower valued agents, the cycles of mutual opinion decrease are strongly attenuated when one of the protagonists is much lower than the other. This can often stop the usual escalations driving many agents to get very low opinions (close to -1).

Moreover, the initial analysis of the Leviathan model shows that the average negative opinion is due to tendency of the agents to have a higher self-opinion than the average opinion on them. Indeed, this difference leads them to be disappointed on average by the opinions of the others, and thus to decrease their opinion about them by vanity. When the vanity is weaker for lower-valued agents, this process is attenuated for such agents.

Therefore, overall the opinions tend to be less negative. .

4 Discussion - conclusion

The Leviathan model includes a dynamics of the esteem based on a coupling between a vanity process and an opinion propagation process. The two processes occur during a direct experience a listener and a speaker have of each other during a meeting. The opinion propagation rules also the indirect experience listeners and speakers have of the others through gossiping. Both these mechanisms make people changing their opinions of each other. The original Leviathan model exhibits a strong tendency of opinions to be negative, and hence a strong dominance of negative gossiping Whereas the literature in social psychology has shown that gossiping can be either majorly negative [2] or positive [3] without explaining why.

We investigate variants of the vanity process that could lead to more positive average opinions and we observe that majority weaker vanity with lower valued agents leads to much larger proportions of positive opinions than with the other variants of vanity, whereas the opinions can still be majorly negative for some parameters. On the contrary, a constant vanity or a weaker vanity with higher valued agents always leads to a majority of negative opinions.

From these observations, we conclude that with a weaker vanity with lower valued agents, the positivity bias (self-opinion higher than the average opinion on the agent) has a weaker effect and does not always leads to a global negativity. It is then, among the tested form for vanity, the only one in accordance with both of the sociopsychological cited studies on gossip. This is also consistent with those about self-esteem values mainly showing that low self-esteem people do not truly dislike themselves; they view themselves positively, just less positively than do high self-esteem people [14].

Dynamic patterns of behaviour of the population emerging from this model [1] have been identified. They are still diagnosed for each of the different vanity variant we consider. With a weaker vanity with lower-valued agents, the hierarchy pattern, is significantly positive on average and shows strong variations. This makes this pattern richer than it was from the original model in which it remains majorly negative. Despite their average level of positivity close in every vanity dynamics conditions, the dominance and elite patterns can be very positive with this vanity variant. We suspect nevertheless that the dominance and elite patterns could be modified with this vanity variant and this would require deeper investigation.

We do not claim that changing vanity is the only way for observing both more positive than negative gossips. Indeed, the positivity bias and a tendency to a global negativity exist also in absence of vanity when the dynamics is only driven by the propagation of opinions. Investigating the change of biases in this case is one of our future goals.

More generally, we think that this model can suggest new views on current issues in social psychology, as well as being improved by incorporating more results from this science.

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The role of emotions on communication and attitude dynamics: an agent-based approach

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Abstract. This paper presents a multi-agent model for simulating attitude formation and change based on individual's affective response to the perception and communication of information. Individuals observe actions performed by social objects, they exchange beliefs about the actions depending on their narrative interest and compute attitude values toward the social objects. The affective response considers the emotional impact of the action for the participants and its unexpectedness. We illustrate, through several simulation experiments, the role of these affective components on attitude dynamics.

1 Introduction

How would a population react to information from a government or a company (ads) about *e.g.* any action, product, or innovation? This could be tackled through the concept of attitude dynamics. This notion of *attitude* derives from social psychology and could be defined as "a mental and neural state of readiness organized through experience, exerting a directive or dynamic influence upon the individual's response to all objects and situations with which it is related" [2].

In this paper, we propose a multi-agent based simulation model that will help us to better comprehend attitudes dynamics. Our goal is to propose a model that articulates the cognitive and emotional dimensions of attitudes within a population. To do so, we consider agents that construct their attitudes through a rational process as proposed by Fazio [8], and we combine this with Dessalles' approach of information interest as a basis for estimating the affective response. We illustrate our approach in the context of stabilization operations simulation: we study how so called "non-kinetic" actions (*i.e.* that do not rely on effective usage of force) alters population's perception, attitudes and behaviors toward the UN Force.

The next section presents related works on attitude dynamics and on communication for attitude formation. Section 3 presents our agent model and the attitude dynamics. Section 4 presents a first validation of our model on concrete scenarios.

2 Related works

Attitude dynamics studies diverse complex social phenomena such as the vote, the expansion of extremism or the diffusion of information and could be studied along three different axes [16]: the representation model of attitude, the communication mechanism and the impact of the interaction network topology. In our work, we will focus on communication mechanism and the attitude model.

2.1 Communication mechanism

One dimension we consider in our research for attitude dynamics is the diffusion mechanism where actors influence each other. In most works, the exchanged information is the attitude's value itself [16, 4]. While it is true that daily communication is heavily based on attitudinal information (*e.g.* assessment without arguments, commercials *etc.*), conversational narratives (reporting facts) also represent a significant part of communication, maybe up to 40% according to Eggins [7]. For this reason, we propose to base our attitude dynamics and communication mechanism on beliefs exchange and update rather than direct attitudinal influence. However, social and cognitive psychology have extensively worked on the topic of the interest of information in social communication (*e.g.* [9]). These works tend to define factors and mechanism that intervene in individual's selection of information that are worth to be retained or communicated. In this context, the Simplicity Theory proposed by Dessalles [6] seems to present a promising approach to fulfil this task. The main idea of this model is to define information's interest to be communicated or retained by an individual as a function of its emotional impact and unexpectedness level experienced by the individual. Integrating this theory in the communication protocol in our model would enable the agents to select the most convincing beliefs to communicate and also to retain. In this paper, agents will exchange beliefs and will select them according to the Simplicity Theory.

2.2 Attitude model

Attitude dynamics mostly depends on the representation model of attitude. The first models of attitudes (*e.g.* [11]) were based on binary or real values. During the last decade, several works proposed more complex representations of attitudes (*e.g.* [12]). However, as was pointed out by [4], most of these models' focus is limited to the interaction between individuals: they do not consider the construction mechanism of the attitude itself.

Other researches in social psychology study the formation of attitudes at an individual level (*e.g.* [13, 8]). In these models, attitudes are composed of three components: cognitive, affective and conative. The cognitive part is based on factual information (*e.g.* beliefs) concerning the social object. The affective dimension corresponds to the emotional response of the subject when he is confronted to the representation of the social object. The conative component refers to previous or intended behaviors that are related to the social object. However, this component is controversial due to its closeness to the cognitive part.

Urbig and Maltz [15] achieved to take into account the cognitive aspect in their model of attitude based on beliefs. Indeed, they proposed to represent attitudes as the sum of the evaluations of the object's features that can be seen as beliefs on the object. While this model constitutes an interesting view on attitude formation, it has two limits with respect to our objectives.

First, the attitude revision is based on the bounded confidence model (*e.g.* [5]): when two individuals have attitude values close to each other, agents converge their attitudes. As a consequence, the attitudes' values are no longer connected to the beliefs of each agents. However, Fazio's model [8] of attitude would enable to keep the attitude connected to its forming beliefs, as a set of memory associations between the object and its evaluations based on information concerning the object. Each of these evaluations is weighted by an accessibility value determining the evaluation's degree of reminiscence. By essence, this model maintains a balance between the cognitive representation of the object of the individual and its corresponding attitude.

Second, their attitude model does not embody an emotional component since it represents only the cognitive dimension. Indeed, the evaluation of features does not take into account the affective response to the information. The agents compute their attitudes in a purely rational way. Here again, the Simplicity Theory proposed by Dessalles [6] seems to present a promising approach to overcome this weakness. As mentioned above, this theory embodies an emotional component in the computation of the information's interest. Integrating this theory into the beliefs evaluation mechanism of the attitude formation would enable individuals to express their affective reaction.

Hence, we choose to base our attitude representation on the combination of Dessalles' Simplicity Theory and Fazio's attitude representation.

3 Model

3.1 General approach

Our model is based on the following principle: a simulation corresponds to the execution of actions (*e.g.* tax decrease, recall campaign of a product, attack etc.) by *actors* (*e.g.* a political party, a brand, policemen, terrorists or others) on a population. Individuals of the population communicate about these actions with the others and form an attitude toward the actors. In our model, we focus on the *interest* of an action, *i.e.* the tendency for individuals to remember it and to communicate about it.

In our model, we consider a set of actors A and a set of individuals Ind. For each $i \in Ind$ and $actor \in A$, we denote $att(i, actor) \in \mathbb{R}$ the attitude of the individual i toward the actor $actor$. Individuals are characterized by their social group (*e.g.* ethnic group) and are organized following a small-world communication network topology [10]. Concretely, each individual $i \in Ind$ is represented by a computational agent and is characterized by his neighbors in the communication network $Cnt(i) \subset Ind - \{i\}$ and a social group $sg(i) \in SG$ with SG the set of social groups. Each group has a static attitude toward the members of the other group, defined as $att(sg_1, sg_2)$.

As actors perform actions on the population, or communicate about such actions, individuals will build a representation of these actions, which forms their set of beliefs. Beliefs about actions will be the core element in our model: attitudes and communications will be based on these beliefs. We note $a(i)$ the belief of individual i about an action a. Each $a(i)$ is a tuple:

$$a(i) = \langle name(a), actor(a), bnf(a), payoff(a), date(a) \rangle$$

with:

- $name$ the unique name of the action
- $actor \in A$ the actor who performed the action
- $bnf \in Ind$ the beneficiary of the action, *i.e.* the individual which undergoes the action
- $payoff \in \mathbb{R}$ the impact value of the action, negative when the action is harmful (*e.g.* attack) and positive when it is beneficial (*e.g.* tax decrease)
- $date \in \mathbb{N}$ the occurrence date of the action.

We also compute $a_{perso}(a, i)$ the last occurrence of the action a on the individual i himself (*i.e.* $bnf(a) = i$), $nbOcc(a(i))$ the number of occurrences of the same action and $nbOcc_{SG}(a(i), sg)$ the number of occurrences per social group sg. For this computation, we consider two different $a(i)$ in the belief base to represent the "same action" if they have the same $name$, $actor$ and $bnf.sg$. These numbers of occurrences are considered from the agent's point of view only.

3.2 Interest of an action

In order to determine what to base their attitude on and what to communicate to other individuals, agents estimate a model of interest of the actions in their belief base. The model of interest is based on the Simplicity Theory of Dessalles [6]. This theory proposes to define the *narrative interest* NI of an information according to the emotion E and the surprise level S it causes to the individual using the following formula:

$$NI(a) = 2^{E(a)+S(a)} \tag{1}$$

E corresponds to the emotional response intensity of the individual when faced to an information, in our model it is based on the payoff amplitude of an action's impact. The surprise level S translates the sentiment of unexpectedness felt by the individual.

Emotional intensity The emotional intensity E corresponds to the emotional amplitude (non-zero) experienced by the individual when exposed to the event. Dessalles [6] shows that, when the stimulus impact is unbound, the emotional intensity follows a logarithmic law in conformity with Weber-Fechner's law of the stimuli (in our case, the stimuli values correspond to the emotional intensity of an action through its payoff):

$$E(a) = log\left(1 + \frac{|pyf(ip(a))|}{\xi}\right) \tag{2}$$

The parameter of sensibility $\xi \in [0, 1]$ modulates the emotional response's intensity value.

Surprise Following Dessalles' theory, the surprise experienced by an individual when exposed to an event derives from a level of raw unexpectedness U_{raw} (*e.g.* "It is surprising that a Taliban saves a citizen"). This level is reduced by a personal reference of unexpectedness U_{perso} based on a personal experience (*e.g.* "But I have once been saved by a Taliban before"):

$$S = U_{raw} - U_{perso} \tag{3}$$

In the Simplicity Theory, several dimensions are considered for the computation of surprise (*e.g.* geographical distance, recency *etc*). In our model, we use two dimensions: the temporal distance and the social distance, which lead to four unexpected values: U^{time}_{raw}, U^{social}_{raw}, U^{time}_{perso} and U^{social}_{perso}. The following subsection presents the computation of these four elements.

In all four cases, the unexpectedness of the event (in our model, the action) can be defined by the contrast between its generation complexity and its description complexity: $U^x = C^x_w - C^x_d$ with x the dimension. The generation complexity C_w defines the level at which it could be anticipated by the individual based on its current knowledge base. The description complexity C_d must be understood in the meaning of Shannon's information theory [14], *i.e.* the size of the smallest computational program that could generate this event.

Raw temporal distance (U^{time}_{raw}) The temporal complexity of generation refers to the probability that the action occurs at a given instant. This notion could be interpreted as the usual time gap between two occurrences of the action: the more the action is rare, the bigger the gap is, the less it is probable, the more it is unexpected.

Therefore we define the usual time gap using the difference between the occurrence date $date(a)$ of the action a and its last occurrence date $date(a_{old})$: $C^{time}_w = log_2(date(a) - date(a_{old}))$. The temporal complexity of description corresponds simply to the elapsed time between the action and the current time t: $C^{time}_d = log_2(t - date(a))$.

Thus, the unexpectedness level for the temporal dimension is obtained by:

$$U^{time}_{raw}(a) = log_2(date(a) - date(a_{old})) - log_2(t - date(a)) \tag{4}$$

Raw social distance (U^{social}_{raw}) The social complexity of generation refers to the probability that the action occurs on a beneficiary who belongs to a particular social group (*e.g.* "It is rare that Pashtuns are victims of a Taliban attack"). We define it with $C^{social}_{w} = -log_2(\frac{nbOcc_{SG}(a,sg(i))}{nbOcc(a)})$ with $nbOcc_{SG}(a, sg(i))$ the occurrence number of the action a whose beneficiary is a member of the same social group $sg(i)$ as the agent.

The description complexity C^{social}_{d} corresponding to the social distance between the individual and the beneficiary of the action depends on two factors: the distance in the social graph and the average degree in the graph. Indeed, the higher the degree, the more complex it will be to describe a single step in the graph (in terms of information theory) and this influence is linear. However, the distance in the graph has an exponential impact on the social distance generation (since it requires to describe all possibilities at each node). Thus, $C^{social}_{d} = log_2(v^d)$ with v the degree of the graph and d the shortest distance between i and $bnf(a(i))$ in the graph.

Hence we obtain the following formula:

$$U^{social}_{raw}(a) = -log_2\left(\frac{nbOcc_{SG}(a, sg(i))}{nbOcc(a)}\right) - log_2(v^d) \tag{5}$$

Personal temporal distance and personal social distance The personal unexpectedness is based on the last occurrence of the action a which has personally affected the individual, *i.e.* the last occurrence of the action (with the same *name* and *actor*) for which $bnf(a)$ is the agent i itself. We denote a_{perso} this particular occurrence.

The computation of the unexpectedness values is the same as above, except that the search of experienced occurrences in the belief base is limited to actions with i as the beneficiary:

$$U^{time}_{perso}(a) = log_2(date(a) - date(a_{perso})) - log_2(t - date(a)) \tag{6}$$

$$U^{social}_{perso}(a) = -log_2\left(\frac{nbOcc_{SG}(a_{perso}, i)}{nbOcc(a)}\right) \tag{7}$$

where $date(a_{perso})$ denotes the date of the last time the action happened to the subject, and $nbOcc_{SG}(a_{perso}, i)$ the number of occurrences for this action. In the case where the individual has never personally experienced the action, his personal unexpectedness is nil, $U_{perso} = 0$.

Subjective narrative interest In order to take into account the attitude of the individual i toward the action's beneficiary, we propose to weight the narrative interest NI by the absolute value of his attitude. Indeed, the more the attitude toward the beneficiary is high, the more the interest of communicating it increases:

$$SNI(a, i) = |att(i, a.subj)| \times NI \tag{8}$$

3.3 Communication

In our model, actions can be perceived via direct perception (the agent is beneficiary of the action), actor's communication toward the population (the agent receives a message from the actors) or intra-population communication (the agent receives a message from another individual). While the first two cases are scripted in the scenario, the intra-population communication is based on the list of contacts of the agent ($Cnt(i)$) and the subjective interest of the action $SNI(a(i))$.

At each time step of the simulation, the agent considers all actions perceived at this step. It performs a probabilistic selection of some actions, based on their subjective interest, and distributes messages about the selected actions randomly to its contacts.

Let $sni_{max}(t)$ be the maximum sni for actions received at this time step. For each action a and for each contact j, the probability that agent i sends a message about a to j is $p_{sending}(a) = \frac{SNI(a)}{ni_{max}}$.

3.4 Attitude computation

When the agent receives a new information about an action a, it adds it to its belief base (if the action is not already present) and, possibly, communicates about it. Moreover, the agent revises its attitude toward the actor of the action.

Our model of attitude construction is based on the model proposed by Fazio [8] (see section 2.2) as in [3]. In our case, the accessibility of an action is the subjective narrative interest $SNI(a(i))$ since the retention interest and the narrative interest are equivalent in cognitive psychology. Also, the benefit is the action payoff weighted by the attitude toward its beneficiary (as proposed by Fishbein and Ajzen [1]):

$$benefit(a) = payoff(a) \times att(i, bnf(a)) \tag{9}$$

Let $aList(i, actor)$ be the list containing the actions performed by the actor in the belief base of agent i. The attitude $att(i, actor)$ of the individual i toward the $actor$ is given at each time of the simulation by:

$$att(i, actor) = \sum_{a(i) \in aList(i,actor)} \left(\frac{benefit(a) \times SNI(a,i))}{|aList(i, actor)|} \right) \tag{10}$$

4 Simulation results

This section presents two experimental studies of our model to analyze the impact of some key parameters on the attitude dynamics in the context of a stabilization operation. First we evaluate separately the impact of emotion E versus surprise in the narrative interest NI (4.2). Second, we consider the impact of social groups by comparing two different scenarios. Beforehand let us describe the experimental settings.

4.1 Simulation settings

All experiments are based on a set of shared parameters settings:

Population: The population is split into three social groups (ethnic group A, B and C) each composed of 33 individuals connected by an interaction network based on a small-world topology. In the first experiment, there is no inter-group attitude (the population behaves as a single social group). In the second experiment, we introduce inter-social group attitudes. We denote the attitude of the individual i belonging to the social group SG_X toward the individual j belonging to SG_Y $att(i,j) = sgAtt(X,Y)$. Theses static attitudes are defined as follows: sgAtt(A,B)=0.8 ; sgAtt(A,C)=-0.5 ; sgAtt(B,C)=-0.2 (*i.e.* social groups A and B are allied against a third group C).

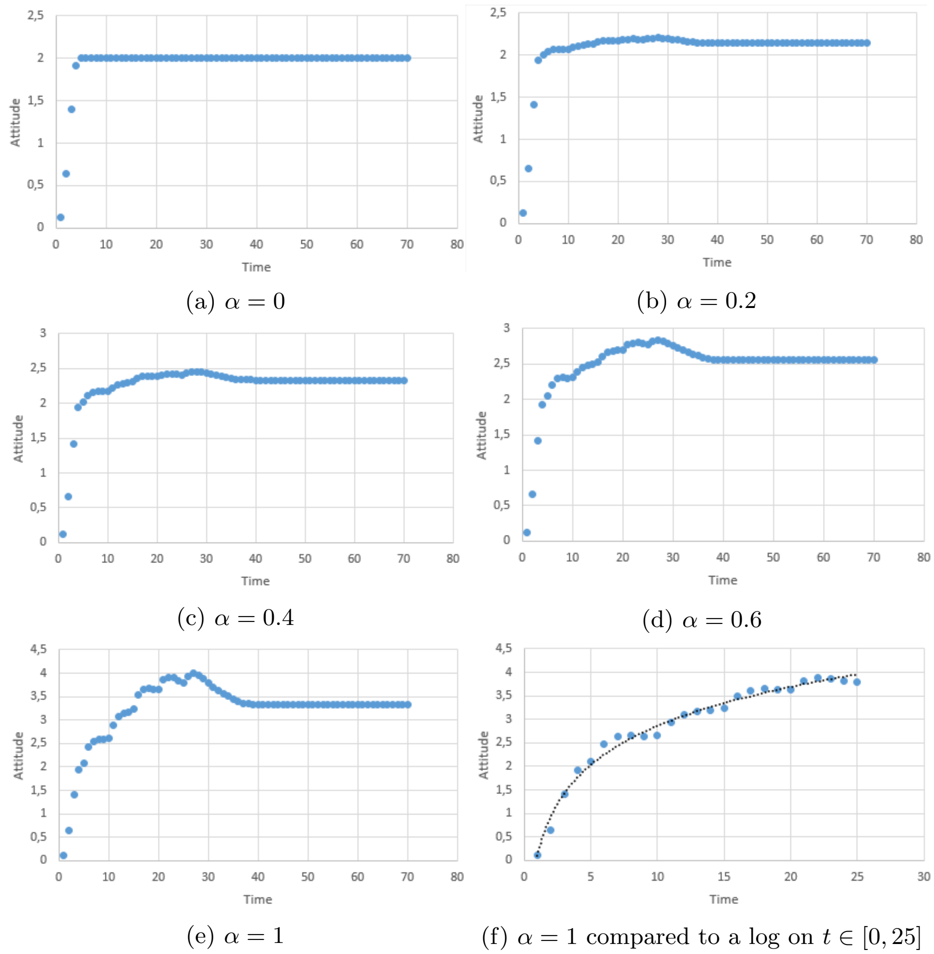
Actor: Only one actor representing the Blue Force (*e.g.* UN) is sufficient for our experimental needs. The initial attitudes of all individuals toward this actor is set to zero.

Scenario: People are confronted to a series of actions with a $payoff = 1$ performed by the actor every 5 time steps (*e.g.* the UN brings food and medic once every two days). In the first experiment all the social groups are affected evenly (random selection on the whole population). In the second experiment we will compare two alternative scenarios: in the first version (called $S1$) the actor affects only random individuals of social group A ; in version $S2$, three phases will affect in order the social group SG_A, SG_B and finally SG_C. Each phase last 30 ticks and affects random people of the corresponding social group. The total amount of action that occurs remains the same across the two scenarios.

Default parameter: ξ is set to 1. In this paper we do not study the sensibility of the model to ξ.

4.2 Analysis of narrative interest components' impacts

The narrative interest is composed of two key components (see section 3.2): the emotional impact E and the surprise S. To analyze the impact of these components on the attitude dynamics, we introduce α and we change the definition of NI into: $NI = 2^{E+\alpha\times S}$. Varying α comes to modify the balance between the emotional intensity and the surprise factors in the narrative interest. The smaller is α, the more emotional and the less surprised will be the agents. When α is very small, the agents tend to ignore the impact of past occurrences of the actions to compute their attitudes. In the case where $\alpha = 0$, the agents will base their attitude only on the emotional impact of the action's occurrences which remains static. Therefore, their attitudes reach the top value and remain stable once all agents have been aware of the information (see figure 1a). The figures 1 show the evolution of attitudes dynamics with α ranging from 0 to 1. Since the communication mechanism is stochastic, each presented result corresponds



(a) $\alpha = 0$ (b) $\alpha = 0.2$

(c) $\alpha = 0.4$ (d) $\alpha = 0.6$

(e) $\alpha = 1$ (f) $\alpha = 1$ compared to a log on $t \in [0, 25]$

Fig. 1: Mean of attitudes in $S1$ with a varying α

to a mean curve obtained over a hundred simulation runs. We can notice three phenomena:

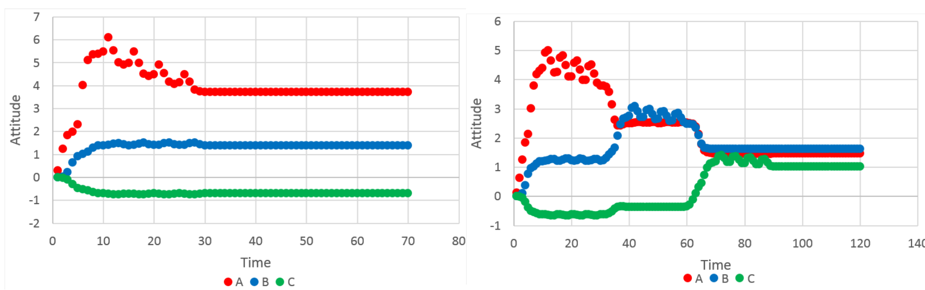
- The attitude value is boosted with the surprise factor: with α growing, the mean of attitudes reaches a higher value. This was predictable since the surprise factor is added to the accessibility of beliefs: its effect results in increasing the attitude value. Moreover, the figure 1f shows that the attitudes' mean increases following a logarithmic law between 0 and 30. This shape is due to the logarithmic components of the surprise.
- Habituation effect: in all simulations, the attitudes decrease after $t \simeq 30$. The repeated perception of the action's occurrences are no more beneficial for the actor since additional occurrences only affects negatively the attitudes. This effect is due to the growing number of people directly affected by the

occurrences. Thus they reduce their surprise using their personal occurrences (see equation 3).

– The mean value reaches a plateau: when $t > 40$, the attitudes' mean remains stable. This stationary state is due to the fact that all the agents have experienced personally the action and also to the fact that the time period between occurrences is stable: the values of both time distance and social distance surprises have reached a threshold value among the whole population.

In further experiments, we analyzed the effect of $\alpha > 1$ and discovered that it has only an impact on the scaling: the shape of the attitudes means' curves remain unchanged while the scale increases. Therefore, we will use $\alpha = 1$ in the following simulations.

4.3 The impact of social groups



(a) $S1$ (b) $S2$

Fig. 2: Scenario comparison

In our model, agents are sensible to the beneficiary's social group, and their attitude toward this group. To understand the sensibility to this factor, we propose to compare the two scenarios $S1$ and $S2$ presented above with the inter-social group attitudes.

Conflicts Figures 2 show the evolution of attitude means per social group in the two scenarios. We can notice that the attitudes of social groups vary in a conflicting manner. At the beginning of both scenario, SG_A being affected positively, its attitude towards the actor increases as explained in section 4.2. Besides, we can notice that SG_B and SG_C's attitudes are also affected despite that these social groups are not directly affected by the action's occurrences. This is due to the intra-population communication that makes them aware of the ongoing actions on SG_A. Along time, more and more individuals come to know the actions, therefore impacting their attitudes. We can notice that the evolution of attitudes of SG_B and SG_C are opposite. This can be explained by their different inter-group attitudes toward SG_A as presented in section 4.1: the evaluation of beneficial actions on SG_A is positive for its ally SG_B and negative for its enemy SG_C. Since SG_B is allied to SG_A, its attitude toward the actor follows SG_A due to the positive evaluation of the action's benefit (see equation 9). Conversely, SG_C being the enemy of SG_A, the action's benefit is evaluated negatively, thus leading to a negative attitude. This phenomenon is also visible on the three phases of the $S2$ (figure 2b).

Agreement While the three social groups have very different attitudes at the end of $S1$ (figure 2a) as it was predictable since only SG_A is positively impacted, they seem to reach a consensus in the scenario $S2$. Indeed, the figure 2b shows that despite conflicting evolutions among groups, they converge to 1.5 since they are equitably affected. However, we can notice that the final attitude values of SG_A and SG_B are very close as they are allied while the "enemy" SG_C is apart with a lower attitude.

5 Conclusion

We proposed a simulation model of attitude dynamics based on socio psychological theories. This model introduces an affective component in the formation of attitude and the diffusion of beliefs through the concept of information's interest which embodies an emotional and an unexpectedness components. Moreover, the introduction of the Simplicity Theory enabled us to only have two paramaters : ξ ¡and α.

We studied the dynamics of this model on several examples that illustrate the impact of theses cognitive components and the inter-social conflicts on the attitudes toward an external protagonist. The first experiment especially showed that repeated actions impacts are not linear. At the beginning, people accentuate their attitudes due to the surprise factor but, after a while, the evaluation is reduced due to an habituation effect. The second experiment presented the impact of having conflicting social groups on the general attitudes dynamics. In particular, we showed that despite diverging evolutions of attitude, when the groups are equitably affected, they tend to reach a consensus. Yet the validation of the socio-cognitive model is a challenging issue. In future works[4], we intend to conduct deeper analysis the sensitivity of the model and also calibrate it using real world data such as opinion polls and action sequences of individuals. Furthermore, we would like to add a behavioral component to enable population agents to express their attitudes through actions.

[4] Note that our model is not limited to military applications and can be applied to civilian use: the actors can represent any kind of active social object such as political parties, institutions, companies or brands

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Improving the Performance of Mobile Application Systems through Agent Deployment Strategies in a Distributed Environment

Case of a Real-time Data Aggregation Problem

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Abstract. To develop machine to machine (M2M) type mobile systems, the role of the Real-time Data Aggregation (RDA) processes for stream data has become critical. RDA is a technology for aggregating the massive amounts of data generated in a short period of time. To improve the performance of an RDA system, in this paper, we address multi-agent challenges of RDA. For the purpose, we discuss techniques such as pipeline processing, parallel processing, high performance data read/update of each of the agents.

1 Introduction

As the growth of the Smartphone market, various services using acceleration sensors and/or GPS loggers equipped in a Smartphone have become popular. These services are characterized by machine to machine (M2M) communication functions without human operations. One of the critical issues of M2M applications is their performance problems: how to continuously process vast amounts of data within a very short time.

So far, such performance issues are solved by scale up techniques of a server system. However, it takes exponentially higher costs to overcome the hardware performance limitation. Another approach is the scale out approach, which is attained by multiple cheaper processors in parallel. The key of the scale out technique is how to distribute data and processes among the processors. One of the typical techniques is stream processing. In the stream processing, continuously generated data or stream data are computed in distributed servers [1] [2]. Because there are no databases in stream processing, complex aggregation calculation is a difficult task. Various distributed computing techniques are used in distributed data among processors [3] [4]. These techniques include both in-memory techniques to achieve high performance data accesses and distributed data store techniques for distributed databases. These techniques are useful for effective process large scale *stored* data.

On the other hand, services to M2M communications, some applications require complex aggregation procedures with stream data. Ranking Application

(RA), in which, for example, every user running a marathon race makes online queries to know the rank of the race, is a typical one. RA processes both real time vast amount of input data or stream data and ranking calculation with complex aggregation processes. Thus, RA is considered as an enough tough problem that we must use both stream and distributed processing techniques.

To solve RA, in [5] [6], they have proposed in-memory data store techniques based on agent-programming models. Their method is characterized by that 1) software agents with the corresponding data and the procedures, which only access the data, are distributed in the environment; 2) the software agents are able to handle distributed data and processes simultaneously; and 3) high performance data accesses and asynchronous processes are attained. Thus, using the techniques, we are able to implement a multiple agent system to communicate each other and to develop high performance pipeline and/or parallel systems.

In this paper, by Real-Time Data Aggregation or Ranking Application, we mean the application system to process continuous generated stream data and to aggregate them in real time. We propose a design principle for RDA agent-systems with both stream and distributed processing techniques. Then, we report simulation experiments on process deployment design of agents in a distributed environment. The rest of the paper is organized as follows: In Section 2, we discuss agent programming models, then in Section 3, we describe the specification of the running application. Section 4 reports the simulation experiments on process deployment. Section 5 gives concluding remarks and future issues.

2 Agent Programming Model

In this paper, to design the application, we use the agent model proposed in [5], which is a typical multi-agent system to realize data processing with agent-agent communication. Figure 1 depicts the configuration of agents on distributed servers. Each agent equips a handler to process messages between agents and exclusive data records. The agent asynchronously processes messages sent from application procedures.

2.1 Agent Processing Model

Each agent has exclusively managed data. The data each agent has been processed by the message handler, which corresponds to the data. When the agent receives the message, the message handler calls a corresponding procedure, then refer to and update the data within the agent. Each agent has a unique key as an identifier. Application programs identify the agent with the key and generate, delete, and/or send messages. The message handler in an agent corresponds to each message, thus does not process messages simultaneously.

2.2 Data Model

The data in each agent are stored as a record. The record, similar to the one of a conventional relational database, consists of a main key and data, retrieves the data by identifying the main key. Each agent has, at least, one master record. Each agent also can have multiple records as a record set. Each agent retrieves record sets in order to get record lists, add and/or delete records. Data records in an agent consist of a tree structure with the root of the master record.

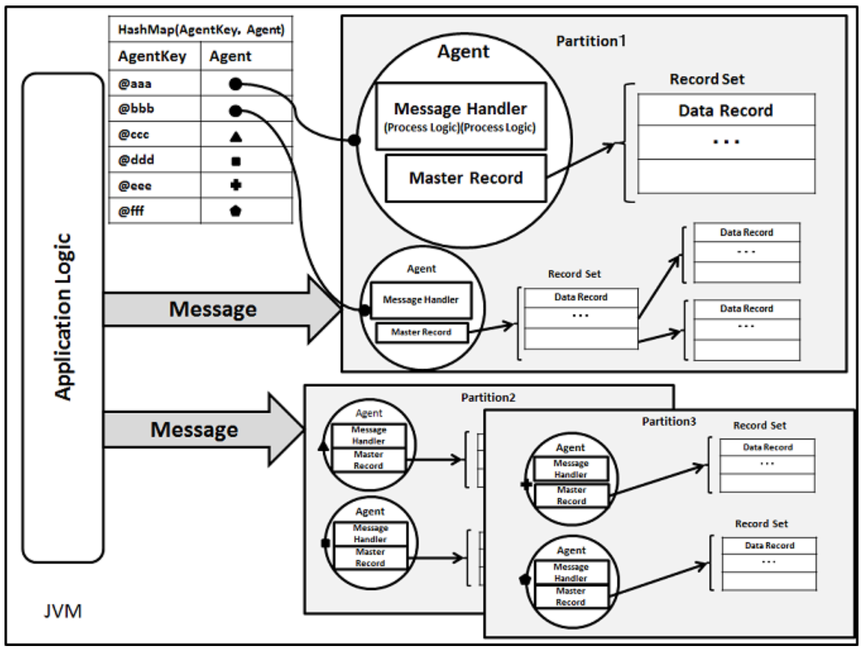

Fig. 1. Configuration of the Multi-Agent System

3 Runnnig Application

In this section, as an example application of real time data aggregation, we describe the design specification of the running application with GPS logs of a Smartphone. The running application aggregates the running distances of each marathon runner, or agent, in real time. The running application requires the following two performance specifications:

a) Each GPS data are updated every second and aggregated per users.
b) Running distance of each user is ranked in real time, and the runner, or agent, is able to access the latest ranks.

3.1 Design of Running Application

When we implement an application system as a multi-agent system, to build distributable agents, we employ the two level design processes: the agent specification design and the agent deployment design to satisfy the performance requirement. In this paper, we apply the design method proposed in [7] and validate the difference of execution performance among the different agent deployments via simulation studies.

Design of the Agent. The process of the design of an agent consists of the four steps. The steps gradually refine the specification of agent-types and prototypes for load analysis.

1. Requirement Specification
   Requirements from clients are described as a scenario specification, which contains concrete data description and processes.
2. System Design Specification
   Using the data and processes in the scenario, we design the process flow and data records. Then, using the scenario, the products are given to the references (Figure3).
3. Design of Agent Types
   Agent types consist of reference data and processes. We give identical names to the agent types to represent the characteristics.
4. Design of Prototypes
   System prototypes are designed by inserting concrete data items into the agent types. Then, we identify the bottlenecks in the sense of the number of both agent communications and data records (Figure4).

Design of Distribution deployment of Agents. We design the distributed deployment of agents in order to avoid agent calculation hot spots, then to improve the total processing performances.

– Agent Decomposition
  In a multi-agent application system for real time data aggregation, there exists an aggregation agent, by which all the data and communication processes are centralized. Therefore, the aggregation agent tends to be a hot spot. In the agent partitioning design, we decompose data of such an agent and also distribute the number of communications among the agents.
  For the purpose, there are the following two ways: a) Range Partitioning, and b) Hash Partitioning. The performances of the both ways depend on the characteristics of the application systems(Table1).
– Agent Deployment
  To deploy agents into the distributed environment, we must consider the conditions of resource usages of each agent and communication frequencies

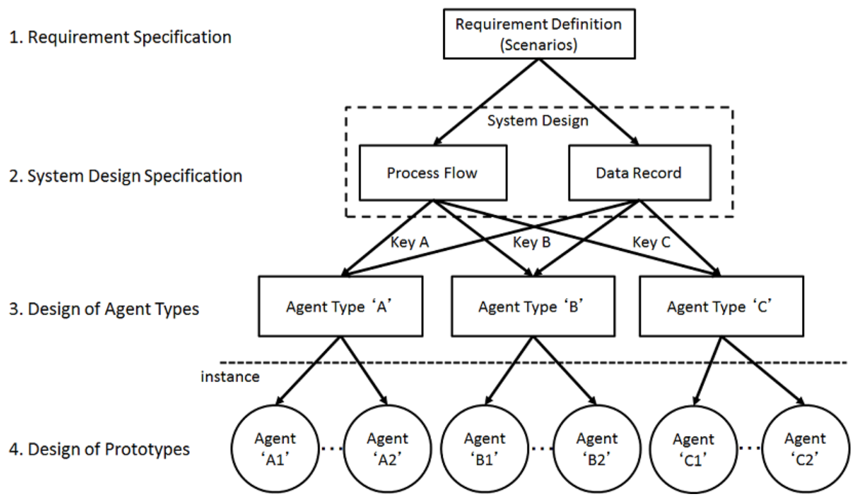

Fig. 2. Four Step Design Processes of the Multi-Agent System

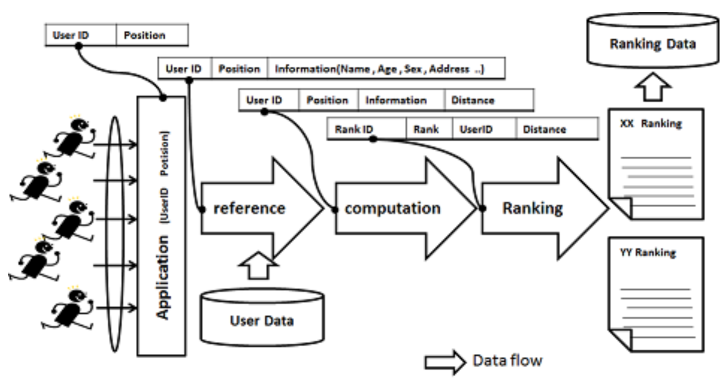

Fig. 3. 2. System Design Specification

among agents. In order to attain adequate performance levels, agent deployment strategies consist of the following two methods: a) Agent cloning to reduce communication costs and to collocate in the environment, and b) Agent typing to assign resources in each type. These deployment strategies affects the performance, if we adequately identify the characteristics of the agents (Table2). How the deployment see Figure 5.

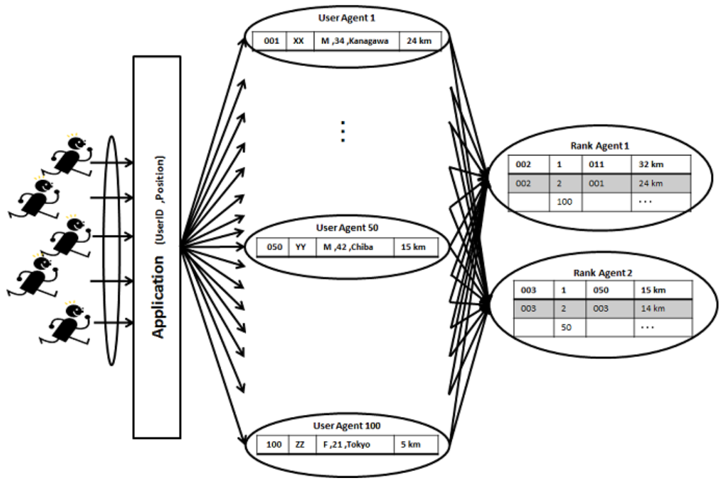

Fig. 4. 4. Design of Prototypes

Table 1. Characteristics of Agent Partitioning

Agent Partitioning	Characteristics	Notes
Range Partitioning	High search performance when partitioning and query conditions coincide each other. Range means a range of the user's running distance.	High performance load sharing when the data value distribution is uniform.
Hash Partitioning	Uniform data distribution attained by the use of data identifiers. Hash value is calculated from the user ID.	Advanced hash calculation techniques required when the query conditions are complex.

4 Simulation Study on the Distributed Deployment

Using the RA described in the previous section, we carry out the comparative simulation study of The execution performance of the distributed deployment. The algorithm calculates the ranks when making queries based on the method shown in Figure 6. The performance equation is formalized as follows. :

Table 2. Characteristics of Agent Deployment Strategies

Deployment Patterns	Characteristics (Upper: Data Aggregation, Lower: Querying)	Notes (Upper: Data Aggregation, Lower: Querying)
AgentCloning	No communication costs required, because of the same communication environment	Synchronization required when the aggregation process executes among copied agents
	Lower query performance because of deployment of data and tasks by cloning	Queries necessary to all the distributed environments, because of the deployment of agents
AgentType	No resource conflicts exist because each agent type independently assigns the resource	Communication costs much because each different agent type requires different communications
	Query processing can be distributed among agent types	The load of the aggregation agents becomes heavy, because they are in the same environment

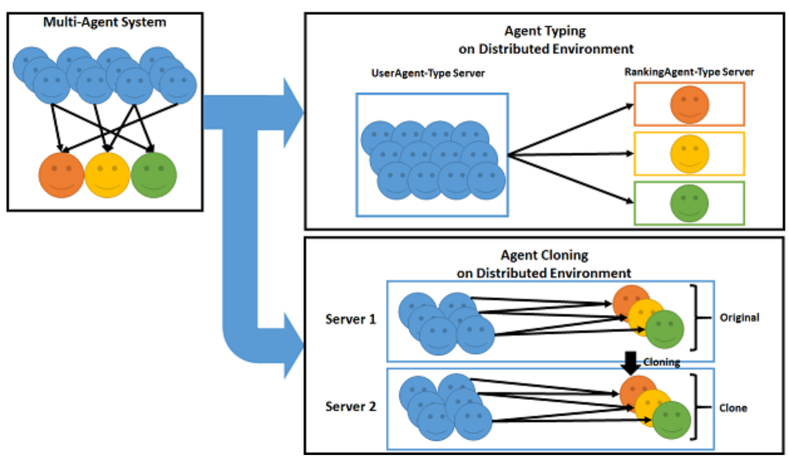

Fig. 5. Design of Distribution deployment of Agents

$AgentCloning$

$$\frac{AllUserAgentCost + AllRankingAgentCost + \alpha}{NumServer} + NumServer * AllQueryCost \tag{1}$$

AgentType

$$\frac{AllUserAgentCost}{NumUserServer} + Comunication_{in} + \frac{AllRankingAgentCost}{NumRankingServer} + AllQueryCost \tag{2}$$

The algorithm makes queries about the ranking in parallel and the user agents aggregates the results, thus, it is good for distributed environments. In this study, we neglect the communication costs against the outside of the environment, because of the difficulty to evaluate.

4.1 Results of the Simulation

The simulation studies on the agent distributed deployment are carried out using both agent cloning and agent types. The parameters used in the experiments are obtained from the ideal condition, where only one agent exists in the environment. (Table3).

The simulated results are shown in Figure 7. The computation time of the case of AgentCloning increases linearly against the server distribution, however, the performance is lower than the case of AgentType, when the number of servers is small.

On the other hand, the case of AgentType shows higher performance when the number of servers is small, however, there becomes no rooms for performance improvement, when the number of servers becomes larger. The limitation of the case of AgentType depends on internal communication costs, therefore, if they had higher communication performance servers, the issues are resolved. If we would consider intercommunication costs, the limitation of the case of AgentCloning depends on the intercommunication costs.

Table 3. Parameters of distributed deployment simulations

Paramters	Values
Number of User Agents	10,000,000
Number of Ranking Agents	100
Costs of User Agent Processes	61 μs
Costs of Ranking Agent Processes	766 μs
Query Costs per Transaction	0.8 μs
Communication Speed	1 Gbps
Block Size of Communication	200 Byte
Process Waiting Time(α)	Costs for AgentClones.

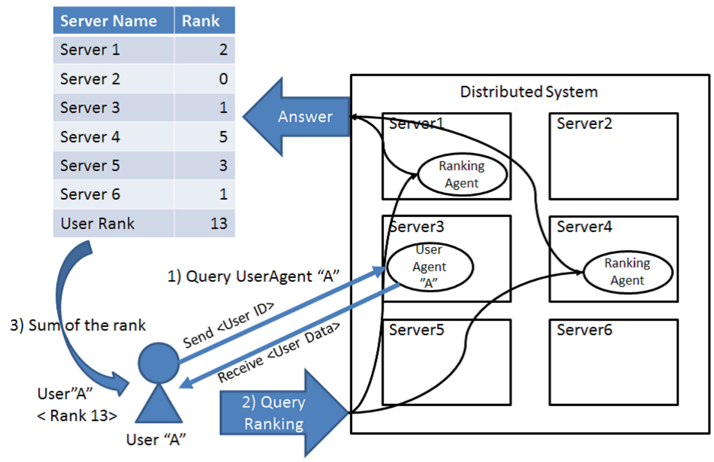

Fig. 6. Query Ranking on the Distributed Environment

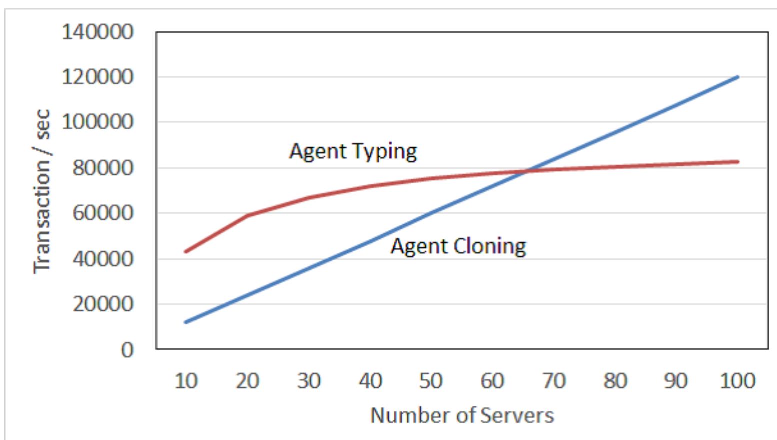

Fig. 7. Simulation Results of the Distributed Deployment Environnment

4.2 Discussion

The results of our simulation studies suggest that when the number of servers is smaller (resp. Larger), AgentType (resp. AgentCloning) is, the better. This means that AgentCloning is more scalable deployment strategy. However, considering the amount of communications, as AgentCloning strategy requires the synchronization processes among clones, the number of inter-communications increases in proportion with the squire of number of servers. AgentType strategy does not require the synchronization processes, so that the number of communications is proportional with the number of servers. However, when the number of inter-communications, i.e., the number of ranking references, is large, the scalability of becoming worse, thus, the performance might be worse than the one of Agenttype. Also, in the environment where the number of agent decompositions is larger, as the similar arguments hold, issues of inter-communications and server resource limitations might cause serious problems.

Such scalability issues of AgentCloning strategy might be resolved by the tactics of agent system designs. The issues of Clone synchronizations also overcome by the tactics that the deployment of UserAgents should be determined by the frequency of communications among RankingAgents and that the clones with no communications should be removed.

The resource limitation issues might be solved by the increase of the number of servers and removal of the clones with no communications. However, these tactics only copes with the limits of performance, and cannot solve the essential performance problems.

5 Concluding Remarks

This paper has addressed the issues of real time data aggregation problems with the example of a Ranking Application (RA), in which, every user with GPS of a Smartphone in a marathon race makes online queries to know the rank of the race. RA is a typical application of mobile agent systems and M2M type ones. In this paper, we have shown the design principle of such agent programming applications by data-store techniques of stream data processing. Our future problems include the improvement of scalability of AgentClone strategy and their evaluations.

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A Social Simulation Study of the Dynamics of Customer Loyalty from the Service-Dominant Logic Perspective

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Abstract. Dynamics of customer loyalty in a competitive market has been studied by formulating an agent-based model of an artificial market. The study aims at seeking answers to the fundamental question of why customers switch brands. The originality of the work mainly resides in the fact that the model is formulated from the emerging service-dominant logic perspective, which is a novel mindset to look at market interactions and value creation. The analysis of the simulation data reveals a regular pattern in the dynamic of customer loyalty and a relationship between loyalty and customers decision to switch.

Keywords: Agent-based Modeling, Social Simulation, Customer Loyalty, Customer Engagement, Service Systems, Service-Dominant Logic, ISPAR Model, NKCS Model

1 Introduction

Nowadays, researchers generally agree that *customer loyalty* is the driving force behind the customers' repeat purchases [1]. Besides, repeat customers are more valued over new customers [2]. There are numerous research studies done on causes of customer loyalty taking into account different perspectives and since about a decade, *customer engagement* has got wider attention of the research community who are interested about the causes of customer loyalty [1] [3]. Furthermore, customer engagement could jointly be discussed with the emerging *Service-Dominant Logic (SD logic)* perspective of customer service provider relationships to come up with better insights about customer loyalty [3].

Our objective in this research is to study customer loyalty from this novel SD logic perspective with the goal of answering the fundamental question of *why customers switch*. In fact, this fundamental question has a substantial history, which has driven all customer loyalty research to date. However, it is still a valid question with increasing business complexity and competitiveness. As SD logic presents a different mindset of looking at business relationships, a systematic study of loyalty from the SD logic perspective would be beneficial for better understanding of customer switching patterns.

We try to approach this problem by focusing on the dynamics of customer loyalty in competitive markets with respect to different parameters. Even though there exist many research studies reported on causes of loyalty there is not much evidence on recent research on its dynamics in competitive markets. Perhaps one reason could be the inability of the popular research methods among business research communities such as case studies and survey methods to adequately capture such dynamics in a vast parameter space. Therefore, we propose agent-based modeling and simulation approach to this study.

Based on the fundamental principles of SD logic [4], we formulate an artificial market model as a *value orchestration platform* [5], on which customers and service providers interact and *co-create* value. We use the *service system abstraction* [6] to define our agents and *Kauffmans NKCS architecture* [7] to enable value co-creation. This paper presents the details of our artificial market model and some of its results.

2 Related Research

2.1 Service-Dominant Logic and Service System Abstraction

SD logic adopts the systems approach to the study of markets by defining markets as systems of resource integrating actors who interact by exchanging services and co-creating value [8]. SD logic has proposed an alternative mindset to the traditional mindset, which they call Goods-Dominant logic based on ten fundamental premises namely 1. Service is the fundamental basis of exchange, 2. Indirect exchange masks the fundamental basis of exchange, 3. Goods are a distribution mechanism for service provision, 4. Operant resources are the fundamental source of competitive advantage, 5. All economies are service economies, 6. The customer is always a co-creator of value, 7. The enterprise cannot deliver value, but only offer value proposition, 8. A service-centered view is inherently customer oriented and relational, 9. All social and economic actors are resource integrators, 10. Value is always uniquely and phenomenologically determined by the beneficiary. Generally, firms that believe in Goods-Dominant logic would focus on producing goods (or its intangible counterpart - services) in surplus with embedded value and distributing that surplus to maximize profits through economies of scale. In contrast, firms that adopt a Service-Dominant logic mindset would focus on increasing adaptability, survivability and system wellbeing through competitive value propositions that primarily involve applied operant resources (i.e. knowledge and skills) and support realizing value in use. A comparison between the GD logic and the SD logic could be found in the the appendix.

The abstract notion of service system [6] enables defining actors of service markets based on S-D logic. In other words, a market could be viewed as a population of interacting service systems of different kinds. According to Maglio et al.

[9], anything ranging from individuals, firms and agencies to worlds and planets could be a service system. A service system is characterized by a value proposition, which helps it to agglomerate its resources in different dimensions and interact with other service systems by exchanging resources [6]. Hence, a market comprising service providers (firms) and their customers could be viewed as a platform, on which service provider service systems interact with customer service systems co-creating value. Furthermore, the possible outcomes of service system interactions have been modeled in the ISPAR model of Spohrer et al. [6]. The ISPAR model basically distinguish outcomes of service system interactions as *service interactions* and *non-service interactions*. According their classification, value co-creation would occur from service interactions whereas the non-service interactions would not result in value co-creation but would help initiating future service interactions. The ISPAR model is further explained in the appendix.

2.2 Customer Loyalty and Engagement

Traditionally, loyalty was considered as emerging from ones satisfaction on a product or service [1]. According to this viewpoint, confirmation of the delivered service to the expectations of the customer, either by matching or preferably exceeding, inspires the customer to make repeat purchases. However, this popular but purely cognitive viewpoint of loyalty has continuously been challenged by the research on the emotional aspects of consumption such as affection and delight [1][10]. Building up on this path, customer engagement (CE) has become a core concept in modern research on customer loyalty [1][3].

Customer engagement has been discussed in different perspectives in the literature [3]. Bowden [1] describes CE as a psychological process, which drives customer loyalty through their trust and affective commitment. They differentiate the formation of loyalty in the cases of new customers and repeat customers by a single model. On the other hand, Patterson, Yu and de Ruyter (2006), Vivek, Beatty and Morgan (2011), Hollebeek (2011) and Mollen and Wilson (2010) describe CE as a psychological state, which drives certain behaviors [3]. Brodie at al. [3] suggest that the conceptual roots of CE may be explained by drawing on theory addressing interactive experience and value co-creation within marketing relationships. Thus, they develop five fundamental propositions based on a S-D logic perspective, to define the concept of CE. Those five fundamental propositions are 1. CE reflects a psychological state, which occurs by virtue of interactive customer experiences with a focal agent / object within specific service relationships, 2. CE states occur within a dynamic iterative process of service relationships that co-creates value, 3. CE plays a central role within a nomological network of service relationships, 4. CE is a multidimensional concept subject to a context and / or stakeholder-specific expression of relevant cognitive, emotional, and behavioral dimensions and 5. CE occurs within a specific set of situational conditions generating differing CE levels.

3 Service System Interactions in Markets - A Hypothetical Use Case Scenario

According to the service system abstraction [6], every entity in a market is a service system entity and every agent is a service system. A service system is characterized by a value proposition, which reflects the level of resources in terms of knowledge and competences the agent possesses. Based on the service system abstraction, we develop the use case scenarios from the hotel industry. In hotel industry, the market basically comprises two types of entities - the hotels (i.e. service providers) and the tourists (i.e. customers). According to the service system abstraction [6], both of these entities become service system entities and their agents, i.e. the respective service systems, could interact with each other. A hotel could be defined using a certain set of attributes, which could be at different states when it comes to different individual hotels. The states of the attributes that define a hotel at a particular destination collectively resemble that hotel into a particular profile in terms of its class (i.e. a star hotel, a budget hotel, an eco hotel, or a cruise), service quality, attitude towards service, etc. In other words, the profile of a hotel reflects its possession of resources, such as knowledge, competences and other tangible resources on different aspects. Similarly, a tourist visiting a hotel too has such profile, resembled from the states of a set of attributes that define a tourist. That profile may determine the class of the tourist (whether he/she is a backpacker, a mass tourist, etc.), his or her knowledge about the destination, interests, attitudes, behavior and the possession of tangible resources such as money.

Once a tourist decides to visit a particular destination, he or she may consider a hotel to stay at during the visit. There, the tourist will ask fellow tourists or follow Internet forums to find out the best place that is most likely to match with his profile (i.e. budget, interests, preferences, etc.). If it is a repeat visit, the tourist may already have some options in mind with a certain level of affection towards each of those options, which make his decision faster and less costlier. The main concern in selecting a place to stay would be how likely the selected place would help making the visit a pleasant experience. From a service-dominant logic perspective, this is called the potential to co-create value. Once a hotel is selected, a tourist would approach the selected hotel for a booking. This could be considered as the beginning of a service interaction between two service systems. There, the hotel would evaluate certain characteristics of the tourist to accept him or her as a guest. For example, it will ask for a proper identification document such as a passport or a security document such as a credit card. Being unable to produce one such would not let the service interaction continue. Once the tourist get lodgment at the hotel, the value is always co-created. That is, the profile of the hotel alone does not help creating value. The tourist, combine the resources of the hotel with the resources he or she possesses to co-create value. For example, a tourist who cannot swim may not be able to co-create value with a nice swimming pool provided by the hotel. The co-created value with each attribute will contribute to the quality of the overall experience of the tourist during the stay and hence to the decision to revisit or not as well.

Moreover, a positive experience that caused a delight may lead the tourist to make a recommendation to his peers about the hotel.

4 The Agent-based Model

4.1 Structure of Agents

We use the service system abstraction [6] to define the structure of the agents. There are two service system entities in the model, which represent service providers and customers. All agents of the model are represented as service systems and belong to either of the two service system entities. Furthermore, all service providers provide one particular service.

Service systems hold value propositions, through which service interactions take place [6]. A value proposition could be considered as a combination of value creating attributes, along which the resources of the respective service system are agglomerated [11]. Thus, we define value propositions of each entity as tuples of a particular number of attributes denoted by N_X, where X = Customer or X = Service Provider. Each attribute could be at any of D states where $D = 0, 1, 2, , d - 1$. For example, providing Internet access could be done by different ways such as setting up Wi-Fi zones inside hotel premises, giving access on request at a charge, giving in-room Wi-Fi access to all residents, etc.

A state reflects a level of resources allocated along the particular attribute and the combination of states of all attributes reflects the overall resource level of the respective service system. Thus, the value proposition of a particular agent is same as its profile. For example, if N for service providers is 5 and $D = 2$, service provider SP1s overall state could be 00011 whereas service provider SP2s overall state could be 11100. This reflects the difference between the profiles of the two service providers in terms of resources. This is same with customers as well.

These value-creating attributes contribute to the overall value co-created in a service interaction [11]. For example, in a service interaction between a particular service provider agent and a service provider agent, the contributions of each of the attributes of the service provider agents value proposition counts in the overall value co-created by the customer agent and vice versa.

Apart from these two types of agents, there is a controller agent, which executes various runtime tasks such as reporting, adding-removing agents, etc.

4.2 Realizing Value Co-creation

In order to facilitate value co-creation in service interactions, we define utility landscapes for each of the two service system entities. The utility landscape of a given entity enables any agent of that entity to perceive the co-created value of a particular service interaction with an agent of the other entity.

In a service interaction i ($i \in I$) involving two instances - *a customer* - x ($x \in \overline{X}$) and *a service provider* - y ($y \in \overline{Y}$)- the perceived utility of x (=

u_i^x) could be represented by Equation 01. In this representation, $\overline{X}$ denotes the entity of *customers* where as $\overline{Y}$ denotes the entity of *service providers*.

$$u_i^x = \frac{\sum_{n=0}^{N_{\overline{Y}}-1} u_i^n}{N_{\overline{Y}}} \tag{1}$$

Here, $N_{\overline{Y}}$ denotes the number of value creating attributes of the value proposition of *service provider* entity and u_i^n denotes the utility contribution of the attribute n of *service provider entity*'s value proposition to the overall utility perceived by x in the interaction i. A similar equation could be written to determine the perceived value of the instance y in the same interaction.

Co-creation of value involves resources of both parties of a given interaction. In other words it depends on the states of individual attributes of the respective value propositions. Thus, we impose a dependency structure to each attribute of value propositions of both entities using Kauffman's NKCS architecture [7]. According to the NKCS architecture, the utility contribution of each attribute of a given value proposition depends not only on the state of that attribute but also on the states of k number of other attributes of the same value proposition as well as the states of c other attributes of the opposite entity's value proposition. Here, k and c are system parameters. This dependency structure is represented by equation 02.

$$u_i^n = f(d_i^n, (d_i^1 ... d_i^K)_{\overline{Y}}, (d_i^1 ... d_i^C)_{\overline{X}}) \tag{2}$$

According to this representation, the value contribution from attribute n at a given service interaction i (i.e. u_i^n) depends on any of the $D^{(1+K+C)}$ different state value combinations possible. Thus we define the function represented by equation 03 to determine the individual value contribution of a given attribute u_i^n based on each state value combination. Here, R is drawn from the uniform distribution.

$$(f^n) : \{0 ... D-1\}^{1+K+C} \rightarrow R \tag{3}$$

4.3 Making a Choice: Selecting a Service Provider based on Loyalty

In this model we assume that the customer loyalty towards a given service provider changes dynamically with increasing number of interactions. This section contains the formalization of our formula that determines the loyalty of a given customer agent towards a particular service provider.

According to Bowden [1], we define *loyalty* as mainly determined by *affective commitment*. We further assume that peer recommendations about a given service provider enhances the affective commitment of a customer towards that provider. Peer recommendations are *non-service interactions*, which act as catalysts for future service interactions [6]. Thus, we define a function for *affective commitment* as in equation 04, in which affective commitment is the sum of *trust* - T and *recommendation strength* - $\frac{1}{b\beta}$. When determining the strength of a given peer recommendation, we take into account the distance between the

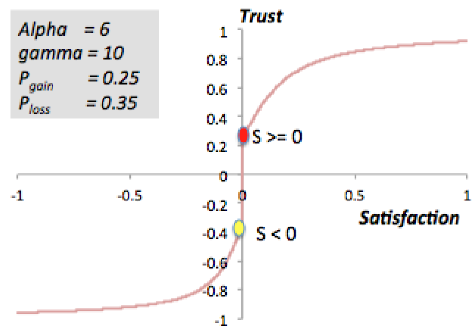

Fig. 1. The Trust Function of Customer Agents

given agent and the recommending peer in terms of their value propositions. In other words, a recommendation from a peer with a significantly different value proposition is very unlikely to help making a successful choice due to the mismatches in resource levels. Therefore we take the inverse of the distance to calculate the recommendation strength and β is a control parameter. Without β, the *recommendation strength* component suppresses the effect of trust in the simulation.

$$A_x^y = \frac{\sum_{i=1}^{q} T_x^y}{q} + \frac{\sum_{j=1}^{z} \frac{1}{b\beta}}{z} \tag{4}$$

Here, q is the total number of service interactions that have taken place between the customer x and the service provider y where as z is the total number of recommendations x has received from its peers about y.

According to Bowden [1], trust is generated from *satisfaction* and *delight*. Hence we define satisfaction as the average of the difference between the *perceived utility* - pu and the *expected utility* - eu of each attribute of the value proposition of the service provider in a given service interaction i, as shown in Equation 05.

$$S_{ix}^y = \frac{\sum_{n=1}^{N} (pu_n - eu_n)}{N_{\overline{X}}} \tag{5}$$

Here, the customer is satisfied when S = 0, satisfied with delight when $S > 0$ and not satisfied when $S < 0$. In order to derive trust from satisfaction, we define the inverse tangent function, which is shown in Figure 02. The corresponding equation is given by Equation 06.

$$T_{ix}^y = \begin{cases} 2(1 - P_{gain}/\pi)\tan^{-1}(\alpha S) + P_{gain} & : \ S \geq 0 \\ 2(1 - P_{loss}/\pi)\tan^{-1}(\gamma S) - P_{loss} & : \ S < 0 \end{cases} \tag{6}$$

This inverse tangent function is based on the prospect theory [12]. Parameters α and γ control the steepness of the function. According to prospect theory, a loss matters more. Therefore, when $S < 0$, γ is set to a value greater than α making the curve steeper to represent a higher negative trust value in that range. Moreover, P_{gain} and P_{loss} represent a sudden gain or loss of trust when $S > 0$ and $S < 0$ respectively.

When a customer agent is about to make a choice about a service provider, it calculates the loyalty towards each potential service provider using the Equation 07, which is based on the *multinomial logic model* [13].

$$L_x^y = \frac{A_x^y}{\sum_{i=1}^{M} A_x^i} \tag{7}$$

Here the loyalty towards a particular provider is computed as a fraction of the loyalty towards all potential service providers. The customer agent then takes the two service providers with highest loyalty and selects either of them using a random value such that the provider with a higher loyalty share has a better chance of getting selected.

4.4 State Variables

State Variables of the Customer The most important state variable of the customer entity is the *current state*, which is the current states of all attributes of its value proposition. In other words, it is the current profile of that customer. When customer agents learn and adapt to market conditions, they dynamically change their current states by moving to neighboring states. Another important state variable of customers is the *expectation*. This could be explained as the expected value from each attribute of a service at the time of use [14]. Initially, we set the expectations of individual customers randomly within a range of $0 - h$ ($0 < h < 1$), where h is controlled by a parameter (*Customers' adequate margin*). In reality customer expectations usually grows with positive experiences [14]. Therefore, we set the expectations of individual customers to grow by a certain quantity determined by a parameter - (*Expectation growth rate*) - when the customer satisfaction is positive. Apart from these two major state variables, *Available Providers, Affection with Providers, Priority Attributes, Need Probability* and *My Neighbors* are other important state variables of a customer. Notably, *Need Probability* is a system parameter. The details are given in the appendix.

State Variables of the Service Provider Similar to the customer agents, the *current state* and the *expectation* are the two most important state variables of service providers. *Current state* reflects the provider's current profile whereas *expectation* reflects he expected value from each attribute of a customer's value proposition at the time of the service interaction. The expected values of each attribute are initially set randomly in the range 0 - v (0 ¡ v ¡ 1), where v is an input parameter (*Providers' adequate margin*). Apart from these variables, *My Check Attributes, Interaction Number* and *My Customer Relationships* are other important state variables of a provider. The descriptions of these variables are given in the appendix.

4.5 Process Overview

The market process in our model starts with getting a service need by individual customer agents. Service need is determined probabilistically by a parameter value. Once a customer agent gets a service need, it looks for a suitable provider. The process of selecting a provider is depicted by figure 02. A description about figure 02 could be found in the appendix.

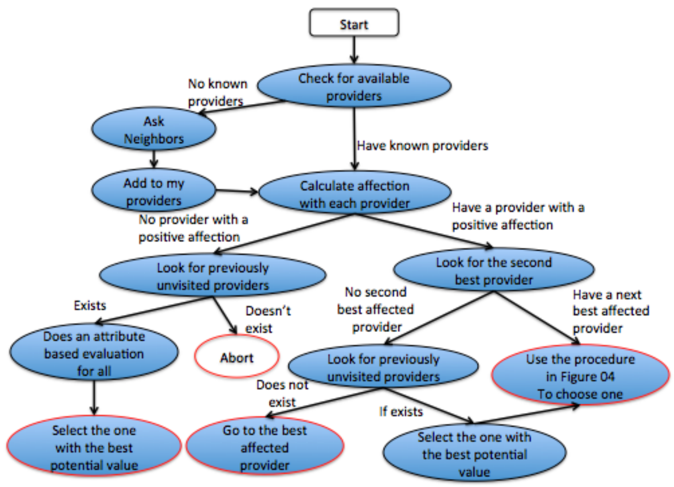

Fig. 2. The Process of Selecting a Provider

Interacting with the Selected Provider In case when the customer agent found a suitable provider, it initiates a service interaction according to the process illustrated in the Figure 04.

In case if the customer agent is delightfully satisfied with the service (i.e. satisfaction > 0), it makes a recommendation of the service to all of its neighbors.

Learning and Adaptation Learning and adaptation of customers occur when agents compare their utility (i.e. service experience) at the current state with the utilities of their peers. If a customer finds a nearest neighbor having a better utility with the same provider, it moves to a one-mutant neighboring state [7] that reduces the distance between value propositions of itself and the said nearest neighbor. We assume that the agents cannot copy the entire state of that neighbor because such a drastic change of profile may not be practical in reality. In the current implementation, providers do not consider the peer performance. They periodically test for better states in their one-mutant neighborhood

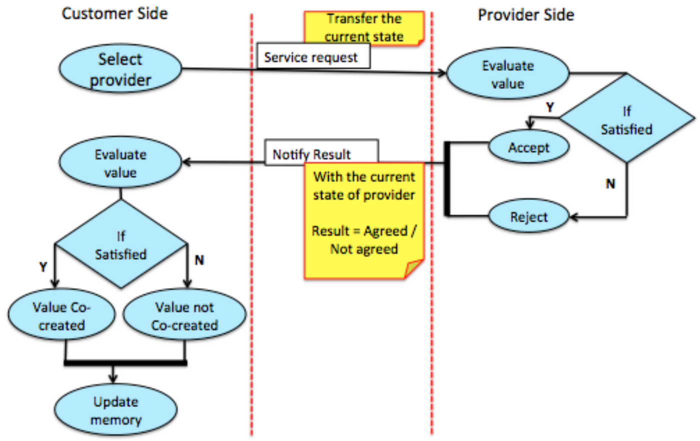

Fig. 3. The Process of Interacting with the Selected Provider

by communicating with a particular number of top customers determined by a parameter.

5 Simulation Results

In order to find out how affection towards a service provider changes with time due to the process of customer engagement, we plot affection (affective commitment) against time in the graph in figure 05. To generate this graph, we used 10 simulation runs, each of which having two competing service providers, one thousand customers and different random seeds. According to this graph, the affection towards a service provider initially goes through a hype but declines thereafter gradually with time towards a stable point. In fact, this result corresponds with a common observation with new offerings where lots of attention being drawn to the particular offering at the beginning through reviews, discussions, recommendations, etc generated through delightful experiences of the early users. However, as customer expectations grow with firsthand experiences with the offering, the trust towards the particular offering in the population of its customers gets lowered gradually towards an equilibrium point. This result is similar to Bruggen et al.'s observation of customers' behavior after a store remodeling attempt [15]. We then evaluated the individual customer agents' affection at each time step and their decision to switch or return, which is shown in Figure 06. The red points corresponds to a decision to switch whereas a blue dot corresponds to a decision to retain. It is possible to see from the graph that all agents who decided to switch have a negative affection with the current provider.

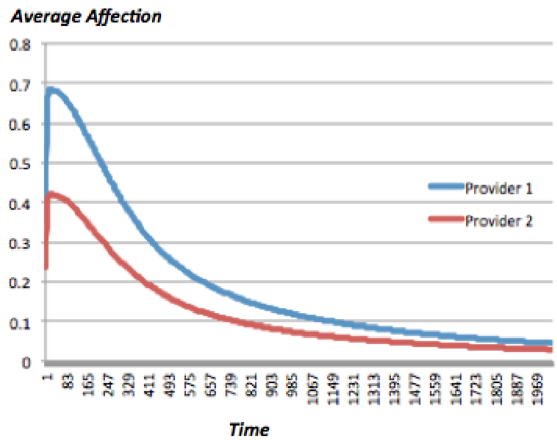

Fig. 4. Dynamic Pattern of Loyalty Formation through Affection

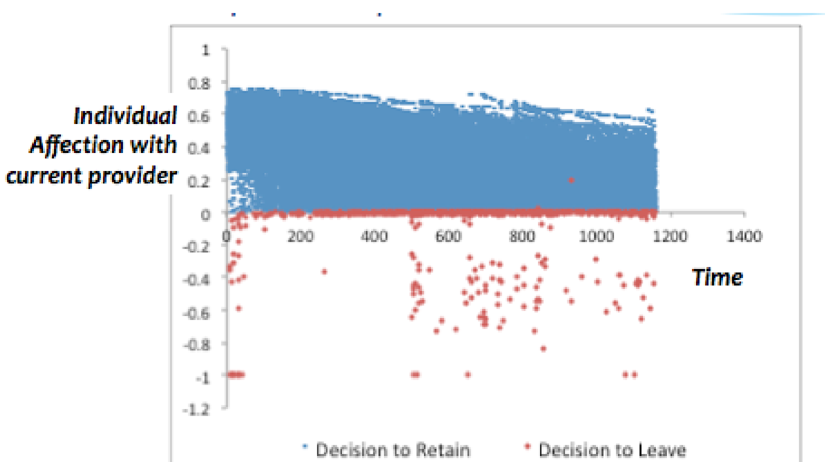

Fig. 5. The number of agents switched the provider despite competition

6 Conclusion and Future Work

The prime objective of this paper was to present the details of an agent-based model developed to study the dynamic patterns of customer loyalty in competitive markets from the SD logic perspective. The results of the simulation revealed a specific dynamic pattern of loyalty with an initial hype and a gradual decline. Further it corroborated that the customers switch when they are no longer loyal to the provider. From an agent-based modeling viewpoint, the agent behavioral rules of the model may be considered as too rigid, which would also be a limitation of this model as it makes the results more predictable prior to the simulation run. Therefore our future work on this model will be to loosen some of the rules to see if the agents develop any interesting and unpredictable patterns in the long run.

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A Multi-Agent Simulation to Study the Impact of Cognitive Profiles on Job Satisfaction

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Abstract. In these pages, we use the *Happywork* framework to study the impact of several cognitive profiles on job satisfaction. We focus here on the cognitive dimension of job satisfaction. The model is intended to model and simulate the core mechanisms that underlie individual evaluation of the job. We present the model and some preliminary results on consequences of job enhancement policy in terms of comparison outcome.

1 Introduction

Job satisfaction is one of the most studied construct in nowadays organizational research [14] [8]. It impacts organizational outcomes (e.g. [4]), and is one of the most important antecedent of individual well-being (e.g. [9]). Studies from psychology and economics are often based on theoretical and statistical models, none of them using the agent-based methodology to investigate job satisfaction.

In this paper, we propose an agent-based framework to model and simulate the job satisfaction cognitive processes. Like most influential models (e.g. [14] [12] [19]) we conceptualize job satisfaction as an attitude toward the job. From a cognitive perspective, job attitude is defined as the aggregation of discrepancies between job features and a set of standards (referents) [2]. Job features are subjective evaluations of the job situation and could be accessible through surveys. Referents are the reference points for the comparison processes, and could refer to alternative situations or abstract standards (e.g. values or needs).

Related Works By contrast with many normative approaches, our methodology relies on *psychomimetism* [10] : we want our model to implement well-established theories in social psychology. While many models of opinion dynamics have been proposed in the agent-based simulation literature, most of them consider attitude as unidimensional (modelled with one vector x, each component x_i denotes the opinion of agent i), and as equivalent to an opinion [3]. This is problematic for job satisfaction, as our attitudinal approach relies on multi-dimensions and multi-facets attitudinal construct.

Yet, some models are inspired by psychosociological theories [11] and some of them incorporate multi-dimensionality [16]. However, though they model the resulting changes in attitude through diffusion, they do not consider the inner mechanism that builds the attitude. In other words, the attitude formation is black-boxed, while we aim to open the box in order to understand and study the determinants of job satisfaction.

The HappyWork framework: Our approach for job satisfaction, the *HappyWork framework* [1], is based on subjective features perception and comparison process with standards. Features are characteristics of the job at different levels such as work load, creativity, salary, etc. Defining standards is a more difficult task, as there is no accepted consensus [19]. We focus in this paper on *social comparison*, where a subject compare his/her job situation with some other individuals. Finally, in HappyWork, we promote a *data-driven approach*, in order to account for real data deriving from field surveys. Thanks to our partner Technologia, we were able to use some of their questionnaires to initialize the agents.

In the next section, we will detail our model of job satisfaction, followed by some experimental results : sensitivity analysis and simulation of one job enhancement policy.

2 Agent-based model of job satisfaction based on social comparison process

Model inputs and initialization Let A be the set of agents in the simulation. Let $Q = \{q_1, \dots q_n\}$ be the set of *job characteristics*, these characteristics being sorted out in a set of *job dimensions* $d \in D = \{d_1, \dots d_m\}$. Q and D will be provided by the questionnaire we aim to study. Every agent $a \in A$ is initialized with values $RQ(a) = [q_{1a}, \dots q_{na}]$ that encode its subjective job features as responses to the questionnaire on each feature q_i. The questionnaires under study are made of Likert scales, so the numerical encoding is straightforward. Note that there is a priori a *direct and monotonous link between satisfaction and questionnaire response values.*

Discrepancy evaluation The social comparison implies a computation of the discrepancies $\Delta(a, r)$ between an agent a and one of his referent r. We have:

$$\Delta(a\,, r) = [\delta(a,\, r,\, q_1), \dots,\, \delta(a,\, r,\, q_n)]$$
$$\delta(a, r, q_i) = \frac{q_{ia} - q_{ir}}{max(q_i) - min(q_i)} \tag{1}$$

where $\delta(a, r, q) \in [-1; 1]$ computes the discrepancy between a and r on feature q, $min(q_i)$ and $max(q_i)$ being respectively the minimal and maximal values for question q_i given by the questionnaire.

Social comparison To design the social comparison process, we take our inspiration from Mussweiler's *Selective Accessibility Model (SAM)* [13]. According to Mussweiler, people compare with each other using three main processes further detailed in next sections: (i) the subject a uses a set $RS(a)$ of referents to compare with; (ii) for each referent $r \in RS(a)$, if a feels similar enough with r, then it engages the comparison process; and in that latter case, (iii) the impact of the comparison is computed either by assimilation or contrast, two different sub-processes we detaile below.

1) *Referent selection.* Classical definition of social referent encompasses closeness and similarity [15]. Referents in work organization could be identified as individuals we interact with, colleagues and generally people in close environment [6]. In absence of data regarding the real social network, we assign for each subject a a set of referents $RS(a)$, with cardinality NR. $RS(a)$ will be made of first-degree neighbours in their social network (see section 3.1 below).

2) *Similarity hypothesis–testing.* In this step, agent a must decides whether it is close enough to referent r. To do so, a computes $modeInit(a, r) \in [0; 1]$ as the proportion of features on which a and r have different values. Hence, 0 means a complete similarity, and 1 a complete dissimilarity. Following Mussweiler [13], $modeInit(a, r)$ is not computed on the entire job feature set. In fact, people typically select few salient information about their referents to engage in a basic, spontaneous and preliminary comparison process. We denote this salient feature set $SF(Q)$ containing readily accessible job features, like employment conditions. If $modeInit(a, r)$ exceeds a given *deflection threshold* $\sigma^{deflect}$, the comparison target is too dissimilar. In this case the referent is deflected and no comparison occurs. Otherwise, the similarity hypothesis is supported and a moves to the third step.

3) *Assimilation and contrast outcomes.* According to SAM theory, comparison outcome depends on comparison content and "on what information is cognitively accessible". *Content* is defined by the *direction of comparison*, namely *downward* when a compares itself with someone a feels to be worse off on characteristic q – in our case when $\delta(a, r, q) > 0$ – or *upward* comparison for the opposite – when $\delta(a, r, q) < 0$. Accessible information is conceived in SAM as priming stimulus focusing on *similarity or dissimilarity* [13]. The model posits that if someone is *primed* to insist on similarities with the comparison target, then assimilation process occurs. This happen when $modeInit(a, r) < \sigma^{assimil}$, where $\sigma^{assimil} \in [0, 1]$ denotes an *assimilation threshold* (i.e. the maximum number of discrepancies to be considered similar). Otherwise, when $modeInit(a, r) \geq \sigma^{assimil}$, a contrast sub-process is triggered.

Moreover, assimilation process makes the subject a feel to be in the same situation as the referent. Hence, if the referent is in a better condition, a forsees it will be better off soon and, this comparison will have a positive impact on its comparison process. Symmetrically, comparing with someone worse leads to a negative impact on job satisfaction ("my situation will deteriorate soon") [20].

Contrast typically render opposite consequences, that is a positive/negative impact when comparing with someone better/worse ("I feel different than my referent, and then happy when I'm better, unhappy when I'm worse"). This could be summarized in Table 1 below, where $IC(a, r, q)$ is the outcome of a's comparison with referent r on feature q. $IC(a, r, q) > 0$ (resp. < 0) means that a's comparison with r will tend to increase (resp. decrease) a's satisfaction on feature q.

Table 1: Assimilation and contrast outcomes

	r is better ; $\delta(a, r, q) < 0$	r is worse ; $\delta(a, r, q) > 0$
Assimilation	$IC(a, r, q) > 0$	$IC(a, r, q) < 0$
Contrast	$IC(a, r, q) < 0$	$IC(a, r, q) > 0$

To encode these effects, contrast outcome is computed using equation 4, where $dissim(a, r)$ denotes the overall dissimilarity between a and r, and computed as the number of features on which a and r are dissimilar.

$$IC(a, r, q) = \delta(a, r, q_i) \cdot dissim(a, r)$$

Symmetrically, assimilation is given by equation 2, where $similar(a, r)$ computes the proportion of features on which a and r are similar:

$$IC(a, r, q_i) = -\delta(a, r, q_i) \cdot simil(a, r) \tag{2}$$

However, several sociopsychologists [20] have found that assimilation process often exhibits *mixed effects* (assimilation *and* contrast), even when the subject feels very close to comparison target. In other words, assimilation process may contain a certain proportion of contrast – denoted $\alpha^{mix} \in [0, 1]$ in our model. Hence, the amount of contrast effect within an assimilation process will be: $\alpha^{mix} \cdot \big(\delta(a, r, q_i) \cdot dissim(a, r)\big)$.

The overall comparison process is summarized in the following algorithm:

Algorithm 1 algorithmic overview of the comparison process

1: **if** $modeInit(a, r) < \sigma^{assimil}$ **then**

$$IC(a, r, q_i) = -\delta(a, r, q_i) \cdot simil(a, r) + \alpha^{mix} \cdot \big(\delta(a, r, q_i) \cdot dissim(a, r)\big) \tag{3}$$

2: **else if** $\sigma^{assimil} < modeInit(a, r) < \sigma^{deflect}$ **then**

$$IC(a, r, q_i) = \delta(a, r, q_i) \cdot dissim(a, r) \tag{4}$$

3: **end if**

The first step corresponds to assimilation's hypothesis testing. If it is successful, comparison outcome is computed through assimilation sub-process with mixed assimilative and contrast outcomes (3). In the other case, comparison outcome is computed using a pure contrast sub-process (4).

Social comparison aggregation The final social comparison outcome for agent a is computed from its $IC(a, r, q)$ values. This is done through a sequence of multicriteria aggregations. At first, we use a $WOWA$ (weighted ordered weighted average) aggregation along the features of each dimension to obtain the aggregated comparison impact $ICD(a, r, d)$ on each dimension $d \in D$. Then, to get $CompSoc(a, d_i)$ – the overall comparison impact on dimension d_i, all the referents $r \in RS(a)$ will be aggregated using an ordered weighted average (OWA) operator [3]. Finally, we compute the *final social comparison outcome*, also named below *job satisfaction*. This global indicator – $SocSat(a)$ – aggregates the job dimension satisfactions, using another $WOWA$. The overall aggregation formula is given by:

$$SocSat(a) = \underset{i \in \{1,2,\ldots,|D|\}}{WOWA} \left(\underset{r \in RS(a)}{OWA} \left(\underset{q \in d_i}{WOWA} \left(IC(a, r, q) \right) \right) \right) \qquad (5)$$

3 Simulation results

We present here some simulation results : a sensitivity analysis on the main parameters, and a simulation of one job enhancement policy. Let us first detail the initialization protocol.

3.1 Initialization protocol

Agent initialization from real word data The set A of agents is initialized from real word data coming from a manager's satisfaction survey conducted by our partner Technologia, within a big French company. We had 178 agents in this dataset, and all the questionnaires Q are made of Likert scales. About the dimension set D we have 4 dimensions : the 3 Karasek dimensions – i.e. job control, job demand, and social support – and employment conditions.

Network initialization The social network is generated using a small-world algorithm based on the Watts and Strogatz model [18], as this type of network has shown to be relevant to firm organization (e.g. [17]). There are two parameters, p^{watts} (the rewire probability), and the network average degree NR (average number of connections and then the average number of referents for each agent).

Cognitive parameters initialization In order to focus our attention on comparison mechanisms and network parameters impact, we restricted agent's cognitive parameters to three pre-defined combinations of $\sigma^{assimil}$ and α^{mix} values we call *cognitive profiles*:

1. *High Assimilation (HA)* : high threshold $\sigma^{assimil} = 0.6$ and low $\alpha^{mix} = 0$. This profile represents high propensity to assimilate with referents.

[3] See e.g. [5] for details on OWA and WOWA aggregation.

2. *Moderate Assimilation (MA)* : high threshold $\sigma^{assimil} = 0,6$ and average $\alpha^{mix} = 0.5$. This mixed profile reflects a moderate tend to assimilate with referents.
3. *High Contrast (HC)* : low threshold $\sigma^{assimil} = 0,2$ and average $\alpha^{mix} = 0.5$. This profile represents a high propensity to contrast with referents.

All other cognitive parameters remain constant :
- $\sigma^{deflect} = 0.8$
- when available from the data set, the weights on dimensions are used to parameter the WOWA aggregation of these dimensions. Otherwise, WOWA and OWA operators are set to compute a mean[4] value.
- $SF(Q)$ contains the employment conditions, the seniority within the firm, and the employee qualification.

Finally, when, for all agents, the rolling average of their satisfaction do not differ by more than a given percentage threshold $\epsilon = 0.03$, we consider the simulation to have reached a steady state, and it is therefore automatically stopped.

3.2 Sensitivity analysis

We performed a sensitivity analysis on two main type of parameters : the cognitive profiles and the number of referents to study the impact of the social network. For these analyses, we compute the *net assimilation effect index* as the proportions of comparisons where actual assimilation occurs (i.e. when the assimilation component in equation 3 takes precedence over the contrast component). All the simulations are initialized using default values - $p^{watts} = 0.1$, $NR = 15$, $Ref^{chg} = 1/3$. The results are aggregated over 50 runs and each run is stopped when stabilization occurs.

Cognitive profiles: First we conducted simulations with different cognitive profiles and mixed populations. Results are depicted in figure 1 below.

Square blocks represent average level together with standard deviation error bars and the line highlights small median blocks. As expected, assimilative profile (HA, MA and HAMA) and mixed assimilative population show the highest possible amount of assimilation comparison, the three other mixed populations containing HC profile render less assimilation comparison amount. However, even for the pure assimilation profile HA, the final proportion of assimilation processes do not exceed 17 %. This is coherent with the psychosociological literature, which well established that assimilation not frequently occurs.

Referent dynamics We study here the impact of changes in agent's interaction network. The idea is to split working partners in two categories: one stable group of friends and/or close colleagues, and one group made of people with whom

[4] For sake of simplicity and to reduce the number of model's parameters. In future works, we will investigate the impact of WOWA and OWA parameters.

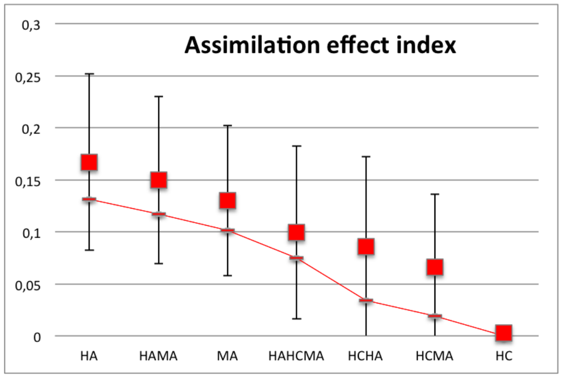

Fig. 1: Net assimilation index for the different cognitive profiles

the agent interacts occasionally. This later group depends on a ratio parameter, $Ref^{chg} \in [0; 1]$, which defines the proportion of referent's to be rewired following a *second degree rule*: each changing referent will be removed from $RS(a)$ and replaced by a new one (randomly drawn from a uniform distribution).

We noticed that job satisfaction average values, as well as their standard deviations, are not sensitive to referent selection at all. This could be explained by the fact that agents' positive comparison outcomes are compensated by negative consequences for others, resulting in an average value near 0. Besides, p^{watts} parameter does not have a significant impact on comparison mechanisms too. This is because of the limited agent interaction capabilities and the absence of contagious mechanism (one's job satisfaction do not depend on other's job satisfaction). Nonetheless, p^{watts} is inversely correlated to the stabilization period duration, meaning that satisfaction stabilized more slowly as the network gets more and more clustered.

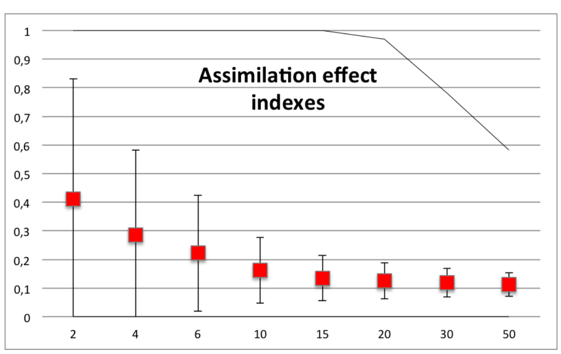

Fig. 2: Net assimilation index variation with NR values

Regarding net comparison indexes, only the number of referents have significant impact. As depicted in figure 2, dispersion of net assimilation index decreases with the number of referents, its minimum value (solid black line at the bottom of figure 2) increases with NR. The more the referents are, the higher the chance is to find referents similar enough to trigger assimilation.

3.3 Job enhancement policy : an exploration

Finally, we aim to study the impact of one job enhancement policy. It is intended to increase employees' motivation and satisfaction through job enhancement advices [7]. In our scenario, this can be done by raising some job feature values in agent job representation $RQ(a)$: each time simulation reaches a stable state, the organization takes a set of NI agents and increases the least satisfying feature. This policy will be repeated 10 times.

To study such an impact, we conducted a quantile-based analysis. We divided agent population into 4 groups from the 25% least satisfied $GQ1$ to the 25% most satisfied $GQ4$ according to quartile values. The policy targeted agents in $GQ1$. Simulations are conducted with network's default parameters (see section 3.2).

Quantile groups distribution For each quantile group, we compute the difference (Δ) between quantile statistics at policy start and policy end. The results for quantile groups' average job satisfaction are reproduced in tables 2 and 3 below: the raw Δ values and the evolution ratios in brackets for the seven cognitive profiles.

Table 2: Δ values for quantil groups and single cognitive profile

	HA	MA	HC
$GQ1$	−0.57 (−16%)	1.31 (+37%)	4.74 (+56%)
$GQ2$	0.38 (+42%)	0.43 (+48%)	0.58 (+23%)
$GQ3$	0.6 (+77%)	−0.06 (−2%)	−1.93 (−123%)
$GQ4$	0.83 (+22%)	−0.81 (−24%)	−2.87 (−35%)

Table 3: Δ values for quantil groups and mixed population

	HAMA	HAHCMA	HCHA	HCMA
$GQ1$	0.19 (+5%)	2.24 (+40%)	2.36 (+40%)	3.25 (+56%)
$GQ2$	0.29 (+38%)	0.65 (+54%)	0.61 (+48%)	0.46 (+42%)
$GQ3$	0.22 (+26%)	0.01 (4%)	−0.02 (−2%)	−0.47 (−41%)
$GQ4$	0.14 (+5%)	−0.92 (−17%)	−0.98 (−16%)	−2.14 (−34%)

As we can see, the cognitive profile has a significant impact on policy outcomes. With high contrast agents, the least satisfied agents (GQ1) show an improvement but at the cost of the deterioration of the most satisfied ones (GQ4). We get a quite different pattern with high assimilation agents, even if assimilation only takes place in 17% of the comparisons (recall results in section 3.2 above): every quantile shows an improvement except for GQ1, even though they were the specific target of the policy. Moderate assimilation is in-between but closer to the contrast outcomes pattern. Most surprisingly, mixed moderate and high assimilation ($HAMA$) reaches a final state that combines the best of each one. In fact, it appears to be the lone configuration where job enhancement policy is able to improve every category.

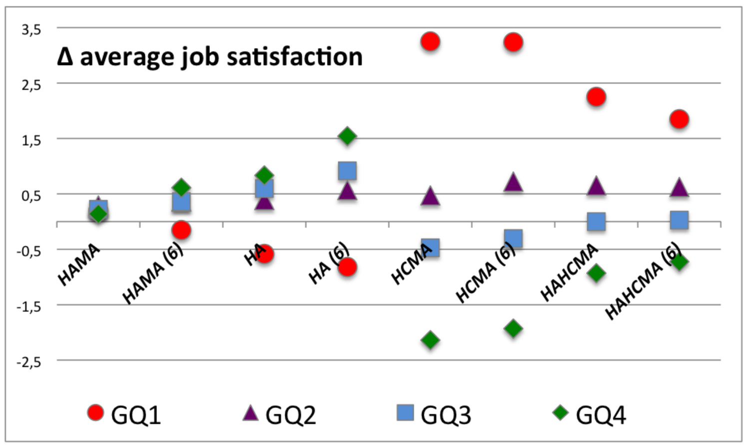

Fig. 3: Δ values by quantil groups for HA and mixed population with $NR = 15$ and $NR = 6$

We now study the impact of the number of referents NR. Results for simulation with network being initialized with default value $NR = 15$ and lower one $NR = 6$ are displayed in figure 3 below ((6) indicates simulations with $NR = 6$). As one can see, $HAMA(6)$ is close to pure assimilation profile HA : the $GQ1$ situation is worsened, while the others are slightly improved. In fact, as we have seen before, lowering NR parameter ends up in more contrasting effects (see figure 2). With a mixed situation profile ($HAHCMA(6)$), there is a contraction in the differences: the gap between $GQ1$ and $GQ4$ is slightly reduced with the same effect as before ($GQ1$ decreased, $GQ4$ increased) but moderated by contrast. Finally, in the more contrasted profile ($HCMA(6)$), we have the same effect again but with a smaller degradation for $GQ1$, thanks again to a higher contrast effect.

Quantile flows Finally, we conducted agents' flows analysis. As in Δ statistics computation, we start from agent's quantile group distribution just before policy begun and record flow transitions at policy end. Resultant matrix should be read as follow: quantile groups initial states are depicted in rows, while final states are represented in columns. For example, in table 5, first row corresponds to agent flows from quantile group 1: 52% stay in this group, 29% go up to quantile group 2, 14% to $QG3$ and 5% in the most satisfied group $GQ4$. Inversely, the final quantile group 1 is made of 29% from $GQ2$, 16% from $GQ3$ and 4% from $GQ4$.

Table 4: flow matrix for HC cognitive profile

	$GQ1$	$GQ2$	$GQ3$	$GQ4$
$GQ1$	0.57	0.32	0.11	0.0
$GQ2$	0.29	0.42	0.27	0.02
$GQ3$	0.16	0.27	0.47	0.11
$GQ4$	0.0	0.02	0.13	0.84

Table 5: flow matrix for HAHCMA mixed population

	$GQ1$	$GQ2$	$GQ3$	$GQ4$
$GQ1$	0.52	0.29	0.14	0.05
$GQ2$	0.29	0.35	0.27	0.09
$GQ3$	0.16	0.27	0.33	0.24
$GQ4$	0.04	0.11	0.24	0.6

Table 6: flow matrix for HAMA assimilative mixed population

	$GQ1$	$GQ2$	$GQ3$	$GQ4$
$GQ1$	0.48	0.30	0.16	0.07
$GQ2$	0.27	0.33	0.27	0.13
$GQ3$	0.17	0.24	0.33	0.26
$GQ4$	0.09	0.13	0.24	0.53

We show three typical flow matrix: the one on the left presents typical results for population with contrast being prominent (HC and $HCMA$), the one in the middle exemplified typical results for contrast and assimilation mixed population ($HAHCMA$ and $HCHA$) while the last one represents typical results for assimilation (HA, MA and $HAMA$). Results show success policy is limited in all cases.

Let us first examine the diagonal values, revealing the proportion of agents remaining in the same quantile group. HC-type are the most conservative, with the highest proportion of remaining agents in the same quartile, especially at the extremes (0.57 for $GQ1$ up to 0.84 for $GQ4$). $HAMA$-like gives the lowest remaining rates. Moreover, assimilation tends to a better improvement than contrasting profile (upper diagonal). In $HAMA$ the proportions of agents jumping to a better quartile is more important than with HC, especially for reaching $GQ4$. Again, $HAHCMA$ lies in the middle. Overall, the flows are more important with assimilation (upward and downward).

Finally the middle groups $GQ2$ and $GQ3$ are the ones with the smallest remaining rates. Agents in these groups are more inclined to change their satisfaction category. They might be more undecided about their job situation and therefore could be of a particular attention as policy targets, as they might better react to improvement.

4 Conclusion and Future Works

In summary, we explored the impact of several cognitive profiles on job evaluation, thanks to a multi-agent model, *HappyWork*, of job satisfaction based on social comparison processes. We showed that assimilation and contrast lead to very different outcomes in term of response to a job enhancement policy. Depending on the population cognitive profiles, very contrasting results could appear : one shows global enhancement for everyone but at a moderate level ($HAMA$, mixed assimilation), while a population with a high contrasting trend will have its extremes spread even more (HC), increasing drastically the inequalities in terms of job satisfaction within the population.

Hence, our simulation results clearly show that, from an organizational point of view, job improvement could lead to varying consequences, from soft to drastic changes depending on employee's cognitive profiles. This is an important finding for managers aimed to enhance the situation within the firm : the cognitive profiles must somehow be taken into account for the policy to be effective.

We also show that network topology do have an impact on satisfaction while in limited range. In order to go further on network effect, we need to enrich the agents' interaction mechanism: biases on job feature communication and also contagion effects might be introduced.

Finally, in order for our scenario to be more realistic, organization has to consider actual job design, and we need to add agent work activity on which organizational policy would act upon.

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Market-level Effects of Firm-level Adaptation, Intermediation and Cost Heterogeneity in Networked Markets

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Abstract. This paper presents a multi-agent simulation that studies market based competition in a multi-stage negotiation with both direct sales and intermediation, in the presence of cost-related heterogeneity at the agent level. Producers sell their products according to an adaptive Q-learning strategy. Product is sold to clients (small shops and consumers) according to two types of marketplaces, which are characterised depending on whether they obtain the product from intermediaries or directly from producers. The model is inspired by a networked market of perishable goods in Bogotá, Colombia. The results show that, contingent upon unit transportation cost and producers' learning rate, intermediation might lead to greater traded quantities than sales through direct marketplaces, although erosion of intermediaries' profits might also become compromised. Thus, we conclude that intermediation could serve as a mechanism for increasing market efficiency.

Keywords: Networked markets, agent-based simulation, market competition.

1 Introduction

In recent years, there has been growing worldwide interest on the supply chain of fresh products, given its importance for the urban population. Some of the most common characteristics in such supply chains are the huge losses of suitable foods for human consumption throughout the handling procedures and high levels of intermediation that increase the price of the product. This paper presents a computational model aimed to study market-level effects of producers' and sellers' strategies in a supply chain of fresh products. In principle, a socially desirable outcome might not only be reducing the role of intermediation, but also assuring an equitable participation of all involved actors, considering that these

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two concerns might be interdependent. A critical problem is the presence of a noticeable cost heterogeneity among producers, which makes economies of scale a factor of dominance in market operations and constitutes an impediment for small producers to access the market. Nonetheless, any proposed mechanism, while guarantying equal access, should not favour the small players to the point that their incentives to seek cost efficiency be eroded. Therefore, throughout the paper, we especially question if reducing intermediation is really desirable. A proposed model that helps explore feasible alternatives of market operations should be able to mimic relevant dynamic drivers, and not just resemble market-level implications of equilibrium solutions [17] Therefore, we advocate for, and develop a so-called, individual-based computational modelling approach. The model aims to represent a set of interacting software agents, who would act on behalf of the users of the above-mentioned platform and would execute the market transactions. We present an agent-based model where several adaptive strategies [11], embodied by the supply chain actors, are explored in order to understand implication on market outcomes (e.g., price and profit levels). Adaptive strategies are understood in the context of repeated interaction [12] and under several interaction structures (i.e., with different degrees of intermediation). The model would allow understanding important tradeoffs between (i) access opportunities for producers and overall cost efficiency of the whole supply chain, and between (ii) considerations of different degrees of intermediation and feasibility of implementation of them. The model is inspired by a networked market in one of the poorest areas of Bogotá, Colombia, characterised by an active presence of intermediaries, and that possesses a recently inaugurated by a not-yet fully functional logistics platform (i.e., direct marketplace) that aims to counterbalance the effect of intermediation.

1.1 Background

Recent advances in Multi-Agent System (MAS) simulations have provided better insight of complex processes in social sciences. MAS are appropriate for systems where interactions, rather than the will of a single entity, define the behaviour of the system itself. The main characteristics of agents are autonomy, social ability, reactivity and proactivity. Autonomy can be understood as the capability of making self-oriented decisions; social ability is related to the inherent communication of the agents; reactivity is the ability to adapt to changing environment and proactivity is defined as their goal oriented behaviour. A multi-agent agent comprises a collection of autonomous, goal oriented individuals who interact among themselves and with the environment or outside world [14]. Each agent acts based on its behaviour [14] that can be summarized in three steps: Evaluation of both the agent status and the environment, (ii) make and execute a decision and (iii) evaluation of the action taken and adjustment of the decision rules according to the changes in the environment. Agents typically cooperate with other agents in the case of common goals and negotiate when there exist conflicting goals. Other important issues related to MAS are: Continuous learning, acting under both uncertainty and incomplete information, and performing in a dynamic scenario [14]. Multi-agent simulation has taken particular strength in supply chains with decentralization and information asymmetry among its members. This is mainly because the traditional models as discrete event simulation, mathematical modelling and system dynamics, are limited and often unrealistic in such situations [14]. The original models of MAS in the supply chain were developed to study the problem of coordination and integration. These works are mainly focused on the importance of mitigating the impact of the demand variation amplification upstream the chain. This phenomenon is the well-known "bullwhip effect" [16], [1], [7]. MAS models for supply chains in agriculture have been scarce. Such models have studied mainly problems of rural credit, crop selection, land use, natural resource management, and irrigation, to say a few [2], [3], [6], [10], [4], [18], [5]. Among the few projects involving MAS in agricultural supply chains, CASA was one of the first [9]. This project involved the application of MAS to support auctions, transportation, and other logistics services. Regarding multi-agent communication, the literature presents several protocols that include bidding (i.e., the contract net protocol), auctions [19], and bargaining [8], [15]. In all these cases the negotiation objects (i.e., the products) and the deals (i.e., prices) are set by the agents themselves. In other mechanisms such as market-based models, agents use auction-based protocols for negotiation based on individual goals; prices however are set by the market [13].

1.2 The model

The general proposed model consists of five types of agents: producers, intermediaries, indirect marketplaces, direct marketplaces and buyers (small shops and consumers). Producers sell their products to the intermediaries or direct distributors; intermediaries buy from the producers and sell only to the indirect marketplaces which in turn sell to the buyers; direct marketplaces buy from the producers and sell to buyers.

Assumptions
We assume that (i) there is only one product to trade, (ii) all agents are located at predefined x, y locations, ((iii) in each round a producer sells its production to either one (and only one) intermediary or to one (only one) direct marketplace, whose trade price is set according to a demand function, (iv) in each round an intermediary sells all production he/she bought to one and only one indirect marketplace, whose trade price is set according to a demand function, (v) not only are producer's / buyer's decisions influenced by price, but also by distance, and (vi) the final price paid by buyers is a mark-up price.

Parameters
We define the following parameters: J = set of producers, I = set of intermediaries, R = set of direct marketplaces, W = set of indirect marketplaces, C = set of buyers, $d_{x,y}$ = distance between agent x and agent y, CT = cost of transport

per unit of distance, CP_j = unit production cost of producer j, and q_j = quantity sold by producer j. We also make use of some coefficients to formulate the demand functions at the indirect and direct marketplace locations (a_1, a_2, a_3, b_1, b_2, and b_3). We assume two distinct ranges of values for CP_j, one for small producers and one for large producers, taking into account that small producers have higher production costs. Cost values are calibrated and drawn according to uniform distributions that are built according to producers' real data.

Variables

X_{ji} = binary variable that establishes if producer j sells to intermediary i
Y_{jr} = binary variable that establishes if producer j sells to direct marketplace r
Z_{iw} = binary variable that establishes if intermediary i sells to indirect marketplace w
Q_{Ii} = quantity bought by intermediary i (from a subset of producers)
Q_{Rr} = quantity bought by direct marketplace r (from a subset of producers)
Q_{Ww} = quantity bought by indirect marketplace w (from a subset of intermediaries)
U_{Jj} = profit of producer j
U_{Ii} = profit of intermediary i
U_{Rr} = profit of direct marketplace r
U_{Ww} = profit of indirect marketplace w
P_{Ii} = unit price paid by intermediary i (to all the producers he/she bought from)
P_{Rr} = unit price paid by direct marketplace r (to all the producers he/she bought from)
$P_{R'r}$ = unit price paid by buyers who bought from direct marketplace r
P_{Ww} = unit price paid by indirect marketplace w (to all the intermediaries he/she bought from)
$P_{W'w}$ = unit price paid by buyers who bought from indirect marketplace w

Equations

The following equations describe the trading process among producers, intermediaries, indirect marketplaces, direct marketplaces, and buyers. At every time step, each producer choses either one intermediary or one direct marketplace:

$$\sum_i X_{ji} + \sum_k Y_{jk} = 1, \forall j \in J \qquad (1)$$

Intermediaries sell to only one indirect marketplace:

$$\sum_w Z_{iw} = 1, \forall i \in I \qquad (2)$$

Quantities bought by every intermediary i, every direct marketplace r and every indirect marketplace w are defined as $Q_{Ii} = \sum_j q_j X_{ji}$, $Q_{Rr} = \sum_j q_j Y_{jr}$,

$Q_{Ww} = \sum_i Q_{Ii} Z_{iw}$, respectively. Profit calculations of producers, intermediaries, direct and indirect marketplaces are defined as follows:

$$U_{Jj} = (\sum_i P_{Ii} X_{ji} + \sum_r P_{Rr} Y_{jr} - CP_j) q_j - CT(\sum_i d_{ji} X_{ji} + \sum_r d_{jr} Y_{jr}), \forall j \in J, \tag{3}$$

$$U_{Ii} = (\sum_w P_{Ww} Z_{iw} - P_{Ii}) Q_{Ii} - CT(\sum_w d_{iw} Z_{iw}), \forall i \in I, \tag{4}$$

For the sake of simplicity, we assume that indirect and direct marketplaces offer a price to buyers equal to a markup (m) over costs, $P_{W'w} = (1+m) P_{Ww}$ and $P_{R'r} = (1+m) P_{Rr}$, respectively. Every buyer k has a reservation price P_{ok}, so that it is a requirement that $P_{ok} > P_{W'w} + CTd_{kw}$ and $P_{ok} > P_{R'r} + CTd_{kr}$, $\forall k$, in order to have buyers participating. If indirect and direct marketplaces manage to sell everything they have bought, their utility values would be computed according to the following equations:

$$U_{Rr} = (P_{R'r} - P_{Rr}) Q_{Rr}, \forall r \in R, \tag{5}$$

$$U_{Ww} = (P_{W'w} - P_{Ww}) Q_{Ww}, \forall w \in W. \tag{6}$$

However, such utility computations depend on comparisons with the reservation price of each buyer, reason why traded quantities might be lower than Q_{Rr} and Q_{Ww} at every time step. Thus, given the nature of perishable goods, we do not assume the existence of inventories, which consequently implies that non-sold product is lost (while cost of it is borne). We also assume that both producers and buyers follow an adaptive rule to select where to sell or where to buy. Producers use a Q-learning adaptive rule that allow them to reinforce their choosing of intermediary / direct marketplace according to perceived positive profits in previous rounds. At every time t, every producer keeps a tracking score labeled Q_c, $c \in I \cup R$ [11] and decides to update its choosing of intermediary or direct marketplace according to the following probability:

$$P(X' = c) = \frac{Q_{c,t} - \min_{x \in I \cup R}\{Q_{x,t}\}}{\sum_{x \in I \cup R}(Q_{c,t} - \min_{x \in I \cup R}\{Q_{x,t}\})}. \tag{7}$$

Q-related values are updated according to a learning rate that assimilates new information, α, so that $Q_{c,t} = (1-\alpha) Q_{c,t-1} + \alpha U_{Jj}$ if $X_{ji} = 1$, and $Q_{c,t} = Q_{c,t-1}$ if $X_{ji} = 0$. Similarly, buyers update their Q-related tracking scores of indirect and direct marketplaces. However, following the Bogotá case, we assume the existence of only one indirect marketplace and only one direct marketplace, and that buyers only buy one unit every time step. Given such a binary choice for buyers, we set their tracking scores as $Q_{m,t}$, $m = \{\text{indirect}, \text{direct}\}$, according to $Q_{indirect,t} = (1-\alpha) Q_{indirect,t-1} + \alpha(P_{ok} - P_{W'w} - CTd_{k,indirect})$ if buyer k buys from the indirect marketplace (otherwise $Q_{indirect,t} = Q_{indirect,t-1}$), and $Q_{direct,t} = (1-\alpha) Q_{direct,t-1} + \alpha(P_{ok} - P_{R'r} - CTd_{k,direct})$ if buyer k buys from the direct marketplace (otherwise $Q_{direct,t} = Q_{direct,t-1}$). Thus, given such a binary choice, the probabilities to buy from the indirect marketplace and from the direct marketplace are computed as $Q_{indirect,t}/\sum_m Q_{m,t}$ and $Q_{indirect,t}/\sum_m Q_{m,t}$, respectively.

Prices at the intermediary, indirect and direct marketplaces are set according to linear demand functions:

$$P_{Ii} = a_1 - b_1 Q_{Ii}, \forall i \in I, \tag{8}$$

$$P_{Ww} = a_2 - b_2 Q_{Ww}, \forall w \in W, \tag{9}$$

$$P_{Rr} = a_3 - b_3 Q_{Rr}, \forall r \in R. \tag{10}$$

Coefficients b_1, b_2, and b_3 are set so that prices become zero when demand is maximum (i.e., when demand is equal to $\sum_j q_j$). For the sake of simplicity, we also assume producers produce one unit of production every time step, so that $q_j = 1$, $\forall j$.

1.3 Background Context

The modelled situation resembles the fresh food supply chain of Bogotá (Colombia) in which farmers sell their products to intermediaries who in turn re-sell the product throughout the city. There are several intermediation channels such as wholesalers, direct sales, small shops, etc. where the product is sold to the final customer. However, most of the trade of agricultural products is done through Corabastos, the largest wholesaler in Bogotá, which is responsible for supplying the capital and much of the country. The food prices there set the standards for trade nationwide. Intermediation levels are dissimilar but on average the overall price increase is around 65 %. Due to these high prices, end consumers have fewer opportunities to access quality foods, especially in some marginal populations of Bogotá.

To deal with such problems, the Mayor of Bogotá, implemented the Master Supply and Food Security Plan (PMASAB in Spanish) back in 2007, attempting a progressive transformation of the food supply system in the capital to ensure timely and uninterrupted availability of quality at fair prices. A key point of the plan was the establishment of "Agri-networks" (a network of farmers that organise food supplies in and out of its territory by integrating the management of agricultural, livestock, and fish products to consolidate production) and "Nutri-networks" (network of small shop owners) whose objective is the generation of collective efficiencies in the supply chain. Collective efficiency of both Agri and Nutri-networks, in theory, would theoretically achieve improvements in transportation, quality, packaging, and generate economies of scale to ensure their competitiveness and sustainability. The trade between Agri and Nutri networks would be accomplished thorough logistics platforms strategically located in the boundaries of the city. These two networks would be linked through Internet thus facilitating order placements and payments.

1.4 Summary of Results

Snapshots of the model are illustrated in figure 1. Producers chose either one of the intermediaries or the direct marketplace as trading partner. After profits have been realised, producers update their Q-related scores and decide the next trading partner according to the probability distribution generated by the Q-learning algorithm. Buyers behave in a rather similar fashion with regard to deciding whether to buy from the indirect or the direct marketplace (recall that, unlike producers, buyers face a binary choice). Profits of intermediaries and producers depend on distance costs and market prices.

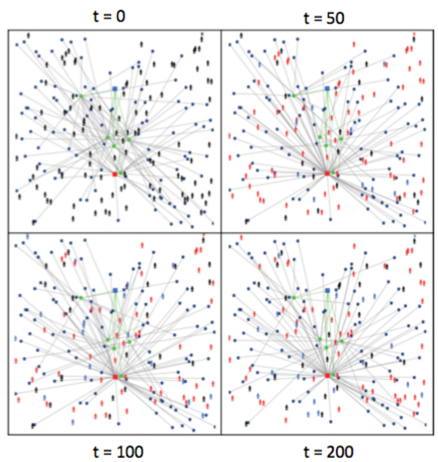

Fig. 1. Sample snapshots that illustrate the market dynamics. The blue and red squares located in the middle represent indirect and direct marketplace agents. Green dots represent intermediaries. Connecting (blue) dots to either intermediaries or the direct marketplace represent producers. Such connections establish who producers trade with. Unconnected agents (in blue, red, and black) are buyers. Black-coloured buyers are not able to buy since their reservation price requirement is not met. Red buyers buy from the direct marketplace, while blues ones buy from the indirect marketplace. Producers and buyers update their choosing according to expectations based on past trading experience, which is controlled by the Q-related scores.

Figure 2 illustrates average indirect and direct marketplace prices according to variations in the number of intermediaries (1, 5, 10) and the unit distance cost (0.01, 0.05, 0.10), assuming a mid-value learning rate $\alpha = 0.5$. We also assume values for a_1, a_2, and a_3 to ensure that intermediaries' profits are positive ($a_1 = 5$, $a_2 = 15$, and $a_3 = a_2$). In the presence of one single intermediary, prices are not significantly affected when the unit distance cost increases. However, increasing the number of intermediaries does reflect an effect of unit distance cost variations: A high unit distance cost and a high number of intermediaries forces the indirect marketplace price to be lower than the direct marketplace price, thus increasing attractiveness of buyers to buy from the indirect marketplace (recall that both indirect and direct marketplaces charge a markup over costs to buyers). In the presence of high transportation costs, intermediation plays a moderating role in relative price reduction in favour of the indirect marketplace.

Result 1. An increase of the number of intermediaries generates an indirect marketplace price relatively lower than a direct marketplace price, as long as unit transportation cost is high. This result implies that intermediation might increase market efficiency.

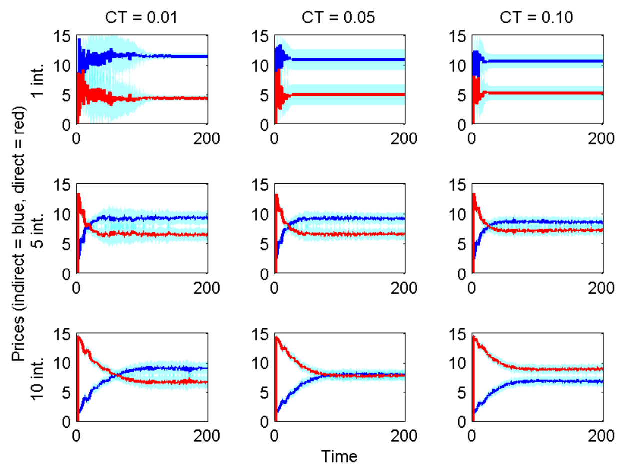

Fig. 2. Average behaviour of indirect and direct marketplace trading prices, P_{Ww} and P_{Rr} respectively, according to variations in the number of intermediaries and the cost of transport per unit of distance CT. Cyan shadows represent a one standard variation.

Figure 3 depicts the average behaviour of intermediaries' profits at time t. Despite the effects of increasing unit distance cost on the price intermediaries pay, unit distance cost alone appear to have no negative effect on their profits. Instead, the presence of additional intermediary agents heavily (and negatively) affect their profits.

Result 2. Increases of unit transportation cost alone have no significant effect on intermediaries' performance, but increases of the size of the intermediary agent population negatively do.

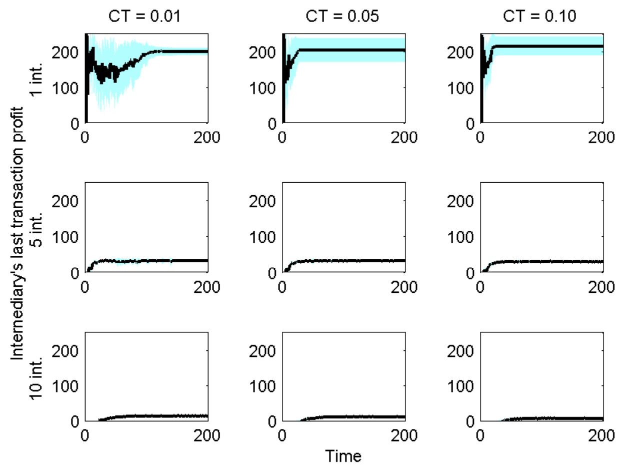

Fig. 3. Average behaviour of intermediaries' most recent transaction profits according to variations in the number of intermediaries and the cost of transport per unit of distance CT. Cyan shadows represent a one standard variation.

Also, both the increase in unit transportation cost and the number of intermediaries have an effect on indirect and direct marketplace quantities sold to buyers. Consistently with what was observed in Figure 2, buyers decisively lean toward the indirect market when both the intermediary population and the unit transportation cost are high. Market sizes also tend to be more balanced when both unit transportation cost and intermediary population are large, with respect to the case when both are small. See Figure 4.

A different set of scenarios was explored by changing the value of the Q-related updating coefficient α (the learning rate). For that, we maintain a constant unit transportation cost of 0.05. Figure 5 illustrates that a higher adaptive capacity of producers (i.e., a higher value of α) coupled with a large intermediary population makes sales to intermediation more attractive in terms of price, which means that producers' strategic response to spot market opportunities (either through intermediation or direct sale channels) also have an impact on indirect market size increase.

Result 3. An increase of producers' learning rate and the size of the intermediary population bring on a reduction of the indirect marketplace price and a subsequent (relative) increase of the indirect market size.

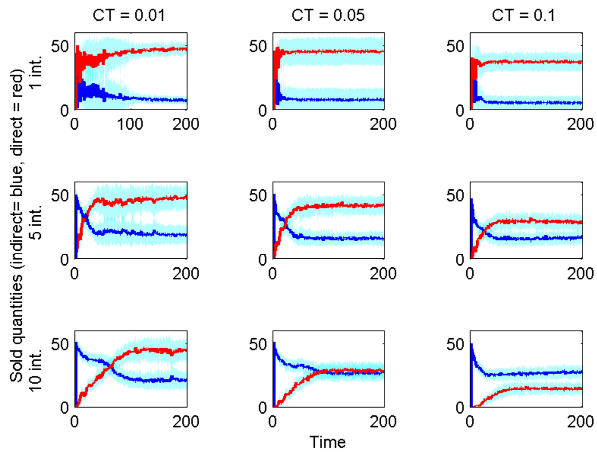

Fig. 4. Average behaviour of indirect and direct marketplace sold quantities to buyers, according to variations in the number of intermediaries and the cost of transport per unit of distance CT. Cyan shadows represent a one standard variation.

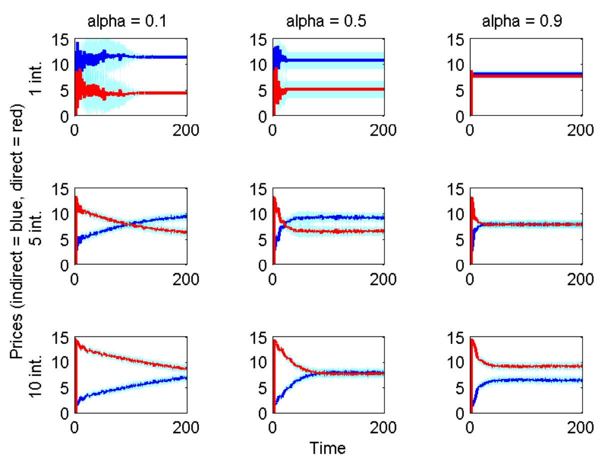

Fig. 5. Average behaviour of indirect and direct marketplace trading prices, P_{Ww} and P_{Rr} respectively, according to variations in the number of intermediaries and the learning rate (α). Cyan shadows represent a one standard variation.

1.5 Concluding Remarks

Networked markets are complex systems where important trade-offs need to be inspected under the consideration of several contingent factors. Here, we have explored a simple model inspired by a case study of a perishable good (fresh food) supply chain in Bogotá, Colombia. Importantly, the model shows the important role of intermediation in influencing prices, contingent on factors like transportation costs and producers' ability to strategically manage market alternatives. Results also suggest that, when transportation unit cost is high, small producers face a huge disadvantage to trade their products, which might place intermediaries as important actors in balancing trading opportunities between large and small producers.

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Banned from the Sharing Economy

An Agent-based Model of the Peer-to-Peer Distribution of Consumer Goods

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Abstract. The emergence of profit-based online platforms for the peer-to-peer sharing of consumer goods provides new means for the end users to derive profit from their possessions. The success of these platforms relies heavily on the behavior of their participants. Using an agent-based model simulating these behaviors via different scenarios, we show how these mechanisms are efficient to improve the information held by the participants. Analyzing the outcomes of these scenarios as the payoffs of a coordination game, we find contrasting results regarding the benefits obtained by each side of the platform: exclusion of some categories of customers, overpricing of some categories of goods, or under-activity on both sides.

Keywords: customer reviews, agent-based model, sharing economy, decentralized coordination

1 Introduction

The Internet has dramatically changed the production and distribution of consumer goods. Thanks to the commoditization of online access, users have seized the opportunity to bypass – and often surpass – well-established businesses for production and trade. In this research, we focus on the online platforms that give anyone an opportunity to share consumer goods, in order to use more efficiently and to generate an income from possessions. These platforms – such as airbnb.com, UBER.com or feastly.com – operate in a grey area between traditional marketplaces (supplied by professionals) and the not-for-profit part of the 'sharing economy'. Their proximity with traditional marketplaces makes them attractive to new participants, while they generate many concerns from the incumbent firms (e.g. Airbnb versus the hospitality industry, Uber versus the taxi companies). As economists, we see here unprecedented market platforms, based on profitable sharing, professional-level services, social networks and online reviews, covering many industries, such as transportation, accommodation or catering.

These peer-to-peer platforms have some market characteristics that are barely studied jointly. The first one is the *information scarcity* affecting both sides of the market platform. Usually, such uncertainty is reduced via the standardization of products (norms, expectations of distribution channels or externalization of components) and the standardization of tastes (marketing and conformity). In a peer-to-peer market, the variety of products and tastes might be overwhelming, making it very difficult for the participants to assess the quality or evaluate the price of products. The second characteristic is the reliance on the *decentralized governance* of transactions. The transactions are governed by platform rules and complex peer-to-peer mechanisms supposed to facilitate and control the transactions. The core element of this system is the review written by the customer. The aggregation of these reviews provides the basis for a self-organized learning (creation and sharing of market information), while introducing inertia and the overabundance of – potentially irrelevant – information. The third characteristic is the *permeability*: participants can switch sides and entry is easy. Similarly, these platforms rely heavily on the sense of community, while stimulating self-entrepreneurship and the ability to grasp opportunities. This apparent contradiction creates a very interesting tension between individual and collective behaviors.

Aggregating these characteristics leads us to our question: are we witnessing the emergence of a new front for the economy or just the experimentations of niche users? To answer it, we will look at the intrinsic properties of these markets, via the simulation of different scenarios of evolution. The simulations are of major interest here, because of the scarcity and sensitivity of the data related to these new marketplaces. Such databases are difficult to gather, due to the novelty and variability of the business models, together with the evolution of participants. Besides the reluctance of platforms' owners to share it, data would be yet insufficient to draw robust conclusions. Moreover, simulations give the opportunity to test existing theories, by putting together theories and empirical findings from various scientific horizons.

As a result, our simulations show how the agents' behaviors influence strongly the attraction and revenue generated by these platforms. In summary, in Section 4, we study four scenarios based on different behavioral characteristics of the agents, by monitoring the prices, user satisfaction and transactions emerging on this simulated platform. The first scenario shows how the suppliers can make the right price adjustments without any direct or centralized knowledge of the market as a whole (i.e. demand curve and product quality relative to the market). The other scenarios show how the individual decisions of suppliers may generate a collective benefit for them while excluding large groups of customers, and, in one case, how their behavior can be detrimental to both sides. Based on a constant population, the results give a strong foundation to our follow-up research: the introduction of dynamics (i.e. entry and exit). In Section 5, we discuss these scenarios using a game theory framework to provide insights for the governance and regulation of these new platforms. Before that, in Section 2, we review the literature to establish the main hypotheses governing the agent-based model, and, in Section 3, we introduce the static version of the model.

2 Literature Review and Hypotheses

Our research follows the tradition of micro-founded market simulations that can be found in Gode and Sunder [1993], and Kirman and Vriend [2001]. Such an approach bifurcates from the classic hypotheses of profit maximization, walrasian auctioneer and perfect information, due to their lack of plausibility [Axtell, 2005]. This makes it particularly interesting to analyze the macro-outcomes of these simulations not in terms of equilibria, but via performance indices, such as the distribution of prices or the extraction of surplus.

In order to adapt this tradition to the characteristics of peer-to-peer platforms, some recombination is necessary. From Gode and Sunder [1993], we borrow three assumptions: (*i*) demand and supply functions can be derived from simple budget constraints rather than maximization-behavior based on costs; (*ii*) the budget constraints being private, the demand and supply functions are unknown to the participants; (*iii*) the transactions occur on single units only. By giving the opportunity to anyone of supplying consumer goods, peer-to-peer platforms encourage individuals to extract revenue from their existing possessions. Even if the platform policies may advise to mimic professional standards and norms, supplier costs are mostly opportunity costs related to the willingness to make transactions with strangers. In a nutshell: the *quantity* is capped (number of guests in an accommodation, number of seats in a car traveling on a specific route, number of meals that can be cooked and so on); the *quality* is mostly fixed by the initial investment ; and the *price* is related to personal preferences or constraints more than production costs.

However, unlike the discussed models, customers cannot bargain the prices[1]. Price adjustments are made sequentially, via experimentations made outside the transactions. Kirman and Vriend [2001] – when they analyzed the dynamics and emergent properties of Marseille's fish market – use the concept of *loyalty* as coordination and learning device for repeated transactions. Such a device is particularly relevant to model peer-to-peer platforms, where social and non-anonymous relationships shape the transactions. However, on these platforms, most of the transactions are involving new participants, so the tacit and idiosyncratic loyalty has to be replaced by a transmissible information, namely the customer review. In fact, the platforms depend heavily on this, because this helps to build trust and reputation. Customers are expected to give credit and contribute to reviews, mostly to determine the quality of goods that would be considered as 'experience goods' and, therefore, to oppose moral hazard. Facing imperfect information about quality, the literature predicts various nuisances for customers: market concentration, limited incentives to supply the highest quality, overpricing (see for instance Shapiro [1982] and Allen [1984]).

On one hand, one can question the happenstance of opportunistic behavior on platforms that promote altruism. As an advocate of non-market peer production, Benkler [2006] shows how introducing monetary rewards in transactions that could be provid-

[1] One of the innovations leading to the emergence of these platforms was to provide a secured payment system directly on the platform. The centralized payment system can also be related to the business model of these platforms, i.e. debiting fees on the transactions.

ed voluntarily via social relations, affect the content of these transactions. The transition from a non-profit to a profit-oriented sharing economy is not harmless: "money-oriented motivations are different from socially oriented motivations" [Benkler, 2006: 97]. For instance, Zervas et al. [2014] point up how Airbnb has affected a specific segment of the hospitality industry, the lower-end hotels. Hotels offering business services do not suffer from the emergence of this platform. Hence, we assume that customers on these platforms are interested in getting lower prices when traditional offers exist. Equally, Teubner et al. [2013] conducted an experiment demonstrating how the reduction of anonymity (i.e. exchanging with individuals rather than groups) increases the contributions. This is important to develop trust in these emerging markets. Based on this finding, we wonder whether the profit-oriented peer-to-peer production would exhibit more price inelasticity of the demand, where excessive prices would be more accepted when they are charged by peers rather than by anonymous firms. Besides, suppliers find here a previously-unexploited source of revenue, so the fear to lose it – due to a wrong strategy – is low.

On the other hand, one can also question the role of customer reviews as a protection against opportunism. Zhu and Zhang [2010] show how the influence of reviews is depending on products and consumers. For new (not well known) products and advanced Internet users – characteristics that match with our research – reviews are influential. Duan et al. [2008] put forward "the dual nature of online user reviews": (*i*) "consumer's assessment of product quality", (*ii*) "product awareness among consumers". They find that higher ratings do not affect the sales, while the number of reviews is correlated with the sales (cf. bandwagon effect). Similarly, Park et al. [2007] emphasizes that quantity together with the quality stated by the reviews have an influence on purchases. In his literature review, Dellarocas [2003] finds a rather general consensus that positive reviews lead to higher prices. At the same time, he shows how reviews have to be handled cautiously, because: (*i*) a critical mass of reviews is necessary to derive a strategy, (*ii*) platform owners control how the reviews are provided; and (*iii*) reviews lack context. This idea is shared by Bolton et al. [2004] who observe the underrepresentation of negative reviews, because reviewers fear retaliations.

We learn from this literature on customer reviews that reviews contribute to reputation building (with a risk of bandwagon effect), while being used as a proxy rather than a fair source of information. For instance, Fradkin [2014] has analyzed search data from Airbnb and he shows that potential customers filter the listings based on objective variables (mostly the location and maximum price) before browsing the remaining listings and evaluating more subjective characteristics (including the number and text of reviews). Such a distinction can be found in the model of an online market with a self-selection bias of consumer reviews built by Li and Hitt [2008]. In their model, they distinguish two classes of attributes: the 'search attributes' which can be inspected before the transaction and the 'experience attributes' which are specific to each consumer based on its experience of the product. A more general approach is proposed by Valente [2012] with an algorithm of product selection including empirically-validated hypothesis on the behavior of bounded rational and adaptive customers. We will follow this algorithm in the model. In its simplest version, products are defined by two characteristics (quality and price). Customers have an order of preference for these characteristics. Based on this order, they cyclically reduce the set of products to the products that provide the best results on this characteristic, until there is only one product left.

3 Model

The objective of these simulations is to understand the evolution of a peer-to-peer market guided by decentralized decisions and customer reviews. We model the emergence of this market as an online platform connecting agents who either supply or request similar consumer goods and keep tracks of the previous transactions. Suppliers expect to extract revenue from the transactions, while customers expect to pay a price which is consistent with the product quality. Customers express their (dis)satisfaction by writing reviews regarding their transactions.

At this stage, simulations are performed with a constant population of agents. Our research plan is to build here a robust model and to develop a clear understanding of its behavior, in order to develop later a dynamic version of the model, introducing the dynamic attractivity to new users and the exit of unsatisfied agents. In order to make the presentation of the model more readable, we will present this model as an online platform for accommodations (such as Airbnb): each agent in the simulated population is either a Host or a Guest. The constant population of agents is $P = H + G$ with H as the number of Hosts, G the number of Guests. Each agent is initialized with a fixed personal characteristic: for a Guest, this is her reservation price (r), i.e. the maximum price she is willing to pay for the accommodation; for a Host, this is the quality level of his accommodation (q). Both r and q are drawn randomly from the uniform distribution $\mathcal{U}(0,1)$.

For the Guests, in our simple design, the fair price of an accommodation is $p = q$. When the simulation starts (at simulation step $t = 1$), the Hosts do not know how to evaluate their accommodations. Hence, they set randomly a starting price ($p_1 \sim \mathcal{U}(0,1)$). By setting r, q and p_1 following the same distribution, we assume that there is a possible market equilibrium where each Guest finds a Host with $p = q = r$. We also assume that at each step t, only a subset of Guests ($G^* = H$, chosen randomly among G) are looking for an accommodation, i.e. there is neither systemic shortage nor surplus. In turn, each one will try to find an accommodation. If she succeeds, she will write a review regarding her experience of the accommodation quality. Once the turns are over, the Hosts have the opportunity to adjust their price.

When looking for an accommodation, a Guest applies the following procedure:

- First, she reduces the set of Hosts to a subset H_r, limited to Hosts with $p \leq r$.
  - If H_r = 0, i.e. no Hosts match with this condition, she is considered unmatched and her search ends.
  - If $H_r > c$, she selects randomly c Hosts from H_r. $c \in \mathbb{N}$ refers to the cognitive ability, i.e. the amount of information that a person can handle.

- Then, she selects one accommodation depending on her preferences.
  - If she is *quality-oriented*, she computes a weight (W_h) for each Host $h \in H_r$. This weight adds up the past reviews received by the Host, $W_h = \sum_{t=1}^{t^*-1} M_{h,t} + 1$, with t^* being the current step. The platform stores the reviews via a simple grade $M_{h,t} \in \{0,1\}$ (see below). Then, she chooses one Host randomly with a probability proportional to his weight.
  - If she is *price-oriented*, she selects the Host with the lowest price p in H_r.
- Finally, she visits this accommodation and she writes a review. The review is stored as a grade which value depends on the similarity between the price paid and the quality she has observed. This quality (q^*) is drawn from the normal distribution $\mathcal{N}(q, \sigma)$ with q being the real quality and $\sigma = \frac{2 \times 1/\sqrt{12}}{v}$ with $1/\sqrt{12}$ being the standard deviation of $\mathcal{U}(0,1)$ and v being the number of accommodations visited in the past (initial value is 1). The grade is $M_{h,t} = \begin{cases} 0 \text{ for } q^* < p \\ 1 \text{ for } q^* \geq p \end{cases}$ (0 means 'unsatisfied' while 1 means 'satisfied')[2].

Once this process is over, the Hosts have the opportunity to adjust their price: either upward for the Hosts who have a match at this step or downward for those who don't. The probability to adjust the price is

$$Prob(\text{adjust price}) = \frac{m}{\ln(a)} \times \varepsilon$$

where a (initial value is 1) is the number of past price adjustments, ε is the energy of the system, i.e. a parameter to control the frequency of actions in the simulation. The variable m depends on the Host's strategy: *occupancy-oriented*, i.e. the grades have no influences on the Host's decisions, the only thing that matters is the number of hosted Guests; *occupancy-and-satisfaction-oriented*, i.e. receiving a bad grade ($M_{h,t} = 0$) is a failure equivalent to not hosting a Guest at all. **Table 1** shows how m is computed.

The repartition between Hosts and Guests depends also on the energy of the system ε ($0 < \varepsilon \leq 0.5$). In this case, it influences how often a Guest will make an action, based on $P = \mathrm{H} + \mathrm{G} = \varepsilon P + (1 - \varepsilon)P$. Together with its influence on price adjustment, ε affects the speed of change in the simulation. Smaller [higher] ε will produce similar results but more slowly [quickly].

For readability, we run the simulations with all the agents in a category following the same strategy. Hence we generate four cases described in **Table 2**.

[2] We assume that the users – whether they are price- or quality-oriented – follow the same procedure to allocate a grade. The platform provides the same form to each customer for reviewing. And, even if the platform orientates the form to be focused on quality, we assume that customers assess the quality relatively to the price.

Table 1. Computation of $\boldsymbol{m}$, using information accumulated since the last adjustment

Strategy		Action: Reduce price (no Guest at this step)	Action: Increase price (Guest at this step)
Strategy	Occupancy-and-satisfaction-oriented	m = number of steps without Guests or positive reviews	m = number of positive reviews
Strategy	Occupancy-oriented	m = number of steps without Guests	m = number of Guests

Table 2. Strategies and scenarios

Hosts		Guests: Quality-oriented	Guests: Price-Oriented
Hosts	Occupancy-and-satisfaction-oriented	Case 1	Case 4
Hosts	Occupancy-oriented	Case 2	Case 3

In order to show how the characteristics of agents influence their success and behavior on this market, we show the results per subset of agents of similar characteristics. Concretely, the Hosts are ordered based on the quality of their accommodation (q) and separated into 10 groups (the 9 cutting points corresponding to the "deciles" of q's distribution): the first [last] group represents the Hosts with the lowest [highest] q. The same principle is applied to the Guests, based on their reservation price (r): the first [last] group represents the Guests with the lowest [highest] r. Since these characteristics are fixed for each agent during the whole simulation, the deciles and the groups are stable. In the following, we show the results of the interesting variables based on these groups.

4 Results

The results discussed below are based on the following parameters: population $P = 1000$, energy $\varepsilon = 0.25$, Hosts' population $H = 250$, Guests' population $G = 750$,cognitive ability $c = 10$. The results are recorded at $t = 1000$ steps and they show the average over 20 repetitions of the simulation with different initializations of the agents[3].

We start by discussing the Case 1. **Fig. 1** shows the Hosts' average margin (i.e. the difference between price p and quality q) and p itself. We observe a limited margin, i.e. a rather strong alignment between p and q. The Hosts have almost found the 'right' price regarding their quality. The only exceptions lie on the extremes, due to the behavior of Guests: because they look for accommodations below their reservation price (r), they create a stronger demand on the cheapest accommodations making it possible for those Hosts to offset the bad reviews. On the other side, the high-end accommodations appeal only a very small fraction of Guests (because these high-r Guests may prefer a cheaper option anyway). In order to increase occupancy, those Hosts have to value their accommodations below their actual quality (and, therefore, their 'right' price). We see on **Fig. 2** how the Guests with the lowest r suffer from the competition on the cheapest accommodation by not finding a match. At the same time, because p and q are well aligned, the satisfaction of finding accommodations with $q \geq p$ is relatively limited, except for the Guests with the highest r who benefit from the limited appeal of high-end accommodations. This is coherent with **Fig. 3** where we see again how the Guests with the lowest r are hardly able to find a match. For comparison, we can calculate the expected maximum number of reservation that a Guest can make during a simulation with $\frac{H}{G} \times t = \frac{\varepsilon P}{(1-\varepsilon)P} \times t = \frac{0.25}{0.75} \times 1000 \approx 333$ in this case. Similarly, on **Fig. 4** showing the expenses related to these reserved accommodation, we observe the clear correlation between r and the average cumulated contribution of Guests to this market.

In Case 2, by removing the interest of Hosts in Guests' satisfaction, the simulation generates a rather different situation. Except for the two highest subgroups of Hosts, the Hosts' margins are much higher, excluding de facto almost 50% of the Guests. However, the revenue generated by this market is still high, due to the highest price, making this strategy rather rewarding for Hosts. The evolution comes from the incentives of cheaper Hosts to increase their prices as long as they can attract Guests with higher r. At the same time, this evolution is limited by the past reviews of Guests, keeping a certain correlation between q and p: between two Hosts with the same p, Guests will prefer the one with the highest q, based on how the Host was satisficing in the past. This emphasizes the difficulty for Guests to choose wisely, when they do not know what was the price paid by the past reviewers.

In Case 3, the Guests are only interested in getting the cheapest accommodation, within the range delimited by their r. Interestingly, all the Hosts converge to the same price, since the Guests will always prefer the cheapest option, no matter how the quality is. Hence, the most expensive accommodations are systematically avoided (and, therefore, reduce their price), while the cheapest accommodations have a clear incen-

[3] Other parameter values have been tested to guarantee the robustness of our results: the results are collected once the platform has stabilized (large t); c and ε do not affect the relative results of the scenarios; population size (P) is meant to guarantee the alignment between p and r based on random draws (a smaller P increases the chance of shortage on either side of the platform, such an interesting outcome is beyond the scope of this paper).

tive to increase their price. The equilibrium is then at $p = 0.5$. The global result is that all the Guests with $r \leq 0.5$ are excluded from this market and the total revenue of this market is relatively low.

In Case 4, the Hosts with a lower q have an additional incentive to reduce their price by comparison with Case 3. These decisions lead the whole market to an even lower price. In return, there is a larger percentage of satisfied Guests, by comparison with all the other cases. However, this strategy is still detrimental for the revenue on this market.

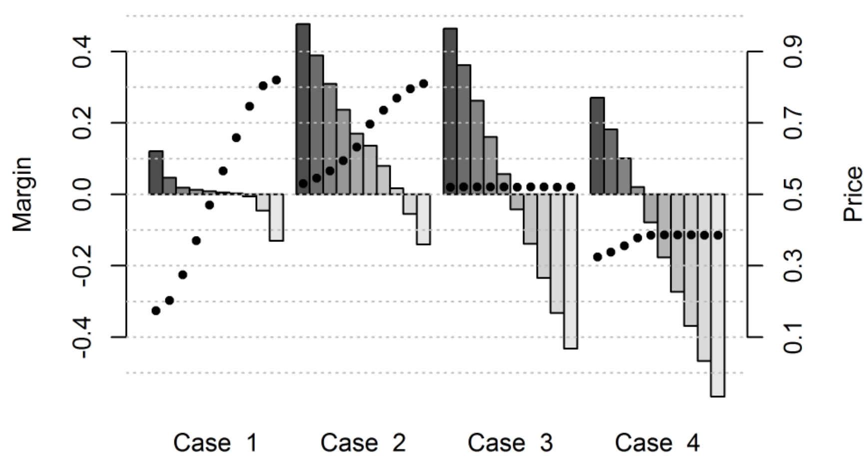

Fig. 1. Hosts' perspective - Margin and price. The left axis shows the average margin of Hosts in each subgroup (bars). The right axis shows the average price of accomodations in each subgroup (dots).

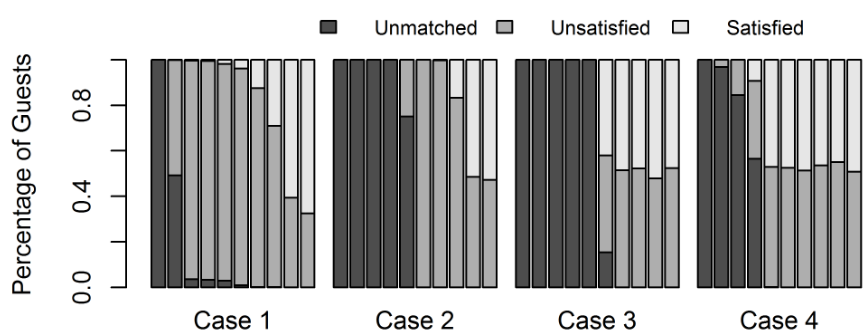

Fig. 2. Guests' perspective – Matching and Satisfaction. The bars show the percentage of unmatched, unsatisfied and satisfied Guests within each subgroup.

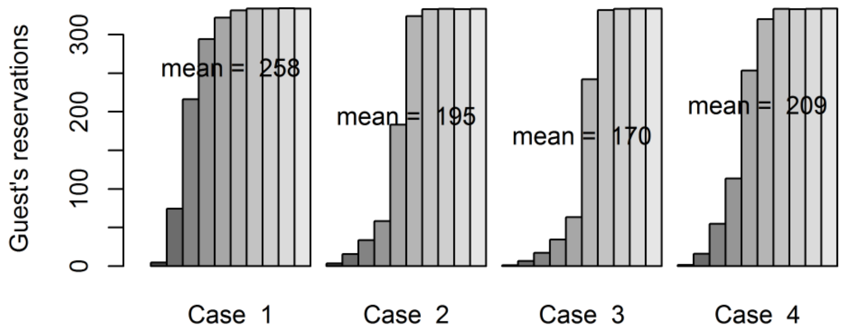

Fig. 3. Guests' perspective – Average number of reserved accommodations over the simulation

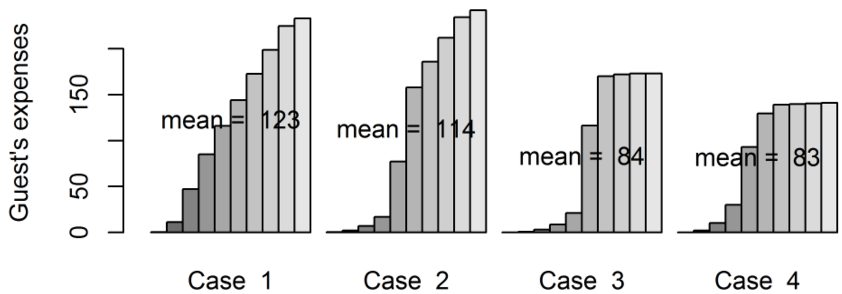

Fig. 4. Guests' perspective – Average cumulated expenses over the simulation

5 Discussion

The decentralized learning and coordination favored by customer reviews have very contrasted results depending on the behavior of agents. Even if our results involve agents with similar behaviors, they give us some clear insights about how the owners could influence the behaviors on their platforms (in particular, to avoid such extreme scenarios). We address this question by using a game theory framework where the quality-oriented [price-oriented] guests and satisfaction-oriented [occupancy-oriented] hosts are the cooperative [individualistic] players. By doing so, we obtain almost a prisoner dilemma where cooperation is dominated by individualism, at least from the host perspective. Case 1 being the cooperation-cooperation scenario, hosts have a clear incentive to ignore the satisfaction of guests, leading them to behave as in Case 2 where the reduction of visits by guests is compensated by the highest price charged. For the same reasons, they would prefer Case 3 over Case 4. The interest of guests is less monolithic, due to the trade-off between satisfaction (for the subgroups with a higher r) and exclusion (for the subgroups with a lower r). However in the dominant scenario of individualistic hosts, one can imagine that guests would prefer Case 3 over Case 2. This individualistic-individualistic scenario is the worst solution for all the agents (except for guests with the highest r).

Consequently, a platform policy supporting a sense of community and cooperation (Case 1) needs to be strongly promoted, if one tries to oppose the individual interests of the participants which would lead them to adopt a non-cooperative behavior (Case 3). Of course, the sharing economy is based on ethical and cooperative behaviors and the permeability between agent categories makes it easier for them to understand the expectations of the other side. The platform owner can also have their own objectives which would influence the orientation of policies. For instance, an owner interested in attaining a critical mass of participants or getting fees per transaction would orient its policies towards Case1. On the contrary, an owner getting the same fees but willing to reduce the costs related to an increased activity on the platform might favor Case 2.

The evolution happening in Case 2 questions the necessity of policies beyond the platform. The hypothesis made here (i.e. customers keep coming even if their satisfaction is very low) may seem extreme. However, assuming that the sharing economy provides goods to individuals who cannot afford transactions on regular marketplaces, we see here the emergence of an overpriced low-end market. By giving more options to individuals who were excluded from those marketplaces, the profit-based sharing economy challenges many markets (see for instance the reactions against Airbnb or Uber in many cities). At the same time, it can produce its own failures by excluding or overcharging its participants. Moreover, the early stage of the market has a strong influence on the future evolution of the product and customer base. Excluding some categories (of products or customers) will affect the future attractivity of this market regarding these categories, via a snowball effect.

6 Conclusion

Using an agent-based model mimicking the emergence of a profit-based platform for sharing consumer goods, we have shown how much this type of sharing economy should emphasize cooperative behaviors more than profit incentives. For platform owners and policy makers, this model can help in two directions: if the market evolution is observable, we can estimate the behavior of agents or, reciprocally, if the behavior is known, we can predict the evolution of the market. In this paper, we have focused on the second direction, while improving the first direction would be a strong incentive to monitor the evolution of these platforms (in terms of user characteristics, price distribution and so on).

Our next stage will be to introduce entry and exit into the model, in order to study the reinforcing dynamics happening on these markets as well as their potential for phase transitions or cycles (e.g. gentrification of customers, strong instability or network effects, for instance). By this way, we will extend our present analysis in terms of sustainability of this type of platforms and as a mass market rather than a niche market. Besides, in the dynamic version of the model, by influencing the population evolving on the market, individual decisions on the supply side will have evolving collective outcomes. Equally, such a model would help platform owners in understanding how they should limit or encourage the entry of certain categories of suppliers to alter competition (i.e. orientate the prices of some categories of suppliers). By doing so, they would be able to facilitate the realization of objectives (platform objective of attractivity, supplier objective of profitability or customer objective of saving).

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Climate

Understanding Migration Induced by Climate Change in the Central Andes of Peru via Agent-Based Computational Modeling

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Abstract. We present the first interdisciplinary scientific effort to understand socio-environmental dynamics in the central region of Peru (Huancayo Province, Junín Region) using a newly created agent-based simulation model (ABM). It investigates how climate change is decreasing the size of the Huaytapallana glacier as sole source of water for the Shullcas River basin and population of Huancayo; and how heterogeneous inhabitants linked by household networks make bounded-rational decisions as environmental changes impact their lives. This new approach allows us to run computer simulations to better understand (1) different local emerging scenarios as people decide to migrate, stay, or protest, depending on how fast they adapt to environmental variability; and (2) how these behaviors affect regional demography, from the central Amazon jungle to the Pacific coast, including the capital, Lima. This study is part of the Mason-Smithsonian Joint Project on Climate and Society, funded by the US National Science Foundation.

Keywords: agent-based modeling • social simulation • migration • glacier dynamics • climate change • coupled human-natural systems • computational social science

1 Introduction

Concern has recently emerged about the future of glaciers in the Andes of South America. During the past 35 years Peru's glaciers shrank by 22%, causing a 12% loss in fresh-water flowing to the coast (highest population density in the country), based on studies by the Andean Community of Nations funded by the World Bank[1]. This

[1] For details visit: http://www.worldbank.org/projects/P098248/adaptation-impact-rapid-glacier-retreat-tropical-andes?lang=en

unsustainable crisis is caused by a decreasing water supply in the Central Andes of Peru while population continues to increase in the region's most important city, Huancayo. The result is increasing potential for serious impacts to the region's environment, economy, and systems of governance. Rural populations suffer a disproportionate share of effects from the current crisis, as validated by field observations during a recent visit by the first author. Such effects include health and economic problems caused by increased variability of rainy seasons, longer duration of dry seasons, and extreme and unexpected temperatures—a situation that forces local rural populations to alter mobility patterns in search for additional income. The crisis is compounded by wealthier city residents urbanizing rural areas, thereby decreasing available arable land and increasing pollutants in the river—the watershed of the glacier and sole source of fresh water to the city.

This paper presents WankaLab1, an agent-based model (ABM) of the Huanca people and their environment in the Huancayo region, created in NetLogo. In the WankaLab1 ABM, bottom-up dynamics emerging from individual agent decisions in rural and urban Huancayo interact with top-down dynamics generated by environmental changes in the Huaytapallana glacier's watershed. The current version (1.0) has been verified to simulate a stylized representation of seasonal rainfall, glacial melt, water supply, and individual agents residing in rural communities and urban Huancayo. We hypothesize that the combination of macro-level climate effects on Huancayo's water supply and micro-level agent decisions to move to areas with better prospects will result in emergent migration patterns. In the full model under development, additional hypotheses related to urban growth and social conflict over land use will also be tested.

2 Literature Review

Warming global temperatures and climate change and variability are emerging policy issues as an increasing number of countries experience their environmental and economic effects. In South America, Peru's changing climate is predicted to result in warming temperatures in the North, the disappearance of its tropical glaciers by thawing, and variable precipitation. As a result, the country—which depends on glaciers to supplement drinking water sources and hydroelectricity—is expected to experience increasing water shortages that will stress an infrastructure already under strain by a growing population. Increased migration is one of several significant effects expected from climate change. Intermediate cities—such as Huancayo—pose the greatest concern because such burgeoning economic centers continue to urbanize without planning or preparing for decreasing water supply. The specific interest in Huancayo is because it has become a critical transitional node where rural and urban populations interact in their struggle for economic advancement. Huancayo is also seen as a place for mitigating immigration from the jungle to the overcrowded megacity of Lima. Moreover, such buffer cities in the highlands—Huancayo and others— may soon reach their urbanization capacity, or saturation level, thereby diminishing their attractiveness.

The top-down process in the WankaLab1 model is the impact of climate change and variability on the Cordillera Huaytapallana, particularly the glaciers supplying Huancayo's water basin. The Intergovernmental Panel on Climate Change (IPCC)—the scientific organization founded by the United Nations (UN) for assessing climate change causes, effects, societal impacts, and strategies for adaptation and mitigation—is currently working on its fifth climate change assessment report, the final draft of which repeats previous findings: anthropogenic Green House Gas (GHG) emissions continue to increase and human behavior, lifestyle, and culture have considerable influence on energy use and associated emissions. At the regional level, a country such as Peru is vulnerable because of its dual dependence on glaciers for (1) operating hydroelectric systems and (2) meeting water needs during dry seasons and droughts. Andean mountain basins provide water for consumption, agricultural irrigation, and half the country's power [1]. The Cordillera Blanca glacier near Huancayo has decreased its surface area by 15% during the past thirty years, which at the current rate will cause the glacier to disappear within a few decades [1]. Although direct measurements are not available, satellite imagery analysis of the Cordillera Huaytapallana—the glaciated area that feeds Huancayo's water sources—shows that the region has lost 56% of the ice-covered surface, decreasing from 50.2 km2 in 1984 to 22.05 km2 in 2011 [2]. As illustrated in Fig. 1, glacier shrinkage in Peru is a complex process comprising rainfall and snowfall patterns (which vary during El Niño and El Niña years), ablation and erosion (from increasing temperatures and variable humidity), and the glacier's ability to reflect sunshine with snow cover (measured by its albedo or reflection coefficient). There is a significant scientific and policy need to better understand this process and this is the first such effort focusing on the Cordillera Huaytapallana.

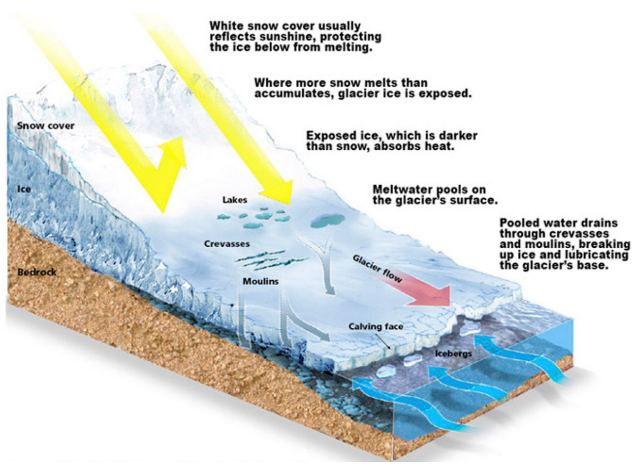

Fig. 1. Glacier dynamics as a complex natural process (Source: Bailey Archive, Denver Museum of Nature and Science)

Climate change has been shown to increase stress on food-production systems and the spread of infectious diseases, but far less attention has focused on understanding complex, multi-causal effects, such as those on migration, economic development, or security [3]. In these domains, migration and displacement—both characteristically bottom-up processes—have been successfully modeled in ABMs [4], although mostly in places where migrants are far from cities. Andean intermediate cities, such as Huancayo, have a peri-urban zone that is economically and culturally associated to the city, not just geographically. Urban and peri-urban zones constitute a complex adaptive system requiring further research [5]. Huancayo is a city to which rural populations immigrate and from which urban populations emigrate toward the megacity of Lima. It therefore a buffer node that mitigates some of the population stresses acting on Lima.

Food insecurity is an issue that Huancayo's rural households address by migrating to urban areas in search of employment opportunities to supplementing their livelihood. As a result, the city of Huancayo has grown by 50% in population since the 1980s [6]. Immigrants are predominantly males from within national borders, driven by basic need to supplement household income and improve skillsets. Net population increase has not been accompanied by an increase in formal job opportunities, so Huancayo has a growing informal economy [5]. Climate change impact studies predict that such migratory patterns in Peru will increase as the economic system is directly affected by water scarcity.

While computer modeling is becoming a standard technique for understanding both global and local effects of climate change, researchers have noted the dearth of models integrating ecological models with social science, recommending merging human variables with climate-glacier runoff models [7]. Few models explore the complexity of regional interaction between changing environments and changes in human behavior. An agent-based model that simulates a complex adaptive system of top-down climate effects interacting with bottom-up migration patterns would improve our scientific understanding and contribute to policy analysis.

WankaLab1 was designed by building on earlier models. A survey of current NetLogo [8] models was conducted prior to creating WankaLab1, focused on models of migration, food production, and ecological processes. Results indicated that the Daisyworld NetLogo model of the "Gaia hypothesis" would be a good initial proxy model for glacier dynamics, combining the interaction of sunlight and neighbors' albedo at the patch level [9,10]. Patches in Daisyworld either reflect or absorb sunlight, depending on albedo ratios. Wilensky's Schelling Segregation model [11] was added to move uncomfortable or unhappy agents to new locations within an urban area. This model adequately simulates the decision-making process whereby rural and urban agents decide to move when they become too uncomfortable. We also explored the "Tragedy of the Commons" as a possible model for agents surviving off the land, but this was rejected in favor of a simplified economic model that uses the same economic dynamics for both urban and rural patches. Urban growth models were reviewed for modeling Huancayo's growth, but they were unable to capture migratory patterns documented in the literature. As future funding becomes available, the modular design of WankaLab1 will enable improvements with empirical models of glacial, hydrologic, and demographic dynamics, thereby improving the model's analytic usefulness for policy making.

3 Model Description

The WankaLab1 model in NetLogo consists of a complex adaptive system with two main interactive components: an agent population that grows and migrates between rural and urban areas of Huancayo, and a glacial area that provides the population's main source of water during the dry seasons. Migratory patterns are bottom-up dynamics and the glacier retreat (varying with sunlight) represent top-down dynamics.

The agent superclass in WankaLab1 has attributes representing age and comfort level as determined by economic status and available water. The subclasses consist of two groups, rurals and urbans. Urban agents have an attribute that counts their neighbors. Rural agents have education (which starts very low and can only increase with wealth gained in the urban area) and economic measures, a Boolean variable representing a family, and other Boolean variables to indicate whether the agent goes to the city and whether it has been able to trade its market goods while in the city. At every tick in the model, rural agents randomly move and decide whether to go to the city; all agents evaluate their comfort level; and agents decide where to move. A tick represents a month, enabling the activation of climate and agent processes.

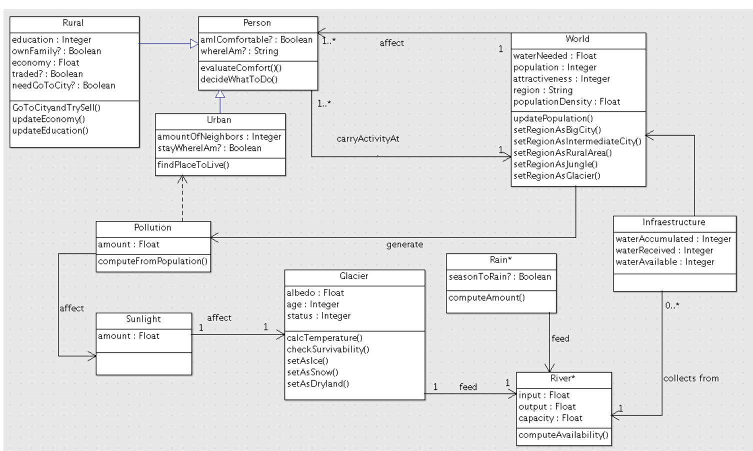

Fig. 2. UML class diagram of the WankaLab1 model

WankaLab1 consists of five regions or patch types; a black area representing a large city (Lima), a yellow area for an intermediate city (urban Huancayo), a green area for rural Huancayo, a red area for the glacier and the jungle in blue. Each patch has region-type as an attribute and glacier patches have temperature. Lima and the jungle are areas from which agents do not return, because jobs are available. Lima attracts more educated migrants, whereas the jungle has more illegal work available, such as logging and coca-related jobs, besides legal coffee farming. Migrating populations in the four livable regions are counted and provided as output in the experimental results. In Huancayo, the model differentiates between native urban agents born in the city and rural agents that either trade or settle permanently in the city. The rural area has only agents from the region, and the jungle area has only agents that migrated from the rural area. Populations born in either Lima or the jungle are not tracked in the model. Population growth rates in urban and rural areas are set at 0.16 [12], and population is increased every year (12 ticks). Agents age and decide whether to move during each tick. If an urban agent has more than 5 neighbors, it will move to a new location in the city. Depending on its economic level, a rural agent will decide to visit the urban area for trade. If an agent's economic level is below the median level of economy for all rural agents, it will decide to trade in the urban area for a period of four months. During that time, the rural agent will move once in a random direction and attempt to trade with a neighbor. If there is more than one neighbor, the rural agent will successfully trade and increase its economy by 1. The education level of a rural agent is increased as its wealth increases, according to the following scale:

1. for 4 < wealth < 6, education level = 1,
2. for 7 < wealth < 12, education level = 2, and
3. for wealth < 13, education level =3.

Agents in urban and rural areas decide to move to Lima or the jungle depending on their economic and comfort levels and whether they have a family. Comfort is determined by the agent's economic level and whether there is enough water available in the urban area. A Huancayo urban agent becomes uncomfortable when there is not enough water for it and neighbors. The efficiency of the city's water infrastructure—its ability to supply water to the population—is a multiplier that varies between 1 and 20 and can be changed by a slider (water-infrastructure condition) at the beginning of each simulation run. If the city is not able to effectively supply water to its population, more urban agents will move to Lima.

Rural agents also move when they are uncomfortable and their economic level is below the median. If a rural agent's education is low (set at 1) and has no family, it will decide to move to the jungle. If a rural agent's education is at a medium level (set at 2) and it has a family, it will decide to move to the urban area of Huancayo. If the rural agent has been a successful trader with an education level of 3 and a family, it will move to Lima. For simplicity, this is encoded by eliminating the uncomfortable agent and creating a new agent in another region. A slider is used to initialize the model with a given proportion of uncomfortable agents.

The glacier region of the WankaLab1 model consists of randomly placed patches of ice, snow, and dry rock. A glacier-agent is a patch set as either snow or ice with attributes of color, albedo ratio, age, and physical characteristics. Each glacier-agent of snow or ice ages at every tick and at age 25 they die. The current model does not simulate evaporation. A new glacier patch is created when an ice or snow agent can diffuse enough of sunlight and local heating. Through this process, ice and snow agents cool the air of neighboring patches, sometimes low enough to allow a new glacier agent to form. Ice and snow patches can generate new ice and snow agents, respectively. Snow agents appear as yellow dots with albedo set at 0.5, and ice agents are white dots with albedo set at 0.85. Because ice agents have a high albedo, they are not able to reflect as much heat as snow agents. Sunlight luminosity and the size of urban population contribute to the glacier's global temperature. Sunlight luminosity is set with a slider at initialization. WankaLab 1 uses the same range of sunlight values as in DaisyWorld: 0.0001 to 2.0. As urban population increases, the region produces enough pollution to increase local temperatures. This dynamic is captured in the update-glacier function when the sunlight variable is adjusted up or down, depending on whether population density has risen or fallen. Pollution effects are the only dynamics in the model that create a feedback loop.

WankaLab1 is endogenized, so external data are unnecessary. The model is initialized with a random distribution of agents and standard NetLogo activation procedures. Agent population is initialized with 40 and 100 "turtles" in rural and urban patches, respectively. The user, using NetLogo sliders, initializes water infrastructure efficiency, sunlight luminosity, and percentage of uncomfortable agents that migrate. Monitors, in the simulation window (shown in Fig. 3), track information, such as patch types in the glacier region, temperature in the glacier region, comfort level of rural and urban agents, population levels in each region, education level of agents, economic growth, changes in sunlight, and overall population density.

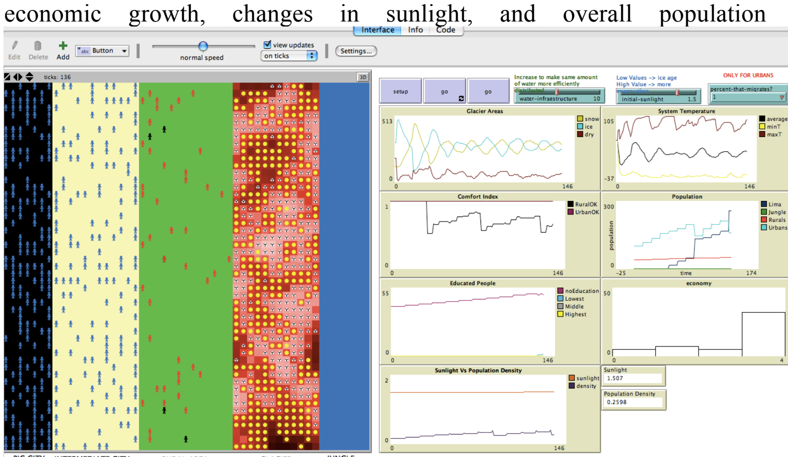

Fig. 3. WankaLab1 NetLogo graphic user interface for initial settings of water infrastructure = 10, sunlight = 1.5, and percent-that-migrates = 1

4 Model Verification & Validation

WankaLab1 cannot yet be validated with empirical data, because scientific glacier monitoring began only recently. (Data have been requested from SENAMHI, Peru's lead government agency for climate science.) Instead, the model was put through a spiral process of component testing. Each module of the top-down and bottom-up dynamics was isolated and tested. The top-down process of glacial retreat and melt was tested to confirm that it operated as designed. Similarly, the bottom-up process of agent migration was tested and confirmed. Temporary monitors in the user interface were used to track changing values and to verify operations. Finally, sensitivity analysis of key variables was performed by providing extreme values and verifying model outputs.

5 Experimental Analysis and Preliminary Results

Change in the glacier patches of WankaLab1 represent top-down dynamics, which interact with bottom-up processes of population change in the other areas (urban area's population size). Sunlight affects the temperature of glacier patches and the supply of water to the urban area decreases as these patches disappear. Human-agents migrate to improve their economic standing, or because they become uncomfortable. Experimentation confirmed that population density in urban area is high when water infrastructure is efficient (high value) and the percentage of uncomfortable agents that migrate is low, as anticipated. However, higher luminosity did not always decrease population density.

Glacier patches, glacier temperature, and agents' comfort levels oscillate. When water conditions deteriorate, rural agents experience the most discomfort for longer periods. Urban agents do not experience discomfort, except for short oscillating bursts. Immediately prior to a full collapse of the system—defined as urban population going to zero—the model generates increasingly large bursts of urban discomfort.

Other general patterns are observed in the glacier areas. The number of snow and ice patches fluctuates with opposite oscillations (i.e., half a period or wavelength apart), and the glacier does not disappear, when luminosity is greater than 1. When the luminosity is less than 1, the glacier disappears, although sometimes snow reappears. When luminosity equals 1, the glacier always disappears and the snow and ice do not oscillate. It was expected that increasing luminosity would decrease population over time, before eventually disappearing, due to loss of water. However, when the water infrastructure is at its most efficient setting (10), population density is higher at luminosity settings of 0.1 and 1.0 and lower at luminosity settings of 0.5. This 0.5 decrease in population density may be a complicated effect caused by the glacier's albedo. Greater luminosity does increase temperatures, but it also increases the amount of heat that can be dispersed. If sunlight luminosity is insufficient, glacier patches are unable to reflect heat away.

Initial conditions were varied in NetLogo's BehaviorSpace, and Population Density in the urban area was measured, to confirm these model results. At each setting the model was run 180 times, with a stop condition of either no urban agents remaining in the urban area or at 2000 ticks. Population density decreased as the percentage of uncomfortable agents migrating increase, as infrastructure decreased (becoming less efficient), and as sunlight luminosity decreased. Results from specific variations of water infrastructure, sunlight, and percent-that-migrate versus population density as independent variable are provided in the Appendix. A box plot summary and statistics of these results with all conditions varied is provided in Figures 4 and 5.

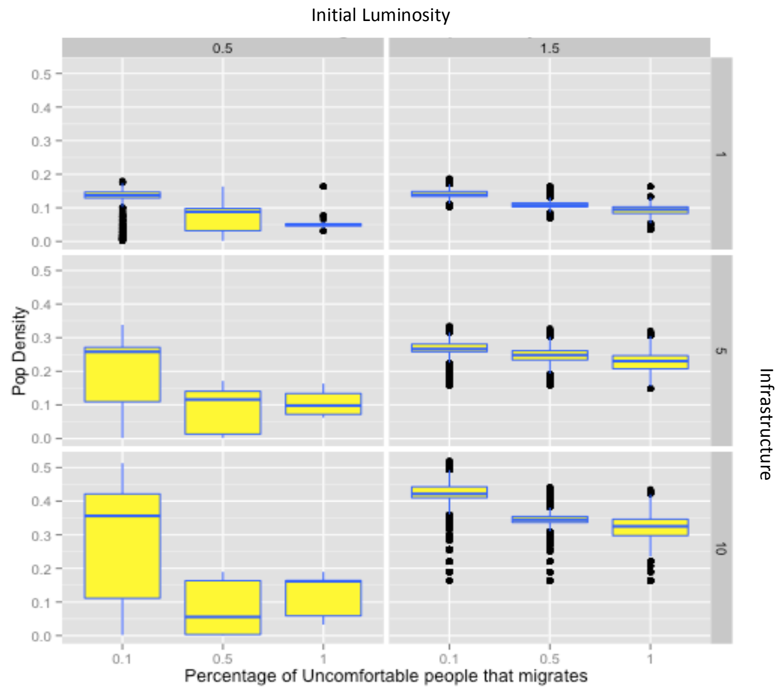

Fig. 4. Population density as a function of percentage migrating, infrastructure, and luminosity

```
##    percent.that.migrates. water.infraestructure initial.sunlight Population.density.median
## 1                     0.1                     1              0.5                   0.13725
## 2                     0.1                     1              1.5                   0.13889
## 3                     0.1                     5              0.5                   0.25817
## 4                     0.1                     5              1.5                   0.26634
## 5                     0.1                    10              0.5                   0.35621
## 6                     0.1                    10              1.5                   0.42157
## 7                     0.5                     1              0.5                   0.08824
## 8                     0.5                     1              1.5                   0.10784
## 9                     0.5                     5              0.5                   0.11601
## 10                    0.5                     5              1.5                   0.24837
## 11                    0.5                    10              0.5                   0.05556
## 12                    0.5                    10              1.5                   0.34477
## 13                    1.0                     1              0.5                   0.05065
## 14                    1.0                     1              1.5                   0.09477
## 15                    1.0                     5              0.5                   0.09804
## 16                    1.0                     5              1.5                   0.23039
## 17                    1.0                    10              0.5                   0.16176
## 18                    1.0                    10              1.5                   0.32516
```

Fig. 5. Population density as a function of percentage migrating, infrastructure, and luminosity

Within the simulations that included all of the model conditions—percent that migrates, water infrastructure, and initial sunlight—the model usually stopped at 2000 ticks (some runs ended when urbanPop = 0). However, as the percent-that-migrates increases, the urban population did collapse, as in Figure 6. This only took place when initial sunlight was set at 0.5, at which point there was not enough luminosity to enable the glacier patches to dissipate heat and the glacier area was too warm to create more snow or ice.

```
##    percent.that.migrates. water.infraestructure initial.sunlight X.step..max
## 1                     0.1                     1              0.5        2000
## 2                     0.1                     1              1.5        2000
## 3                     0.1                     5              0.5        2000
## 4                     0.1                     5              1.5        2000
## 5                     0.1                    10              0.5        2000
## 6                     0.1                    10              1.5        2000
## 7                     0.5                     1              0.5          99
## 8                     0.5                     1              1.5        2000
## 9                     0.5                     5              0.5         123
## 10                    0.5                     5              1.5        2000
## 11                    0.5                    10              0.5          28
## 12                    0.5                    10              1.5        2000
## 13                    1.0                     1              0.5          13
## 14                    1.0                     1              1.5        2000
## 15                    1.0                     5              0.5          60
## 16                    1.0                     5              1.5        2000
## 17                    1.0                    10              0.5          64
## 18                    1.0                    10              1.5        2000
```

Fig. 6. WankaLab1 maximum time-step under different conditions

Regression analysis showed that population density was significantly sensitive to the percentage of agents that migrate due to low comfort levels and initial sunlight, but not very sensitive to water infrastructure. In fact, water infrastructure efficiency and population density showed negative correlation (Fig. 7).

```
Call:
lm(formula = X.step..max ~ percent.that.migrates. + water.infraestructure +
    initial.sunlight, data = regreData)

Residuals:
   Min     1Q Median     3Q    Max
-714.2 -451.4  -96.8  486.0  840.7

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)              623.21     420.61    1.48  0.16058
percent.that.migrates. -1042.79     376.71   -2.77  0.01510 *
water.infraestructure     -0.48      37.67   -0.01  0.99002
initial.sunlight        1290.33     277.39    4.65  0.00037 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 588 on 14 degrees of freedom
Multiple R-squared:  0.677,  Adjusted R-squared:  0.607
F-statistic: 9.77 on 3 and 14 DF,  p-value: 0.000982
```

Fig. 7. Regression Output of Model Variables

6 Conclusions and further directions

The WankaLab1 model behaved as designed and produced results with significant face validity, while awaiting further validation tests based on empirical glacier data. The combination of macro-level climate effects on an urban area's water supply and the micro-level agent population decisions to move to areas with better prospects resulted in emergent migration patterns. Top-down dynamics acting on the lowest initial sunlight decreased population density; larger percentages of agents moving due to being uncomfortable decreased population density; and poorer water infrastructure decreased population density. Luminosity and glacier albedo provided the most interesting dynamic in the model. When the initial sunlight setting was too low, there was not enough luminosity for glacier patches to survive. Without luminosity the glacier patches could not dissipate heat and melted away. This impacted population density, and only when luminosity was high could the urban population be maintained.

Planned components need to be built into the WankaLab1 model. Although urban and rural agents appear to be appropriately affected by reductions in water supplies, these are currently direct effects from glacier melt. The model needs to include a reservoir to simulate the delays that water storage can provide to the system and rain to allow the climate effects to refill the water system. This addition will allow the model to simulate the effects of droughts on water access and migration. Monitors also need to be added to the interface for tracking the numbers of agents migrating during each tick.

Overall the WankaLab1 model functions as designed, but work remains to validate model components. Further experimentation in the model is needed to understand agent fluctuations with varying levels of glacier types, system temperature, comfort index, and population levels. Also, initial dips in the model agent populations indicate that default population levels require adjustment to ask further questions. What are the population migration rates as a result of diminished access to water? How much delay can water storage introduce into the water system, and how will fluctuating rainfall refill the water system? Finally, further research is needed to determine better measures of economic effects on agent populations. Do glacier-agents in the model adequately react to sunlight luminosity in the appropriate number of ticks? Does a global temperature need to be added to affect the glacier system temperature?

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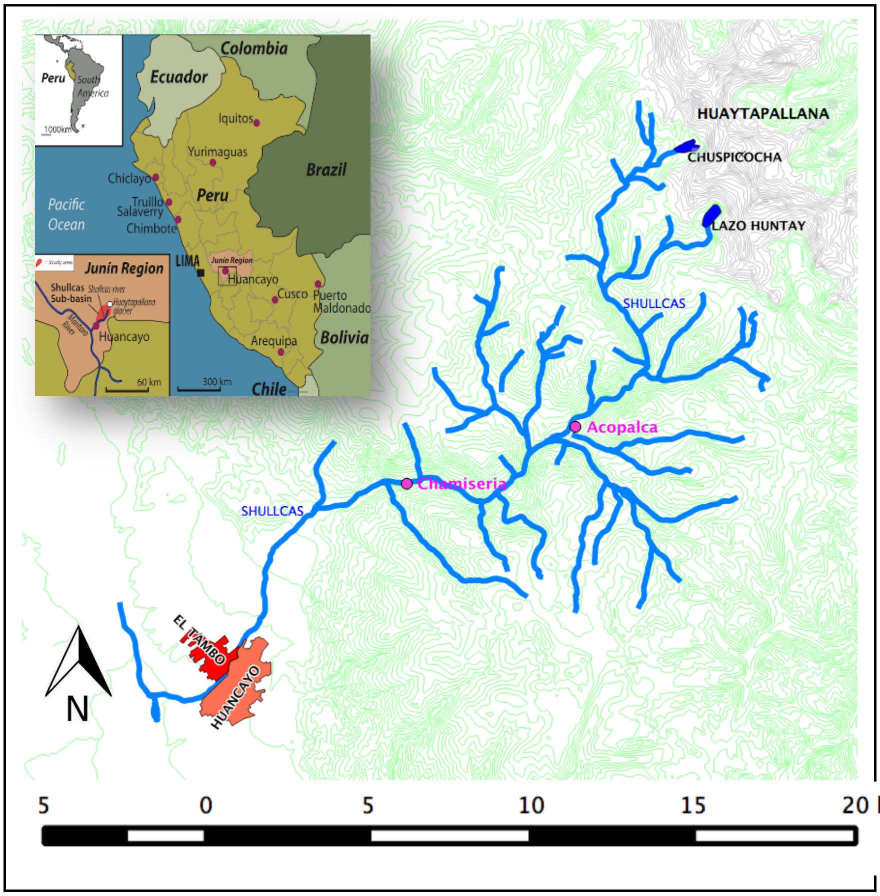
8 APPENDIX: Map of the research area



Map 1. Area of Study
Source: Cartas Nacionales 24 m & 25 m, and [13]

A Causal Mapping Simulation for Scenario Planning and Impact Assessment in Public Policy Problems

The Case of EU 2030 Climate and Energy Framework

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Abstract. The ultimate objective of studying, modeling and analyzing policy problems is to incorporate the newest management technologies in the public policy decision-making in a meaningful and practically feasible way that adds significant value to the process. Simulation techniques can support the policy decision process by allowing empirical evaluation of the system dynamics present in the policy situation at hand. This paper presents a decision support simulation model for the European Union (EU) Climate and Energy targets 2030 as a case study of public policy decision making on the EU level. The simulation model is based on the problem structuring or framing by derivation of a system dynamics model from verbal descriptions of the problem, the graphical representation and analysis of change scenarios using the 'Causal Mapping and Situation Formulation' method. This approach supports the analysis of qualitative and quantitative information in order to facilitate both the conceptualization and formulation stages of the system modeling process. The resulting model, which is simply a topology of quantified causal dependencies among the problem key variables, can be used to simulate the transfer of change. The aim of simulation herein is to apply cognitive strategic thinking and scenario-based planning in a public policy problem situation in order to design alternative options and provide foresight or ex-ante impact assessment in terms of economic, social, environmental and other impacts.

Keywords: Public Policy Analysis, Scenario Planning, Impact Assessment, Problem Structuring, Causal Mapping, Systems Dynamics, Climate Change, Renewable Energy.

1 Introduction

In order to make well informed decisions about public policy programmes and projects, it is important to put the best available evidence from research at the heart of policy development and implementation, this attempt extends the idea of governing based on facts [1]. Policy analysis in an evidence-based policy making approach needs to draw upon a wide range of existing data and knowledge (including factual

adfa, p. 1, 2014.

information, scientific knowledge, and expert knowledge), in order to provide public policy makers and stakeholders with informative hindsight, insight and foresight. Key information sources for a public policy problem include: (i) Evaluations and impact assessment reports from governmental institutions' websites; (ii) Reports from industry, research institutions and NGO's; and (iii) Published literature (mainly from refereed journals).

A large part of the decision support activities occurring within a policy cycle is about understanding, formulating and structuring "problems". Since policies are designed to address problems in society, the problem must be kept in mind as the foundation to any policy analysis both if the intent of the analysis is prescriptive or evaluative. The accuracy of the definition of the problem allows identifying appropriate policy alternatives or evaluating the success of an existing policy. Thus, problem structuring is a key element of the public policy analysis process. "*Problem structuring methods (PSMs) are widely acknowledged as part of decision analytic tools and there is a growing but still small body of research and practice on how to integrate such methods with other formal and/or quantitative methods*" [2]. Therefore, case studies for practical engagements of PSMs with strategic and actual public policy problems is considered to be of great importance in order to identify challenges on how PSMs can be conducted for modeling and analysis of complex problem situations [3].

System dynamics modelling made significant contributions to policy making [4] [5]. Although system dynamics models are mathematical representations of problems and policy alternatives, it is recognized that most of the information available to the modeler is not numerical in nature, but qualitative [4]. There is a lack of an integrated set of procedures to obtain and analyze qualitative information, which creates a gap between the problem modeled and the model of the problem, especially when the model involves the use of qualitative or "soft" variables that need to be quantified. The application of these procedures with textual data to support the modeling process in one or more case studies could lead to specific recommendations to enrich system dynamics practice through the development and testing of reliable formal protocols that can be replicated and generalized [3].

Most decision problems discussed in the literature consider the set of alternatives on which they apply as "given", while in practice, policy makers rarely come with established alternatives. Actually, most of the policy making is about designing or constructing alternatives in a process aiming to support forward looking thinking and design of innovation policies [6]. There is a lack in operational and/or formal methods for addressing the cognitive activity of designing policy options or alternative actions to be taken. The long-term implications of policy making imply the need to consider the range of possible futures, sometimes characterized by large uncertainties and calling for the development of future scenarios. Scenario planning, a widely employed methodology for supporting strategic decision making, helps decision makers in devising strategic alternatives (policy options) and thinking about possible future scenarios. Further research on how scenarios are constructed and how to address issues of robustness in scenario planning is needed.

In order to address the abovementioned research problems, this paper presents an illustrative case for the application of qualitative social research techniques, Text Analysis and Natural Language Processing (NLP), and the application of a problem structuring method labeled “Causal mapping and situation formulation” [12], to build a simulation model for a public policy making problem on the EU level, the model supports scenario planning for the design and impact assessment of the policy options. The case of choice is the EU 2030 Climate and Energy targets, which is a case of policy legislation with multiple and interrelated economic, environmental and social impacts. With respect to the case herein, the main characteristics of the policy making on the EU level are: (i) the commitment to an evidence-based policy making approach; (ii) the co-decision legislative procedure of the three main institutions involved in policy making on the EU level: the EU Commission (EC), the European Parliament (EP), and the Council of EU; and (iii) the influence of external factors such as media coverage and the lobbying effect of interest groups and Non-governmental organizations.

2 Decision Support for Public Policy Design/Formulation

Public (government) policy can be defined as a purposeful, goal-oriented action that is taken by a government to deal with societal problems or to improve societal conditions for the well-being of its members. It results from the interactions, both official and unofficial, among a number of influential actors forming what is called the “policy network”.

Fig. 1 illustrates the decision support framework for public policy making advocated in this paper, the framework maps a set of methods and tools to the following steps of public policy formulation process:

(i) Analysis of the policy problem: identification of the problem elements (actors, stakeholders, key variables, links, objectives, resources, risks, related technologies … etc.); problem environment (conflicting goals, inter- and intra-group negotiations); and decision dynamics (interrupts, feedback loops, delays, and speedups).

(ii) Developing policy proposals: the formulation of policy proposals by policy-planning organizations, interest groups and government bureaucracies.

(iii) Multi-criteria evaluation of policy proposals.

(iv) Policy decision: after evaluation of alternatives encompassing different perspectives, multiple objectives, and multiple stakeholders using integrated assessments.

This study focuses on steps (i) and (ii) through the problem structuring and modelling and design of policy options (action alternatives). For the purpose of this study, qualitative information refer to text based information on the policy problem, which is simply either a recording of information from the mental database of policy decision-makers, stakeholders and domain experts, or concepts and abstractions that interpret scientific evidence and facts from other information sources. Further, the quantitative data include historical data sets for the different variables and parameters of the problem identified through the qualitative analysis, in addition to data for linking parameters like associated costs or benefits.

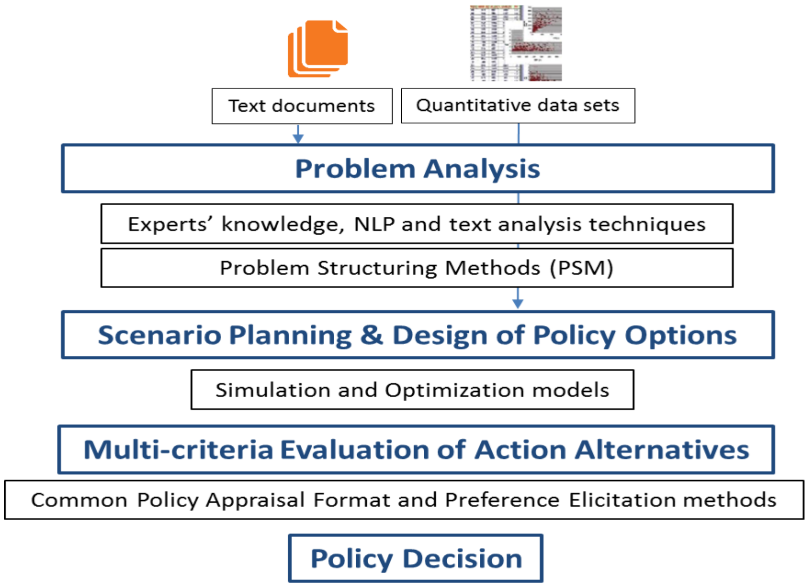

Fig. 1. Decision support for public policy formulation

3 Methodology

3.1 Derivation of System Dynamics Models from Qualitative Information

Text analysis of verbal descriptions of problems has been the subject of considerable work in the cognitive sciences, with related although somewhat different goals, with a focus on understanding and summarization of text into "units" and then connecting these units in a summary or a graph, or in a sequence of inferences. Herein, we define a methodology for text synthesis based on a methodology by Câmara et al. (1991) for grammatical and semantic analysis of the verbal description of the problem in order to construct a representation of the problem that is adequate for its solution, a causal diagram [8]. The methodology can be summarized with the following steps:

Step 1. Decomposing text into a series of inferences.

- The text is browsed searching simultaneously for keywords from one of the following categories. Read in sentence by sentence and extract sentences which contain a word from at least one, two or all the three categories.
  - Inference indicating words: because, thus, then, however, mean, compare, etc.
  - Modal words: will, would, can, could, must, may, etc.
  - Influence indicating words: result, impact, influence, relate, cause, affect, increase, decrease, reduce, hinder, improve, support, benefit, important, etc.
- Put chosen inference sentences and attached reference into desired format.
- *GUI that displays all inferences with references. (User engagement)*

Step 2. Inferences are scanned for nouns, adjective-noun combinations to identify variables and entities.

Step 3. The initial set of variables (entities) is processed and refined by the user to identify synonyms, group and rank entities in order to reach to the final set of key variables.

Step 4. An adjacency matrix $A = [a_{ij}]$, is constructed with the identified key variables to indicate interdependencies, where $a_{ij} = 0$ if a variable x_i is not related to variable x_j; $a_{ij} = 1$ if x_i is related to x_j and changes are in the same direction; $a_{ij} = -1$ if x_i is related to x_j and changes are in opposite directions.

Step 5. Translate the matrix into a causal diagram with directed polarized relationships.

3.2 A Problem Structuring Method – Causal Mapping

Causal mapping and situation formulation is a powerful tool for scenario driven planning developed by Acar (1983). It endows causal mapping with rich computational properties. By including in the method indications not only of the signs of the presumed causal influences, but also of their intensities, minimum threshold values and the possible time lags, Acar developed a technique for simulating manually (on the causal map itself) the propagation of change through a causal network. The rich computational semantics of Acar's causal mapping approach support automated modeling and simulation in ways that other varieties of cognitive mapping and causal mapping do not [11] [12].

The input to the causal mapping simulation model is the qualitative causal diagram of the modeled problem, which is derived from text analysis of verbal descriptions of the problem or defined by a domain expert. The primitive elements used in the causal mapping method are the following: *Independent variables* (sources of change), *dependent variables* (middle and outcome variables), *change transmission channels* (Full channel and Half Channel), *change transfer coefficient*, *time lag*, *minimum thresholds*, *status-quo level of the system* (base line scenario), *current state of the system*, a *goal vector*, and a *change scenario*.

Causal diagrams may be redundant or insufficient in capturing the information richness of verbal descriptions. In addition, the subjectivity associated with diagram drawing makes the process a source of potential conflict [11]. While constructing those diagrams by using text analysis could be a more objective way for diagram drawing. The phase of diagram construction and analysis is purely a qualitative modeling process, we need to be careful with the quantification of the model in order to develop a reliable simulation model of the problem [7]. It is important here to avoid using qualitative (soft) variables in the simulation phase, one way we suggest is to replace them with relevant quantitative indicators or indices to minimize the subjectivity associated with defining scales for such variables. Also, we suggest the calculation of interval estimations of the regression coefficient for all linked variables to guide the quantification of change transfer coefficients, the calculation is done based on time series historical data, using simple or multiple linear regression, according to nature of the link.

Graph Change Analysis. [12]
Graph change analysis allows us to investigate the dynamic consequences of entering a change in one of the graph origins, thus simulating a change scenario. Table (1) shows some examples for graph change analysis using the causal mapping method in case of a full or half transmission channel.

Table 1. Causal mapping, graph change analysis examples

If channel XY is activated: $\frac{dY}{Y} = a\,\frac{dX}{X}$,	$X \xrightarrow{a} Y$
Considering both channels XZ and YZ are activated: $\frac{dZ}{Z} = a\,\frac{dX}{X} + c\frac{dY}{Y}$, integrating both sides $\ln Z = a\,\ln X + c\ln Y$ (log-linear)	$Y \xrightarrow{c} Z$ $X \xrightarrow{a} Z$
If both channels are activated $\frac{dZ}{Z} = c\,\frac{dY}{Y} = c\left(a\,\frac{dX}{X}\right) = ac\,\frac{dX}{X}$ Thus it can be reduced to:	$X \xrightarrow[t_a]{a} Y \xrightarrow[t_c]{c} Z$ $X \xrightarrow[t_a + t_c]{a\,c} Z$
Consider the case of three half-channels: Have to be all activated to allow change transfer to node Z. If t_X, t_Y, t_W are the times at which upstream nodes X, Y, W are activated. Then, times at which the signal to change reaches Z from each of the upstream nodes X, Y, W are: $t_X + t_a$, $t_Y + t_c$, $t_Z + t_d$ respectively. Change occurs at Z at the latest time of the three. Values of change transferred to Z from each of the upstream nodes: X, Y, W are: $a\,\frac{dX}{X}$, $c\,\frac{dY}{Y}$, $d\,\frac{dW}{W}$, the lowest one in magnitude is acting as the limiting factor or constraint for capacity to affect change.	$Y \xrightarrow[t_c]{c} Z$ $X \xrightarrow[t_a]{a} Z \xleftarrow[t_d]{d} W$

Scenario Simulation.
A base line scenario with initial values for the problem's key variables is defined as a status-quo level of the system with zero initial relative changes. The desired state of the system is represented by a goal vector (targeted relative changes in outcome variables compared to the base line scenario). A policy option or proposal is represented by a change scenario. Simulating a scenario of change from the status quo level requires a change to be entered at a particular node. The casual mapping model allows

running change scenarios on a graph. The transfer of change once initiated propagates from the source of change throughout the network. The method allows triggering change transfer by a 'Pure scenario', a single change at one source, or a 'Mixed scenario', change in several sources all at once or with a time lag. In addition, it defines 'Willed scenarios' against 'non-willed' (environmental) scenarios.

3.3 Case Study - the EU 2030 Climate and Energy Framework

There is an ongoing debate on what should be the EU's climate and energy targets in 2030. At present, the EU's climate and energy targets by 2020 are approved, however by 2020, the EU strive to reduce climate change-causing emissions by 20% compared to 1990 levels and to ensure that renewable energy sources would make at least 20 percent of all energy. The need to move ambitious and binding climate and energy targets for 2030 has to go in line with scientific findings on climate change. It is estimated that in order to avoid the most severe consequences of the greenhouse, gas emissions have to be reduced by 80-95% compared to 1990 levels by 2050 [13]. In practice, this means learning how to live without fossil fuels, even if it was enough for centuries and that is possible even to existing technologies, and is not more expensive than retrofitting an outdated with fossil fuel -related infrastructure. [14] [15].

The identified policy issues are: (i) new targets for renewables share in EU energy sector, (i.e. 30 % proposed by the EP), considering the main energy sectors: Transport, Buildings (electricity/heating/cooling), and Industry; (ii) commercial interest and fuel market competition (renewables vs. fossil fuels and vs. nuclear energy sector); (iii) issues of land use and environmental impact to the land/soil; and (iv) environmental advantages –greener climate, less Co2 and etc.

The textual data analyzed is obtained from 'Fifth Assessment Report: Climate Change 2013, Summary for policy-makers, The Intergovernmental Panel on Climate Change' [19] and sample research papers [16] [17] [18] on renewable energy planning and climate action that present facts and scientific knowledge about the problem.

4 Results

This section shows the results of applying the "text synthesis" methodology and the resulting qualitative causal diagram of the public policy problem use case.

Table 2. Sample text units (inferences), obtained from input qualitative / textual data (Step 1) with the information source indicated.

Limiting the effects of <u>climate change</u> is *necessary to* achieve <u>sustainable development and equity</u>, including poverty eradication. [19]
The <u>security of Europe's primary energy supply</u> is *improved* in the <u>decarbonized pathways</u>. Substantial *benefits* can be expected in terms of the resilience of <u>the economy</u> to volatility in <u>fossil fuel prices</u>. [19]
<u>Social</u>, <u>economic</u> and <u>ethical</u> analyses *may* be used to inform <u>value judgments</u> and *may* take into account values of various sorts, including <u>human</u> and <u>non-human values.</u> [19]

Climate policy intersects with other societal goals creating the possibility of co-*benefits* or adverse side effects. Mitigation and adaptation *can* positively or negatively *influence* the achievement of other societal goals, such as those related to human health, food security, biodiversity, energy access, livelihoods, and equitable, sustainable development. [19]
Globally, economic and population growth continue to be the most important drivers of *increases* in CO2 emissions from fossil fuel combustion. [19]
Mitigation policy *could* devalue fossil fuel assets and *reduce* revenues for fossil fuel exporters, but differences between regions and fuels exist. [19]
Efficiency enhancements and behavioral changes, in order to *reduce* energy demand compared to baseline scenarios without compromising development. [19]
Nuclear energy *could* make an increasing contribution to low carbon energy supply, but a variety of barriers and risks exist. [19]
Conversion to a wind, water, and sunlight (WWS) energy infrastructure *will reduce* world end-use power demand and power required to meet that demand [18]
Conversion to a WWS energy infrastructure *will reduce* air pollution mortality and morbidity, health costs associated with mortality and morbidity, and global warming costs [18]
Additional jobs and earnings are associated with the enhancement of the transmission system and with the conversion to electric and hydrogen fuel cell vehicles, electricity-based appliances for home heating and cooling, and electricity and hydrogen use for some heating and high-temperature industrial processes. [18]
Changes in State and local tax revenues and *maybe* tax policy *changes* are required to ensure that state revenue remains at the level needed. The *increase* in the number of jobs is expected to *increase* personal income tax receipts. [18]

Table 3. Initial set of identified entities to be refined by the user (Steps 2)

EU Climate action Mitigation and adaptation Climate change	CO2 emissions Greenhouse gases (GHGs) emissions	Thermal pollution Global average temperature increase
Climate Costs Air/ Water pollution	Health-related mortality and morbidity costs of Air pollution	Energy end use demand Economic growth Population growth
Security of Europe's primary energy supply Energy access	Fossil fuel prices Value of fossil fuel assets Revenues for exporters	Energy Efficiency measures Energy-conservation
Fossil fuels Coal, Oil, Natural gas Nuclear energy Uranium refining,	Fossil fuel combustion Carbon Capture and Storage (CCS)	Decarbonized pathways Renewable Energy Sources Conversion to electric and hydrogen fuel
Renewables share in electricity, heating & cooling	A Wind, Water, and sunlight energy infrastructure	Decarbonizing electricity generation
Societal goals: local environmental quality, equitable, sustainable development Quality of life, food security and Biodiversity (wild life)	Value judgments: human wellbeing and non-human values Human health,	Social, economic and ethical analyses Jobs and earnings State and local tax revenues increase in number of jobs

Table 4. Key variables of the problem (Step 3)

A	Energy End-use Demand	
B	Population and Economic growth	Origin node
C	Share of Fossil fuels Coal, Oil, Natural gas	Origin node
D	Carbon Capture and Storage (CCS)	Origin node
E	Share of Nuclear power	Origin node
F	Share of Biofuels	Origin node
G	Share of Renewable energy sources (WWS)	Origin node
H	GHG emissions: CO2 emissions	
I	Air and Water pollution	
J	Thermal pollution – Climate change	
K	Energy generation costs	
L	Energy Imports	
M	Energy efficiency measures	Origin node
N	Value of fossil fuel assets and revenues for fossil fuel exporters	
O	Conversion to Electric / Hydrogen fuel (transport, buildings, industry)	
P	Security of Europe's primary energy supply	Outcome
Q	Number of jobs created	
R	State and local tax revenues	Outcome
S	Health-related mortality and morbidity costs	Outcome
T	Climate Costs	Outcome
U	Equitable, sustainable development	Outcome
V	Land use for energy production	Outcome
W	Quality of life	Outcome

Table 5. Adjacency matrix (Step 4)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
A												+											
B	+																						
C								+	+		+	+		+									
D								–			+												
E									+		+											+	
F									+		+						+					+	
G											+				+		+					+	
H									+	+											–		
I																			+				–
J																				+			
K																–							
L																–							
M	–																						
N												+											
O	–																+						
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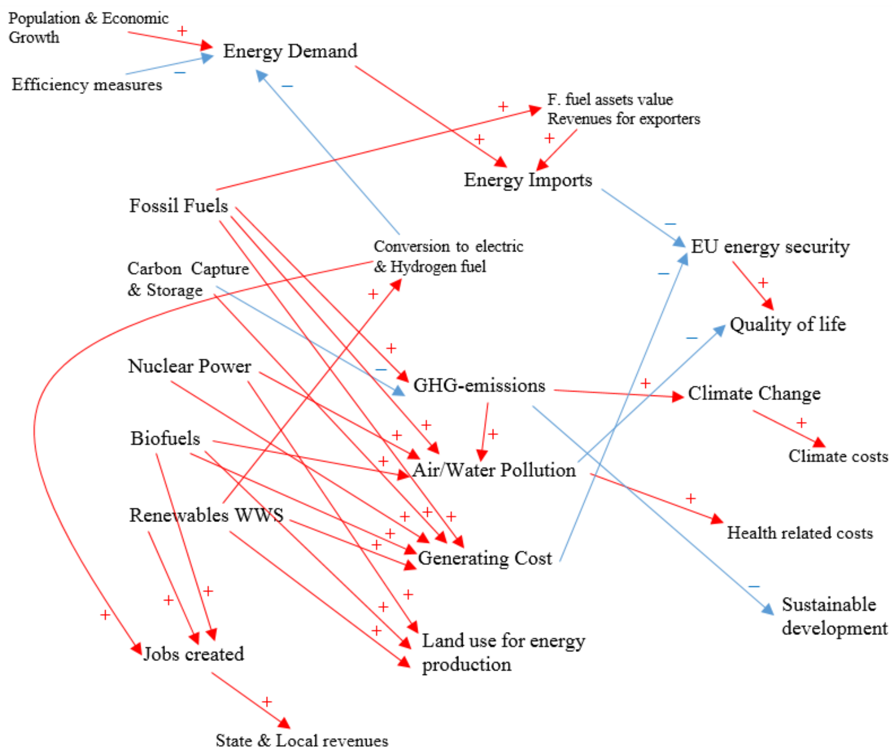

Fig. 2. A qualitative causal diagram of the problem (Step 5)

5 Simulation Model

A web-based simulation tool was developed based on the causal mapping method, which allows the user, through a friendly user interface, to define the quantified causal mapping representation of the problem. Through this simulation model it is possible to: (i) discuss the actual values of change transfer coefficients and time lags defined; (ii) try out different pure or mixed scenarios for change and assessing the sensitivity of the scenario results; (iii) review the structure of the diagram and discuss more views of the problem; (iv) run change scenarios, assess the impacts by calculating the transferred change throughout the network at different time slots; (v) discuss the notions of "strategic flexibility", "tactical effectiveness", "goal compatibility" and "scenario feasibility"; and (vi) accommodate the social processes of group decision-making, collaborative model editing, competitiveness and goal negotiation.

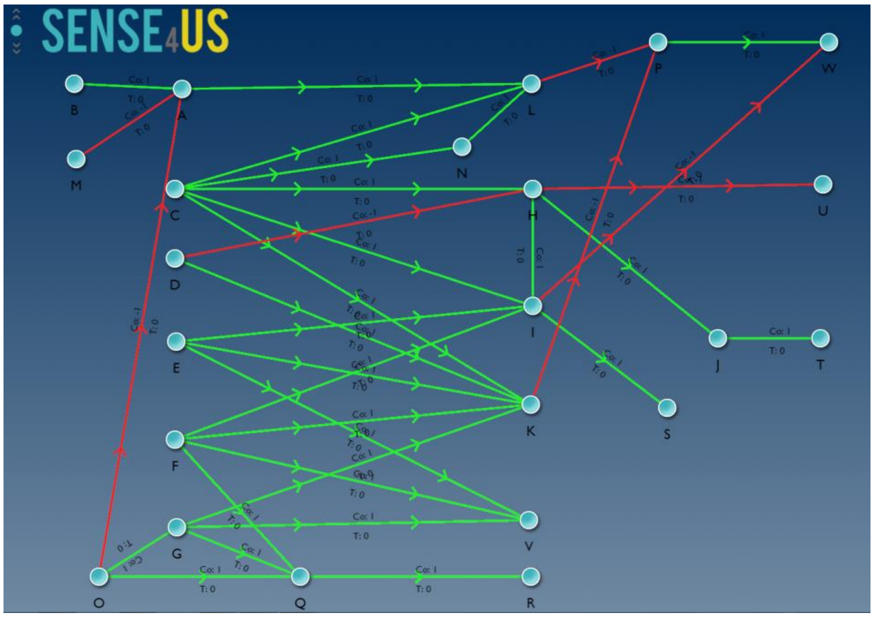

Fig. 3. A screen shot for a prototype of the simulation model developed as a web-based tool.

6 Conclusion

The use of a formal methodology for identifying the key variables and links, in a complex problem situation, enhances the possibility of reaching a more consensual diagram and thus a better problem structuring and system dynamics model.

By providing a user-friendly interface for data input to the simulation tool, we can involve the end user in all stages of the modeling process. The proposed approach allows policy makers to base their ideas and understanding of a policy problem on scientific evidence, map them in a graphical representation. In addition, multiple perspectives of the problem from different end users can be integrated in a causal mapping that involves all relevant problem parameters and defines their interdependencies, also targets for different actors of the problem can be defined as targeted changes in outcome variables of the causal mapping The simulation supports scenario generation, integrated assessment of the consequences of each implemented change scenario and thus the design of policy options. Further, it facilitates the goal negotiation and compromise processes.

The resulting model for the case at hand can be integrated to multiple simplified decision models, e.g., optimization models and decision trees, to improve the scenario generation and design of policy options by taking into account costs, benefits, resource constraints and risks associated with natural, socio-economic, and technological systems as well as decision processes, perceptions and values.

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POSTER ABSTRACTS

The Leviathan model to study the link between self-opinion and group structure

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The Leviathan model (Deffuant, Carletti, & Huet, 2013) simulates a group of agents holding opinions on each other. During dyadic meeting, they influence each other by talking about themselves and gossiping. Speakers highly valued by their listeners are more influential. Listeners decrease their opinion about the speaker when feeling undervalued and increase it when feeling overvalued. Various dynamic opinion structures emerge in the group: absolute dominance of a single agent, hierarchy of opinions, crisis in which everyone hates all the others, including himself, small world networks of very positive links between agents with positive self-opinions.

Crozier & Luhmann: social theory as a support for a systemic socioterritorial modeling and simulation

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Abstract. This paper shows how a socioterritorial system could be computationally modeled by means of two social theories, Sociology of Organized Action (SOA) and Social Systems (SS) to study power relations among social actors. It is concluded that both approaches helps the empirical research and that they complement each other, while SOA emphasizes the power relations, the SS focuses on the generative process of communication.

Keywords: sociology of organized action. social systems. regional analysis. power.

1 Introduction

Territories may be conceptualized as complex systems composed of three subsystems (social, symbolic and spatial) that frames the socioterritorial system (STS). The symbolic subsystem represents the gateway that drives how the social system observe and act over the spatial system [1]. STS can be analysed as organizations with some kind of governance arrangement towards a general goal. It is characterized by a fuzzy relationship among social actors and is geographically bounded. STS can be informal or formal as some brazilian initiatives from the Territorial Development Program from the Ministry of Agrarian Development. One of the key issues about STS is how social actors act collectively to achieve their goals and how they react to territorial public policies. So, this implies that we need to pay more attention to a sociological understanding of how people make collective actions on a regional scale. In this work two systemic social theories were compared as support for formal modeling and for empirical research on STS. The aim is to establish a correspondence between the STS proposed by Moine with each of these social theories, separately, discussing how these theories are or could be formalized to allow an empirical work on modeling and simulation of STS's. For now, it has been investigated the Sociology of Organized Action (SOA) by [2] and the Social System (SS) by [3].

2 Sociology of Organized Action

The SOA has its roots on the bounded rationality and field theories, and is based on empirical research about formal organizations. Its main focus is on human decision and collaboration and tries to explain how well-defined or fuzzy organizations maintain their stability. [4] proposed a formalization of the SOA and implemented it into a software called SocLab where all the SOA's conceptualization is transformed into a relational database that stores a list of social actors, resources, relations among social actors and resources, the weights for each relation and the meta-data about how social actors act taking into account the state of each resource. In this work we will use the SOA social theory as reference and the SocLab as framework as supports for empirical research on a socioterritorial system. The simulation process using SOA/SocLab will search for a stable state, considering all possible social actor's strategies.

3 Social Systems

The SS is quite abstract theory inspired by the structural functionalism and is based on a set of frameworks and theories as the autopoiesis. It is more concerned about the communicative process and attempts to explain how organizations evolve by a recursive reduction of complexity. Due to the high level of abstraction, the formalization of the SS is not an easy task at all. While the SOA emphasizes social norms, rules and values, the SS is looking to the differentiation between system and environment (other systems) and to how social entities (not individuals) transform communication into meaning. Some works formalized key aspects of the SS theory, using agent-based paradigm, as: social emergence [5], evaluation of anticipatory behavior [6], study of a simple economic system [7], the micro-macro link [8] and implementation of expectation structures [9]. In this research we will focus, by means of an agent-based model, on generative features associated to the Luhmann's communicative process inside STS's.

4 Modeling socioterritorial systems with SOA and Social Systems

Despite of these differences between the SOA and the SS it is important to notice that both can be used to study an key element of the STS, power and its implications on collaborative actions. The SOA see power as the capacity of one social actor to constraint the action of the other by means of changing the level of access to the set of resources that he controls. In the Luhmannian interpretation power is the capacity of one social actor to transform their communication into meaning, when something happens, which rule the differentiation between the STS and the environment that increases the social dynamism of the STS.

When we are trying to model a STS, it is worth to establish a connection between social and spatial subsystems. But, neither SOA nor SS treats explicitly spatial constraints of social behavior in their social theories. However, we propose that the spatial constraints may be mapped as resources or relations in the SOA based modeling. In this case a concrete spatial object could be a resource controlled and desired by social actors, as well as a relative proximity that may be represented by social relations. The symbolic subsystem from Moine is part of the social system in the SOA formulation because this theory does not separate social action from individual cognition. Analogically, in the SS approach, the social system could be viewed as a political functional system, the symbolic subsystem should be interpreted as a psychic system, and the spatial system could be a set of various coupled functional systems that interact and change the way that people use the geographic space. Here, the process of differentiation between the STS and the environment increases the spatial dependence between the political functional system and the spatial subsystems by means of the psychic system, and this implies that we will observe, again, an increase of social dynamism.

5 Conclusion

In conclusion, this work shows that both social theories contributes to empirical research on STS's, providing enough guidance to data gathering and the formalization needed to do simulations using strategic decisions (SOA) or observing the emergence of social systems differentiation (SS) taking into account spatial constraints.

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Simulations, Games and Social Processes in Science

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1 Poster Abstract

Science is a very successful human enterprise. It has allowed us to explore environments where humans could not survive in, it has extended our life expectation and it is behind the technological advances we grew accustomed to. Its success is due in large part to its social characteristics, to the way the system is built so that the biases and errors of each individual are eventually corrected.

Many different processes help the self-correcting aspect of scientific endeavor. We are continuously checking the validity of each other results, from the peer-review phase in the evaluation of a new article to the reproduction of the reported observations in other laboratories. In some fields, both the proposal of new ideas as well as their testing is performed by the same team. In other areas, we can observe a very clear distinction between theorists, who simply advance the ideas, and experimental scientists, who test them.

On top of that, the structure of the universities and companies where we do our research can have unforeseen impacts. The constant pressure to publish new results in order to advance our careers certainly causes a number of effects, some detrimental to the reliability of our knowledge. One example is the fact that in some areas published results are no longer replicated by an independent team. That this is happening in areas such as the testing of new medical drugs is obviously cause of much concern.

This leads to an interesting question. Can we explore the scientific business as a social process and try to find more reliable and efficient ways to do research? In order to answer this, the first question that we need to pose is what is the purpose of Science. Here, we will assume it is basically to find useful descriptions of the reality, that resemble the way the world really works as far as we can tell. If that description is actually true is a question we will not even try to address.

However, even simply by requiring an equivalence between the theories and the observations, we arrive at a serious problem. How can we verify if the process can be improved if the objective is to get as close as possible to the way the world really works when we, in principle, do research exactly because we don't know it? In this paper, we will propose a new way to explore this question, by using not only simulation of the social processes in Science, but also integrating those simulations with computer games.

It is interesting to notice that the idea of creating a simulator to the scientific enterprise is similar to the basic concept of many games that simulate other types of human activities, such as the management of a city or a business, to the creation and expansion of an empire. By creating a game framework where we can implement social rules, we can gain a number of advantages over a simple research simulation. First and foremost, by presenting the question as a game, we can open the discussion about the way Science operates to a wider public, who can actually contribute to the problem with their own observations about the problem. This should help make things clearer to policy-makers and all the actors involved with decision-making involving research. Of course, presenting the question of how to make improvements to how we organize the area in a way that is fun and interactive is both a bonus and also, more importantly, a way to atract more people to the area.

Another clear advantage in a simulated world is that, since the programmer plays the role of the creator of that particular universe, its is possible to know which rules are actually valid in the simulated universe. This makes exploring strategies of testing theories far simpler than in our own world where no access to that knowledge is possible. Therefore, the objective of this paper is to present a couple of proposals to address these issues and to stress the importance of investing in this promising area.

Bottlenecks, Bridges and Barriers:

Applying Social Network Analysis to Climate Change Adaptation Research in Agriculture

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Abstract. Successful adaptation of agriculture to climate change will require effective communication across geographic, political and disciplinary boundaries. Social Network Analysis is a tool that measures the interactions between actors in a network, providing researchers with a conceptual framework and methodology for studying dynamic relationships across scales. Social Network Analysis can be used to pinpoint barriers to effective communication. It can also be used to identify potential change agents, and highlight existing and possible network structures that can increase resilience in agricultural systems. This poster provides readers with an overview of tools for improving climate change adaptation research using the networks approach.

Keywords: Climate Change, Agriculture, Systems, Adaptation, Resilience, Innovation, Networks, Social Network Analysis, Adaptive management, Farmers, Communication

1 Introduction

Successful adaptation of agriculture to climate change will require effective communication across geographic, political and disciplinary boundaries. Social Network Analysis (SNA) is a tool that measures the interactions between actors in a network, providing researchers with a conceptual framework and methodology for studying dynamic relationships across scales. SNA can be used to pinpoint barriers to effective communication. It can also be used to identify potential change agents, and highlight existing and potential network structures that can increase resilience in agricultural systems. Few studies apply SNA to agriculture, and no known studies use the social networks approach to integrate agriculture and climate change adaptation. There is great potential for researchers to gain a new understanding of the processes and drivers of agricultural adaptation to climate change using SNA. This poster puts the existing adaptation literature in the context of SNA and its utility for improving climate change adaptation in agriculture

2 Climate Change Across Scales

Most climate and agriculture research relies on climate change scenarios derived from General Circulation Models (GCMs), and incorporates climate, atmospheric and economic models to predict the sensitivity of agricultural productivity to climate change [2]. GCM modeling is primarily suited for research at the global, ocean-continent, or sub-continent scale. Studies that rely on GCMs fail to capture the variability and the complex interactions between physical and social systems at regional or smaller levels of observation. Crossing boundaries from the local to global levels is important for social change processes like adaptation, yet the dynamic nature of linkages between levels of governance is not well-understood, and issues of scale are often ignored in research [1]. SNA is one way that researchers and policymakers can "connect the dots" between highly localized human impacts, and global environmental changes.

3 Adapting Agriculture to climate change

Adaptation is defined by the IPCCC as an adjustment in ecological, social, or economic systems in response to observed or expected changes in climatic stimuli [3]. Agricultural adaptations can occur at all levels. Decisions to adopt or modify practices are contextual and made based on a combination of conditions and risks like climate, trade policies, prices, and social norms that influence decision-making. There is no single effective adaptation strategy in agriculture. Adaptation response at any scale depends on context, including political, environmental and economic conditions, and on the risks and costs of adaptation. Success of an adaptation strategy depends not only on how the action meets the objective, but also how it affects the ability of others to meet their adaptation goals [1]. Understanding the relationships between adaptation options and the existing processes in place that hinder or promote adaptation is a key component of any evaluation of adaptation options [4]. SNA can provide researchers with the tools to better understand some of these processes and identify how they influence both the availability of as well as implementation of adaptation strategies.

4 Social Network Analysis in Adaptation Research

The multiscalar, multitheoretical framework of SNA makes it useful for studying relational dynamics in complex systems. SNA uses empirical data and diagrams to identify structural and process information within a system by measuring the interactions, or ties between actors in a network [5] rather the ties between them. Because SNA encompasses both structures and entities, it provides a conceptual framework and methodology for linking micro-level dynamics to changes in network structure on the macro-level, making it useful for studying change across scales. Where a climate scenario is limited by scale, a longitudinal, network study can show connections across political, social and physical boundaries.

SNA seeks to uncover the set of theoretical mechanisms by which social relationships affect entities and vice-versa. Graphs and models can be tied to existing theories of change and communication, helping identify change agents in the system, target collaborative efforts, and measure the information flow and sharing potential of a network. Applying the network perspective to climate change adaptation can uncover barriers to change like low levels of trust, communication bottlenecks, and lack of access to information or resources. It can reveal the underlying network structure of a system, providing a better understanding of how to facilitate change. Network modeling can offer a roadmap for implementing social and organizational structures that optimize adaptation response and promote stakeholder involvement, moving research and policymaking from a scale-dependent, hierarchical process to a more integrated approach.

5 Conclusion

There is no model or research method sophisticated enough to effectively predict how changing environmental, social and economic systems will affect agriculture and food security. Ensuring the resilience of our agricultural systems and minimizing risk will require large systemic changes in policies and practices. SNA is not a panacea, but when integrated with other approaches, like climate scenarios and GCM-modeling, it offers a methodology and theoretical framework that researchers and leaders can use to identify systemic barriers and bridges to effective agricultural adaptation across scales.

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London Riots with ABM+GIS

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1 Poster Abstract

In recent years we have observed several uprisings of urban populations around the world. Examples are 201012 Greek, 2011 Spanish, 2011 Portuguese, 2011 London, 201213 Egyptian, 2013 Brazilian protests, among others. Those uprisings, despite their heterogeneous and eventually contradictory aggregation of protesters, share quite a few similarities. The protesters manifest rejection of the current political system and ask for many basic human rights, both in quite general terms. Many millions attended to the public squares, called mainly by informal organizations based on virtual social networks, frequently based on mobile devices.

In this work, we addressed space-temporal dynamics of social urban manifestations, frequently displayed as a series of episodes of street disorder, generally consisting of looting, rioting and violence. Such big and generalized crowd manifestations are social phenomena of great interest, built of individual decisions taken with partial information. Despite the long range information flux through virtual social networks, the ultimate decision to riot is made based mostly from local events.

We concentrated on the London riots of August 2011, events already treated by DAVIES et al. [2013]. This choice was due the availability of space-temporal data of rioters and police force to those events. The cited work used an approach based on a set of differential equations, approach that is inherently of mean field character. To overcome this feature, we created an agent based model (ABM) able to translate the rioter individual decision to protest to the system macro behavior. The system is referred as the aggregated collective actions of rioters and police force. Moreover, is was possible to compare both approaches.

Those manifestations in England were the lager in the last 20 years, started on August 6, 2 days after a man casual death by the police. Departing from a small pacific demonstration of victim friends and relatives, the course of events quickly escalated, with hundreds of rioters in the streets, leaving behind 200 injured, 5 dead and millions on material losses [DAVIES, 2013 and references therein].

We present an ABM that reproduces the space-temporal dynamics of the London 2011 riots as good as the original model, from a bottom-up approach, with a smaller number of parameters. Our aim was to identify and correlate the main factors leading to the protests population accession and the police force response.

The London neighborhoods population and relative distances were accessed with NetLogo GIS extension. There were 2 kinds agents in these spaces: residents and cops. The residents can be in 1 of 2 states: rioting or resting. The number of residents were taken as 0.001

The 31 neighborhoods centroids are the point were rioters and cops met and can see one another, accessing their relative number without error. The residents take firstly the decision to adhere or not to the riots, and then take the decision of where is the best neighborhood to riot, based on the global information of the relative number of residents and cops in each neighborhood.

Beside the relative number of residents and cops, an agent consider to riot based on his wealthy condition and the distance from his neighborhood to the best neighborhood to protest. His wealthy is interpreted as his satisfaction with the government while the relative number of cops as a proxy of the probability to be arrested.

Regarding the rioter satisfaction with the government, we assumed that inferior social condition of living imply less satisfaction. Indeed, the unemployment rate among young were higher in the affected neighborhoods. Actually, most of the arrested rioters were from poor and degraded neighborhoods. To evaluate the social condition of the rioters, we adopted the Index of Multiple Deprivation (IMD), calculated after income, employment, health, education and habitation disposal [DAVIES, 2013 and references therein]. We also assumed an intrinsic random variation of the predisposition to protest among the residents to represent the individual character. This last characteristic prevents of everybody going to riot at the exact same moment, a reasonable assumption.

The spacial distribution of the riots can not be explained by random choice of the rioters. The role of the distance of the local of residence of the rioters to the local of the riot and the place accessibility most be accounted. In this way, the cost of displacement is an important factor guiding the rioters decisions. Furthermore, in addition to these 2 rational factors, dissatisfaction with the government and displacement cost, we also introduced a herd dynamics, an instinctive self protective behavior to avoid being arrested.

In short, we assumed that the local population life standards affects the likelihood of a neighborhood to adhere and the riot to escalate and found the model to be consistent with empirical data. As opposite, protests starting on wealthy neighborhoods tend to vanish. The increasing number of police force as the riots repeated day by day was also present. Although theoretically reasoned, the role of long range communication, as provided by virtual social networks, were not quantitatively tested.

DAVIES, Toby P. et al. A mathematical model of the London riots and their policing. Scientific reports, v. 3, 2013.

Taming a Million Learning Agents for Recommender System through Distributed Computing

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Poster Abstract

These days, more and more people are using on-demand media streaming services instead of watching on-air channels. The streaming service is attractive due to ability for the audience to choose any show at anytime from anywhere. However, there are times when people simply have no idea what to watch on their free time. A recommender system can recommend items to its users to watch. Research dealing with recommender systems typically has the goal of finding which items may attract which users. One popular method for item recommendation is Collaborative Filtering (CF). CF takes the history of users interaction with the system, and recommends particular items to similar types of users. Another popular method is called Content-Based Filtering (CBF). When a user likes several items, CBF detects the similar traits between the items (such as genre, publication date, and so on). Then, it recommends another item that closely similar to the previous items. Both CF and CBF approaches are fast and relatively accurate, however they do have some downsides. CF cannot recommend items to new users and CBF ends up recommending too similar items too often that it might bore the users.

There are factors that affect the reason why a particular movie is interesting to a user, such as the genre, the actors/actresses, the directors, the studio, or the combination of any of those. It could be anything. On top of it, users that have similar preferences for a particular genre might have a totally different preference for another genre. Add this consideration to the other factors mentioned earlier, and there could be hundreds of billions of possible combination to consider before the system can finally make a good recommendation.

To address this issue, we propose a Multi-Agent System approach (MAS) using Learning Classifier System (LCS) techniques. In our MAS, each agent is designed to learn both as individual and as an organization. They are distributed across multiple clusters of computing nodes. One node acts as a manager to distribute knowledge and task between agents living in different clusters. When an agent finishes its learning loop, it shares its best knowledge to other agents by sending them to the manager. The manager then may give the agent new task to learn, or it may order the agent to continue learning to improve its current knowledge even more.

As for the learning method itself, the agents learn by using LCS techniques. An LCS is essentially a collection of condition-action rule-based knowledge. The knowledge are evolved though Genetic Algorithms (GA) and evaluated by Reinforcement Learning (RL) method. GAs are good to find solution candidates when the search space of possible solution is massive (such as the case in recommender system described above). In LCS, the solution array (the chromosome) in GA may have a “don’t care” flag that means that particular trait is considered as noise and may not weigh as much as the other traits. This is useful for our recommender system because a user may like a movie because of the genres and the actors, regardless of the studio name. By using five-fold cross validation the solutions proposed GA are tested, and the system gives reinforcement learning’s reward feedback in terms of the accuracy. Based on the reward it gets, the GA continue learning by doing crossover and mutation across the proposed solution to detect which traits of the chromosomes that lead to the reward.

Typically LCS works with single agent in mind. However, in our proposed method, we implement LCS to work with multiple agents (one million agents). In our architecture, each agent maintains its own LCS, and once it finds a good collection of knowledge, it shares the knowledge by promoting it to the organizational level by sending it to the manager node mentioned previously. To test whether the knowledge also works globally (instead of only works in the agent’s local environment), the manager sends the promoted knowledge to other agents living in other clusters and analyzes if it produces the same performance. After passing all these batch tests that the knowledge are considered globally-good and finally be used for recommend items to general audience. The locally-good knowledge (but not globally-good), may be used to recommend items to specific user groups that are considered as having similar preference as the agents producing those knowledge.

This research is still a work-in progress, and our early simulation result shows a promising accuracy (better than standard CF and CBF methods) but suffers a little bit in terms of computing time. The globally-good knowledge are useful when the system encounters new users, and the locally-good knowledge often offers pleasant surprises to existing users. Future works include optimization to produce faster performance, and improving the architecture design to adapt not only to batch processing, but also to stream processing.