The Importance of Product Space Complexity in Agent-Based Computational Economics

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***Abstract*—Agent-based Computational Economics (ACE) refers to modeling an economy as a complex adaptive system of agents. Empirical studies have shown the importance of product space complexity for innovation and macro-economic value [1], [2]. Despite the significant literature on ACE, a missing component in most models is the incorporation of evolutionary dynamics, in particular a larger product space subject to evolutionary forces. This study explores the role of having a diverse product space for the evolution of the product transformation network. We demonstrate the importance of having a larger product space to observe systemic growth due to entrepreneurial support interventions. In particular, we use our agent-based innovation ecosystem model, EconoSim, followed by a traditional ACE model, to showcase the importance of evolutionary dynamics for policy experimentation using ACE. Experimental results of entrepreneurial support interventions on both models support our argument that the heterogeneity in the product space and the underlying evolutionary structure of the ACE model are vital for innovation and innovation-related policy experiments.**

I. Introduction

The neoclassical approach for studying economic ecosystems utilizes statistical general equilibrium models. This approach is founded on the assumption that an economy actually exists in equilibrium [3]. However, during a financial crisis or a shock such as the introduction of new start-up companies into a local economy, the system is pushed out of equilibrium giving rise to various research questions. Will the system ever reach the previous equilibrium again? What modifications can be done to improve the system with least disturbance to the prevailing equilibrium? Or even: will the system simply fail to reach equilibrium and collapse inevitably? Answering these questions demands the application of a dynamic modeling technique. Agent-Based Computational Economic(s) (ACE) models have been shown to tackle the problem of unstable equilibria by modeling microeconomic interactions. However, there are fundamental differences in the design of ACE models according to the economic phenomena that each model aims to investigate.

Classical agent-based macroeconomic models used representative agents; agents are stereotyped into households, firms and banks [4], [5]. During a simulation step each agent selects a subset of agents out of a fixed population of agents to trade with. Production and demand functions govern the quantity traded and the trade partner selection processes. These models provide an excellent basis for experimentation on economic processes between these agent types and understanding how macroeconomic values such as GDP change non-linearly with the micro-interactions between households and firms.

However, the classical approach tends to consider transactions within a limited product space. Although a restrictive product space is sufficient for studying how economic growth changes within a short timespan, it is important to consider the entry and exit of new products into the market in the long run in order to model cycles of innovation [6]. Having a larger product space allows for firms and households to explore a more diverse market giving room for innovation. Further, empirical evidence supports the need for product space diversification and shows product space complexity correlated to macro-economic performance measures [1], [2]. We argue that a binary product space constantly allows for near perfect macro-economic value; whereas in a diverse product space agents must "explore" the market and "exploit" sustainable transformation networks in order to survive. This imperfectness of agent performance allows the modeler perform policy experimentation such as entrepreneurial support policies, which would not be viable on a fixed population-restricted product space ACE model.

In this paper we suggest that a restrictive product space will cause a lack of evolutionary dynamics and inhibit innovation. To demonstrate our hypothesis, we use an agent-based model of innovation ecosystems, Econosim [7], [8]. In our previous work, EconoSim was used to compare the effects of different entrepreneurial support techniques on the survival of innovative agents within an incubated environment [7], [8]. Agents in EconoSim are binary product transformers; they purchase one product type from agents selling that product in the environment, convert it into a second product type according to a transformation rule and offer to sell the transformed product to other agents. EconoSim uses a three-tier architecture as shown in figure 1 to simulate economic transactions. The foundation of this model defines the basic socio-economic building blocks that define the agent-to-agent micro-interactions. The second layer defines an innovation ecosystem that incorporates ecological concepts such as selection, trade networks and most importantly innovation of transformation rules. These processes create Darwinian evolutionary dynamics of new product transformation rules within the population of agents, allowing for complexification of the product space. The third tier defines policy interventions such as business incubation, taxation and environment sustainability experiments conducted

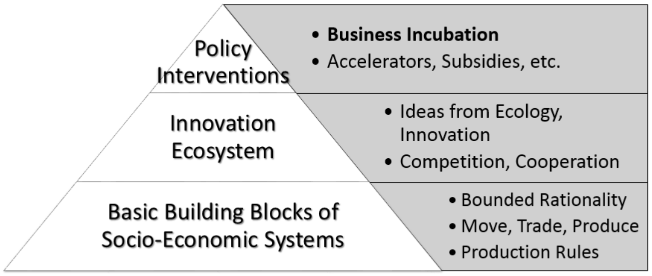


Fig. 1: Conceptual representation for the role of the innovation ecosystem in ABM.

using the ACE model.

We perform experiments on, first, a restrictive binary product space, and second, a diverse product space. In the binary case, agents do not have to explore for viable trade partners, instead, trade partner relationships are established immediately. Therefore, macroeconomic performance is solely determined by the trade volume among agents. In the diverse product space, agents have to explore the landscape of products to identify viable trade partners. Therefore, trade partner discover-ability plays a greater role in macroeconomic performance and certain transformer types become more prominent in the population than others.

To further our point, we perform basic entrepreneurial support experiments on both the binary product space and diverse product space. These experiments showed to have little effect on the binary product space case. However, a considerable improvement in macroeconomic performance was observed in the diverse product space case.

We performed on a prominent ACE model in the literature, JAMEL [9] which uses the classical representative agent style model of economy. JAMEL associates Keynesian thinking with agent-based approach to investigate economic phenomena. The version of JAMEL used in our experiments consist of households, firms and banks. Households provide labor to firms which sell a single consumer product. The product space therefore, essentially consists of two possible products: labor and consumer good. Our entrepreneurial support experiments failed to have any sustained effect on the macroeconomic performance of JAMEL, which leads us to the conclusion that product space diversity is needed to model innovation.

It is important to note that this study does not perform a critical comparison between JAMEL and EconoSim. Instead, it highlights the importance of evolutionary dynamics in agent-based computation economics models for certain policy experiments (business incubation in this case). We argue that despite the underlying economic principles of most successful agent-based models, without evolutionary dynamics and the described heterogeneity, they are unsuitable to simulate the effects of certain economic phenomena such as entrepreneurial support, in contrast to EconoSim.

II. Related Work

Economic phenomena have been modeled using neoclassical approaches [10]; evolutionary approaches [11]; econometrics [12] and computational agent-based approaches [13]. These approaches differ in their represenation of economic behaviors and structure. Agent-based approaches offer flexibility and they are the natural fit for the stochastic and nonlinear nature of innovation ecosystems [14], [15]. Agent-based modeling also allows the representation of knowledge in ways that are mathematically intractable.

One of the earliest attempts at agent-based modeling of socio-economic ecosystems is the Sugarscape model [16]. Since then, various models have been developed throughout the last decade encompassing different aspects of economics. The sophistication of ACE models have increased rapidly in the past few years and the capabilities of the models have expanded for economics [17]. ACE models have proven to be a powerful tool for policy experimentation by being able to embody the heterogeneity of innovative strategies in production [18] and trading strategies [19].

A notable trend in the ACE literature is towards representative agents that model typical classes economic entities such as firms, households or banks. In addition to an increase in the number of agent types being represented, representative markets have also been modeled [4] by using agent-based approaches. Diversification of firm types has also been experimented with by modeling consumer-goods producing firms and capital-goods(machinary/tools) producing firms[20]. One of the highly representative ACE models in the current literature is EURACE [21], [22]. This model has taken on the most ambitious feat of making a one-to-one mapping of the European economy. Darabi et al. [23] modeled the enterprises by agent-based modeling to analyze different modes of governance. Dougherty et al. [24] presented a multi-scale data analytics approach for modeling the U.S. healthcare system and explores agent-based methods to portray the movement of patients in the state-space in the context of the overall economy. Laarabi et al. [25] used an agent-based approach to introduce an architecture for a visual Dangerous Goods Transport (DGT) simulation system. Scott et al. [26] presented a framework to model public facing government services as a business ecosystem perspective.

A common property in the traditional computational economics models is the lack of innovation or diversity in the product space and production process. However, innovation and technology diffusion are critical components of economic growth [27], [10]. To take these components into account, EconoSim uses an agent-based approach, which models the economy as an ecosystem. The agents in the model are treated as components in an ecological network [28] and this network summarizes the technological structure, production and innovation capabilities within the economy. JAMEL is a macroeconomic laboratory, which is used to conduct experiments on economic phenomena such as the flexibility of wages and instability with endogenous money [5] and inflation targeting [29]. JAMEL is used in this paper along with EconoSim to demonstrate the effects evolutionary dynamics in agent-based models of ecosystems.

III. A Comparison of Product Spaces

In this section we observe how product space diversity effects macro-economic performance. The product space, as defined by [1], [2] is the network of product types linked by their proximity measurements. Greater proximity represents an easier transformation between the products. In EconoSim, the relative popularity of a transformation rule would represent how often one product type is converted to another, which is analogous to proximity in the product space. We perform experiments on two cases of EconoSim: 1) using a binary product space and 2) using a diverse product space of 32 products (16 times larger).

A. EconoSim

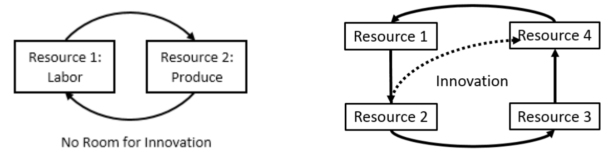
EconoSim is a model of innovation ecosystems, built to test policy experiments such as incubation. EconoSim consists of a single agent type called an adaptive resource transformer (ART), which embodies a single transformation rule. However, there are various product and resource types within EconoSim and ARTs can embody different transformation rules that convert a resource into a product type, creating a heterogeneous population of agents. During its lifetime, an ART attempts to find trade partners, product type of which is its resource type, and purchases required resources for money. The selling price is adjusted at the microlevel according to the demand for the ART's product. ARTs demonstrating high fitness are selected to reproduce new agents which have mutated transformation rules, simulating innovation. ARTs may die upon low fitness. Therefore, the population of ARTs is constantly subjected to evolutionary dynamics and agents' survival depends on whether or not they form a trade network with other ARTs in the population.

B. Case 1: Binary Product Space

In the first case we use a binary product space. In other words all agents either convert product type 1 to product type 2 or vice versa. Therefore, the product space consists of 2 nodes with a maximum of 2 possible links and a minimum of 1. The minimum cannot be zero as we assume that agents must conduct some form of transformation. This implies that innovation is limited from a degree of 1 to 2 transformation types.

C. Case 2: Diverse Product Space

In the second case, we use EconoSim with a less restrictive product space of a maximum of 32 products. This space allows for 992 types of product transformations and therefore, more room for innovation. Figure 2 demonstrates how having a larger number of products allows for new transformations to emerge, representing innovation within the existing transformation network.



(a) Restrictive binary product spaces have no room for innovation.

(b) Diverse product spaces allow for emergence of innovative resource/product transformations.

Fig. 2: Comparison of the innovative capacity of a restrictive binary product space and a diverse product space.

D. Simulation Results

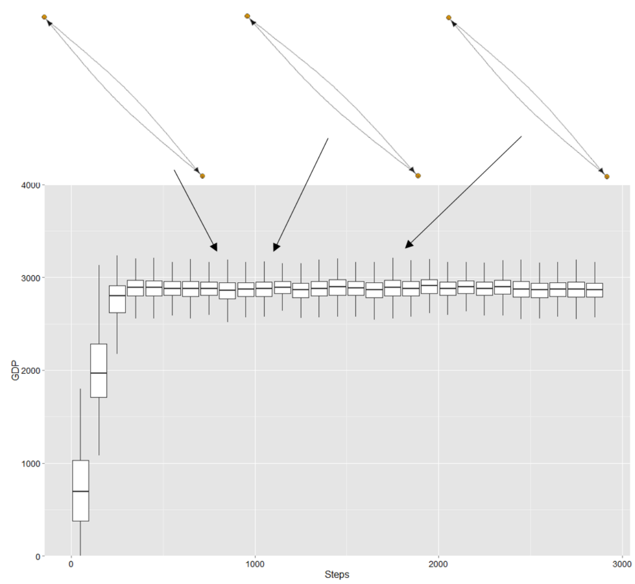
We initialize a population of 100 adaptive resource transformers. As EconoSim allows for agents to reproduce, the population grows during initialization of the simulation. Agents with better performance (collected money and resources) are allowed to reproduce. A population cap of 3000 agents is used to prevent infinite population growth to occur and represents population control due to restricted resources in the real world. 15 runs of each of the two cases above are simulated.

As a macroeconomic measure of performance, the gross domestic product of the runs are measured and aggregate. In this study, we define the gross domestic product, GDP, as equal to the total value of product traded between the ARTs in a given time step. GDP was calculated for both product spaces and aggregate over 15 runs.

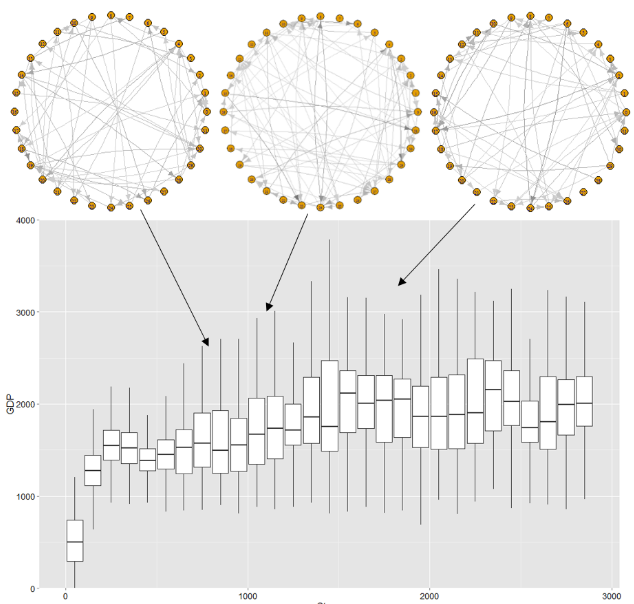
As seen in figure 3a, the GDP tended to remain close to 3000 for the binary product case. The population of agents in the binary case also remained close to the maximum possible population 3000. This implies that every agent in the population performed a purchasing transaction, however, was unable to continue with consecutive sales, to raise the demand and hence the selling price of the products being bought. This reasoning is further supported by figure 4a, where the popularity of both transformation types show to remain slightly less than 1500 agents.

Observing the network structure shown in 3a, it is clear that no new transformations can be made within this transformation network due to the restricted product space, indicating that economic performance cannot be improved through innovation. Instead, the only option to GDP improvement would be by creating new agents that use the same two transformation rules (which is restricted to 3000 agents).

In the diverse product space, the GDP remains at a lower median throughout the simulation, yet maintains a high variability. The diverse product space even allows some simulation rules to achieve GDP values beyond that typically found in the binary product space. Yet, due to the wider variety of trade partners to choose from, the chance that a viable trade partner is encountered is reduced. In other words, there is a constant "room for improvement." Further, the transformation network is in a state of constant reorganization as new transformation rules emerge and new trade partner relations are established. This dynamic behavior is further demonstrated in figure 4b,

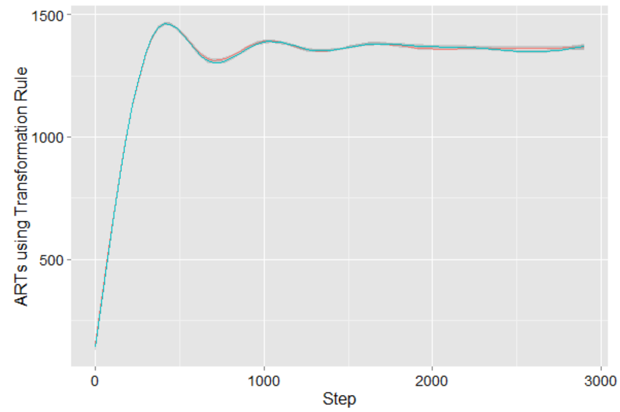


(a) Transformation network structures and aggregated GDP for the binary product space.

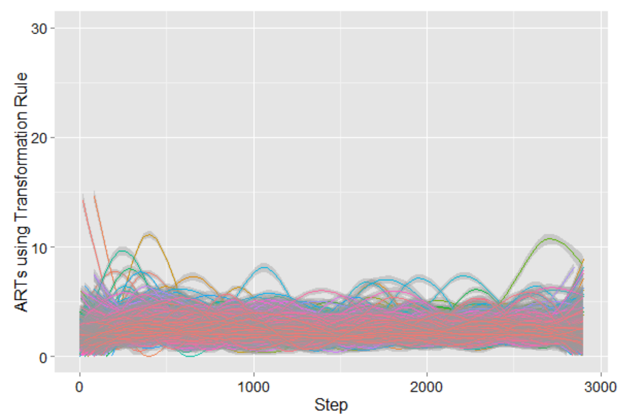


(b) Transformation network structures and aggregated GDP for the diverse product space.

Fig. 3: Transformation network structures at step 800, 1100, and 1800 respectively, and GDP aggregated over 15 runs of EconoSim on different product spaces.



(a) Number of active agents using either transformation rule over time for the binary product space.



(b) Number of active agents using a particular transformation rule over time for the diverse product space.

Fig. 4: Popularity of each transformation rule over time for both product spaces. Each colored line represents the popularity of a single transformation rule over time.

where the most popular transformation rules are constantly falling out of dominance, to be replaced by new emerging transformations. This is comparable to innovation cycles and domain shifts in the real world.

IV. Policy Experimentation Demands Evolutionary Dynamics

Policy experiments such as entrepreneurial support policies aim to improve the performance of the population of economic agents in a system. In this section, we show how policy experimentation, entrepreneurial support in particular, requires evolutionary dynamics to be simulated, for which a diverse product space is required. We perform entrepreneurial support experiments on the binary product space case and the diverse product space case of EconoSim. Our results support that having a diverse product space allows us to perform entrepreneurial support experiments on ACE models.

A. *Entrepreneurial Support on Binary Product Spaces*

Entrepreneurial support was performed on both the binary product space and the diverse product space. GDP, active transformation rule distribution, and network structures were compared for both cases. Entrepreneurial support was performed with the aim of imitating the entrepreneurial support of new entrant ARTs with external resources and money. In our previous work [8] we found that providing a resource to money ratio of 80:20 to the ARTs selected for entrepreneurial support proved to be a desirable method of entrepreneurial support, which we have employed in these experiments as well.

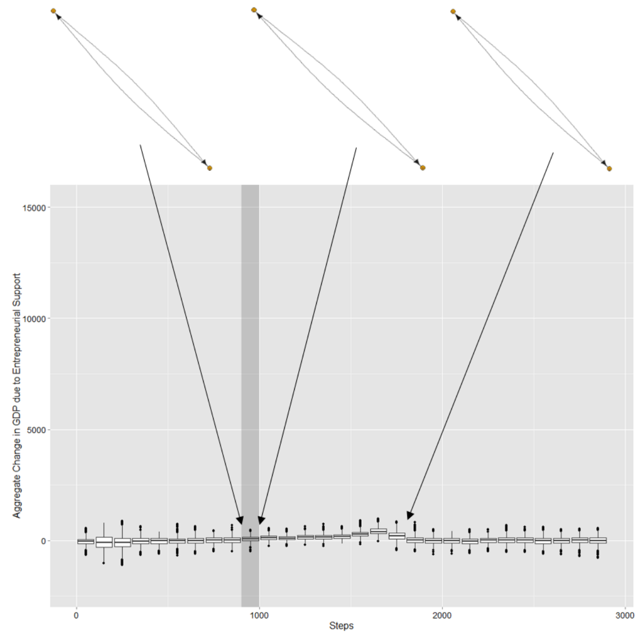
Figure 5 compares the change in GDP due to entrepreneurial support for both cases. It's clear that when the product space is diverse, there is a much larger effect on GDP than when a restrictive product space is used. Comparing the transformation networks for both cases, it is apparent that for the diverse product space, entrepreneurial support triggered the agents to self-organize themselves into a much more highly connected network of product transformation following entrepreneurial support. In other words, they were able to use the energy provided during incubation to form more trade relationships with emerging products.

Figure 6 describes how the popularity of transformation rules themselves were effected due to entrepreneurial support in both product spaces. In the binary product space, the abundance of both transformation rules increased due to incubation, until the sum was equal to the population limit of 3000. After this point, no further improvements to the macroeconomy could be made. In contrast, in the diverse product space, entrepreneurial support caused multiple transformation rules to emerge and dominate over previously dominant transformation rules, representing a period of high innovation. Furthermore, it was observed that 100 steps of incubation triggered around 500 steps of dominance of the new innovative product transformations.

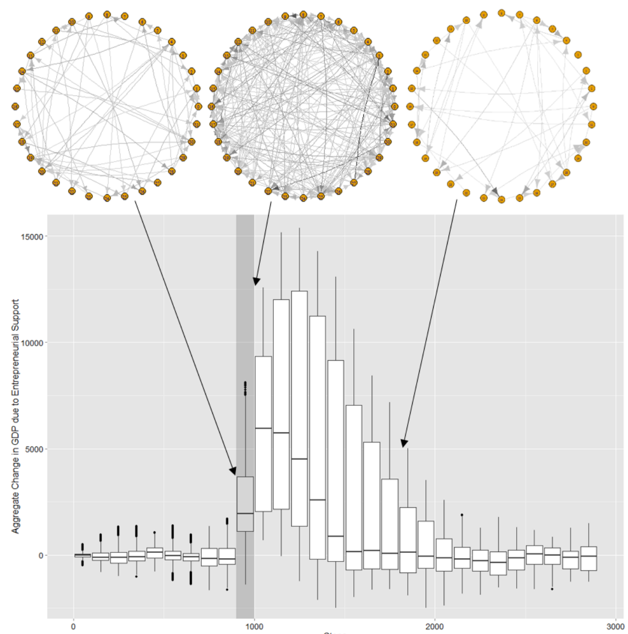
Futhermore, we see that the aggregate improvement in GDP due to incubation, 1000 time steps after incubation has stopped, shows a behavior as shown in figure 7. Since incubation is performed for 100 time steps, 300 agents are incubated and 200 units worth of resources and money are provided a total of 6000000 currency units are provided during incubation. According to 7, for the case of 32 products, at time step 2000, there is a considerable risk of loss (p = 0.7291) due to entrepreneurial support (mean improvement due to incubation at step 2000 is 3692946 units).

V. An Example from the Literature

In addition to experimenting in EconoSim, we replicated our results on an agent-based economics model from the literature, JAMEL [9], [5]. The version of JAMEL we used employed the classical representative agent modeling approach with households, firms and a bank and used a binary product space of labor and consumer good. Our results show that JAMEL, under a binary product space, will not allow for innovation and shows no sustained macroeconomic changes caused by entrepreneurial support.

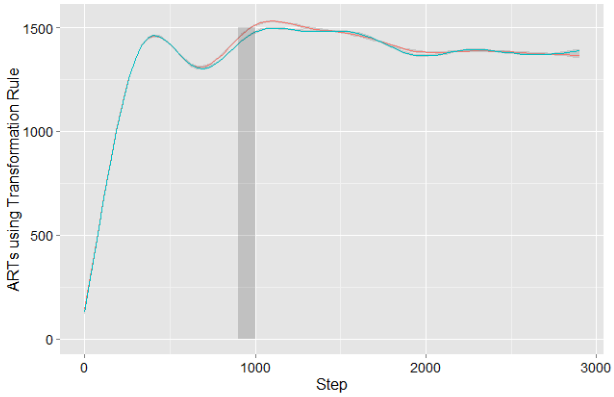


(a) Transformation network structures and aggregated change in GDP caused by entrepreneurial support for the binary product space.

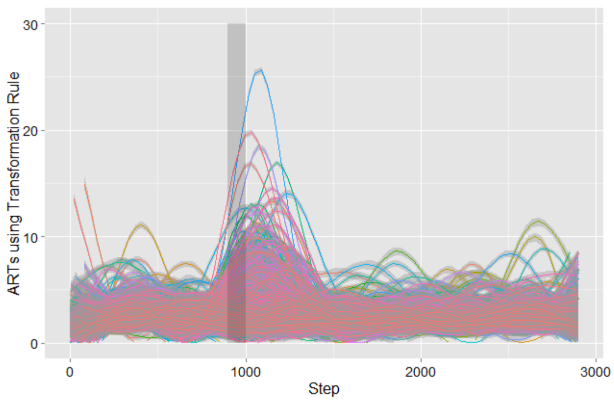


(b) Transformation network structures and aggregated change in GDP caused by entrepreneurial support for the diverse product space.

Fig. 5: Evolution of transformation network structures at step 800, 1100, and 1800 respectively, and the aggregated difference in GDP between the incubated and non-incubated runs on EconoSim.



(a) Number of active agents using either transformation rule over time for the binary product space.



(b) Number of active agents using a particular transformation rule over time for the diverse product space.

Fig. 6: Popularity of each transformation rule over time for both product spaces. Each colored line represents the popularity of a single transformation rule over time.

A. JAMEL

JAMEL employs a representative agent approach for economic modeling and has three main types for agents: *Firms*, *Households* and *Banks*. In addition, JAMEL uses sectors as collections to contain and process the functions of similar agent groups. For example, a household sector, a banking sector and an industrial sector, holding households, banks and firms, respectively. In addition, there would be a capitalist sector of households, which shows the intent of investment in industry. The same household agents can be in both capitalist and household sectors depending on their purposes.

B. JAMEL with Entrepreneurial Support

Entrepreneurial support in JAMEL was performed using a closed system approach using the agent structure of JAMEL to recycle resources to new firms, as well as using an open system approach, where resources and money were injected into the system externally (as done in EconoSim).

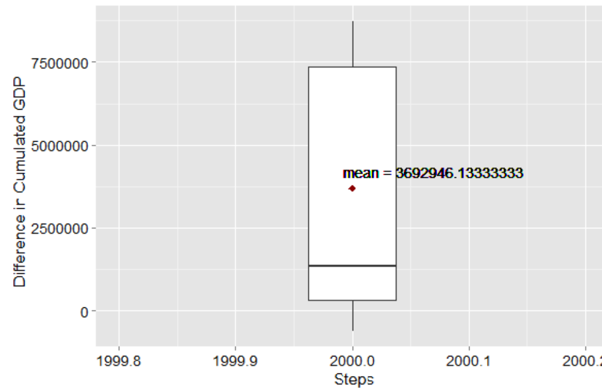


Fig. 7: Aggregate change in GDP due to incubation, accumulated over 1000 steps after entrepreneurial support has been withdrawn for the diverse product case in EconoSim.

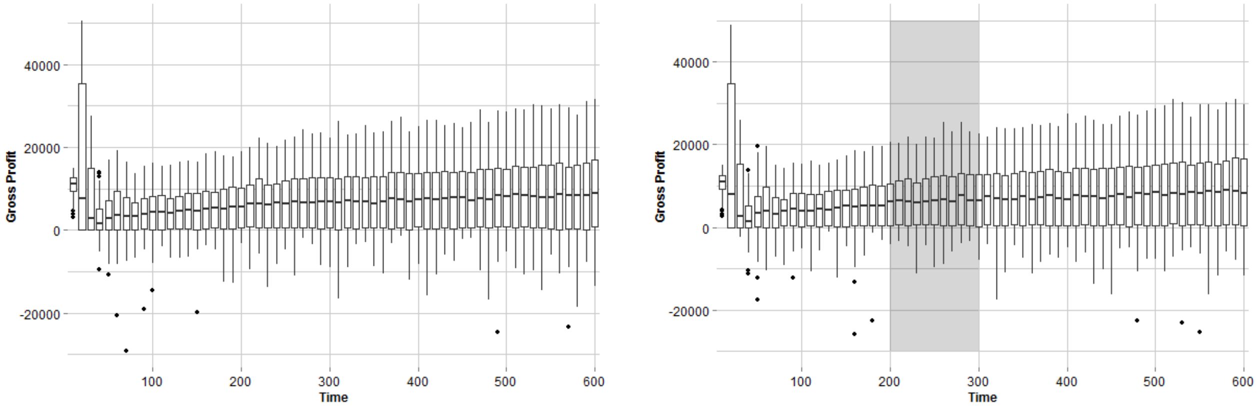
We modeled the closed system entrepreneurial support without modifying the JAMEL's main system characteristics. The entrepreneurial support technique represented resource provision through an external incubator source. Thus, entrepreneurial support involved the injection of energy as direct, external deposits into the incubated firms' bank accounts during the support period. Neither money or labor was being drawn from any internal source. The incubated firms were provided 20% of its worth over the incubation phase.

Entrepreneurial support experiments were performed on JAMEL while gross profit distributions and net value of production were measured. The scenario for each case was initialized with 2000 Households and 95 firms. At period 200, five new firms were introduced into the population and the simulations were ended at period 600. Each experiment was repeated over ten runs. The economic parameters as provided by the baseline experiment definition of JAMEL were used throughout the simulations.

The previous work on EconoSim has identified that selection of the youngest agents from the population proved to result in the highest systemic growth. Therefore, the youngest firms were selected for entrepreneurial support and incubator size was five, effectively selecting the five new firms introduced to the system at step 200. Entrepreneurial support was initiated at time step 200 and continued for 100 time steps. 2% of each firm's gross profit was collected as tax at each time step during the incubation phase and the tax was used to fund the incubatees.

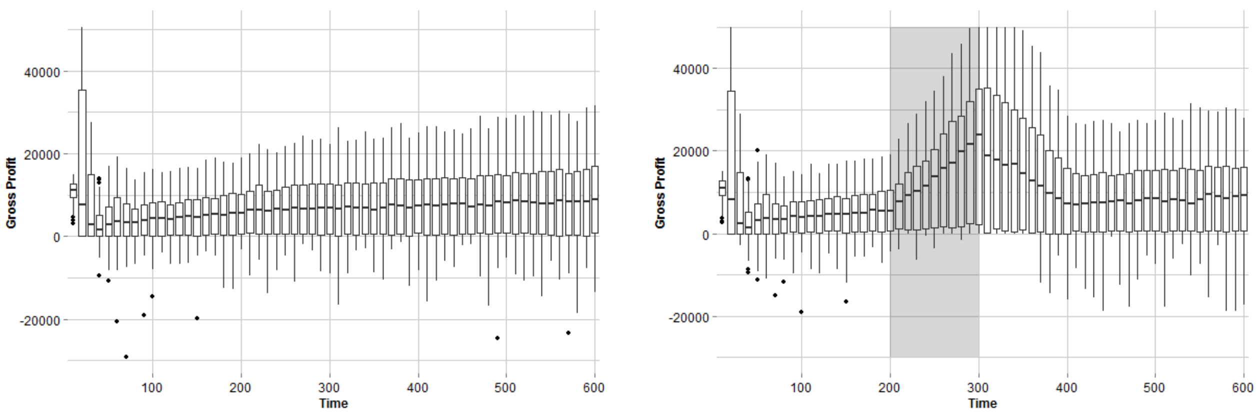
Fig. 8 compares the distribution of gross profit of all firms over time without entrepreneurial support (Fig. 8a) against with entrepreneurial support (Fig. 8b). The results show that there is no significant difference between either case. In other words, entrepreneurial support had no effect on the gross profit distribution of JAMEL over time.

The second experiment involved JAMEL being incubated using an open system approach. Entrepreneurial support was performed as the injection of funds through external deposits



(a) (b)

Fig. 8: Gross profit distribution over time (a)without entrepreneurial support and (b)with entrepreneurial support through redirection of internal funds on JAMEL.



(a) (b)

Fig. 9: Gross profit distribution over time (a)without entrepreneurial support and (b)with entrepreneurial support through external funds on JAMEL.

directly into the incubated firms. In this case the energy was not being drawn from an internal source unlike in the tax-fund entrepreneurial support experiment. The incubated firms were given 20% of its worth during the incubation phase to match the assistance gained by an incubated firm in the previous experiment. Simulations were repeated using selection of youngest and worst performing agents for incubation.

Comparison of gross profit without entrepreneurial support (Fig. 9a) and with entrepreneurial support (Fig. 9b) for the open system approach showed a marked improvement in gross profit during the incubation phase (considering only five of the 100 firms were incubated). Yet, as soon as support was withdrawn, the gross profit returned to the state it was expected to reside in without incubation at the same rate it had increased. In other words, the system was unable to emerge innovative firms, which could have thrived on the external funds provided by reorganizing the internal transformation networks to maintain a state of higher economic value. This can be attributed to the lack of heterogeneity in the resource space and the absence of evolutionary dynamics within JAMEL.

VI. Conclusion

In this paper, we emphasize the importance of evolutionary dynamics within agent-based systems of computational economics by demonstrating the importance of modeling larger and diverse product spaces. A common setback of many models in the literature is the absence of an underlying evolutionary mechanism for agents. We discuss that an economy can be modeled as an ecosystem and evolutionary dynamics form a critical component of these ecosystems.

To demonstrate our argument, we simulated two product space cases on EconoSim, a model of innovation ecosystems

[7], [8], where each agent represents an Adaptive Resources Transformer (ART). An ART buys products from other ARTs, converts it into another type of product according to its transformation rule, and sells it to other ARTs at a rate adjusted by its demand. In the first case, the product space was limited to 2 products creating a binary product space, with 2 maximum possible transformation types. For the second case, the product space was increased to 32 products, allowing for 992 possible transformation types; a much larger space for innovation.

Our results show that in the binary case, agents easily acheive the best possible transformation network configuration, which is to have near equal numbers of ARTs using both transformation types. Therefore, when we attempt to perform a policy experiment in the form of entrepreneurial support we see no change in macro-economic measure.

In contrast, having a diverse product space forced ARTs to discover viable trade partners, while ARTs with new transformation rules emerged in the population. In order to survive, an ART had to discover a viable trade partner before it expended its resources. Therefore, the macro-economic measures were generally less than in the binary product space. However, upon receiving entrepreneurial support, the diverse product space showed a great improvement in the macro-economy. The additional energy provided through entrepreneurial support, helped the ARTs survive long enough to discover their fit within the transformation network. This was seen with the marked increase in the complexity of the transformation network during and right after the incubation period. Furthermore, our experiments showed that in the diverse product space, we had an opportunity to improve the macro-economic value over time by an amount greater than that spent during entrepreneurial support.

It was seen, however, that even in the diverse product space, the transformation network eventually returned to its low complexity state. We attribute this to the lack of *loyalty* between trade partners; although entrepreneurial support allowed for the formation of a stronger network, when an ART within this structure would identify another viable trade partner offering a lower buying price, it would break its stable trade partner relationship and move to the new ART. However, this new relationship is not always as supported by the rest of the population as the previous one. This *disloyalty* among trade partners resulted in the gradual breakdown of the improved transformation network structure.

Repeating these experiments on another ACE model, JAMEL [9], lead us to further support our theory. JAMEL uses a representative agent modeling technique with a binary product space (labor and generic consumer goods). We performed two types of entrepreneurial support on JAMEL, 1) recycling taxed resources into new firms, 2) injecting external energy into incubated firms. In the first case, no change in the macro-economy was observed due to entrepreneurial support. In the second case, the macro-economic measure used (gross profit), showed a momentary improvement with entrepreneurial support but immediately returned to the original state when support was terminated. In other words, the lack of space for innovation left the system with no ability to learn a better structure which could harness the provided energy to greater effect.

In conclusion, we have demonstrated the importance of embodying a diverse product space in ACE models, in order to allow for innovation. Including product space diversity in ACE will allow modelers to study innovation in relation to macro-economic growth and perform innovation-driven policy experimentation as we have, in regards to entrepreneurial support. This work also sheds light on the need to identify and improve the fidelity of modeling *loyalty* or stickiness of the agents, to calibrate the sustainability of stronger transformation network structures discovered during the evolutionary process.

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