An Agent-Based Simulation of Stock Market to Analyze the Influence of Trader Characteristics on Financial Market Phenomena

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Abstract. In this work, an agent-based model of stock market is developed to study the effects of trader's psychological and behavioral characteristics on the overall properties of financial markets. A key feature of this model is local interactions, which allows for global market protocols and behavioral norms to arise from the bottom up. The model stresses interaction and learning between two general types of agents: fundamentalist traders and chartist traders. The behavior of the market as a whole, such as the dynamics of asset prices, is an emergent property of the agents behavior. Statistical analysis of the generated data showed that the model was able to replicate some of the important stylized facts frequently observed in real markets, such as random walk price dynamics, fat tail of the returns and volatility clustering. The time-series generated by the model has been tested with respect to a benchmark provided by the Bank of America (BAC) stock over an adequately long time period.

Additional Key Words and Phrases: Agent-based modeling, Financial market, Learning, Emergent property, Self organization

1. INTRODUCTION

Financial markets play a critical role in todays societies and are extremely important to the general health and efficiency of an economy. Solid understanding of the behavior of financial markets can benefit investors, governing organizations and in general, the whole economic growth. The classical approach to the process of analyzing such systems requires the use of experimental and theoretical models that assume all market participants are perfectly rational and homogeneous and that market price movements incorporate all information rationally and instantaneously [Lo 2005]. Such approaches, with the assumption of market efficiency, have lacked the ability to explain many of the important stylized facts that are present in financial time series and market inefficiencies such as crashes [Hommes 2006]. The field of behavioral finance can handle the aforementioned issues by viewing finance from a broader social science perspective. Previous works presented in this field have provided evidence that, in addition to information, emotions play a significant role in decision-making process [Nofsinger 2005]. Behavioral finance considers non-standard models, in which the price movements are influenced by the actions of heterogeneous boundedly rational traders, whose decisions are significantly driven by emotions such as fear or greed. These type of models are able to explain and replicate stylized facts and market inefficiencies.

Financial markets consist of boundedly rational participants whose interactions and adaptive behaviors lead to a world of complexity. Such systems often create internal structure and dynamics that give rise to unique and unexpected (emergent) macroscopic properties. This has led us to Agent-based Modeling (ABM), which is the methodology followed in this paper. An agent-based approach models the financial markets in an incremental bottom-up fashion, as an evolving adaptive system of autonomous interacting agents. This approach makes it possible to start from very simple setting and add different variables and components as the system goes on. Therefore, the agent behavioral rules can be set along the way according to the requirements of each given experiment. This makes it possible to analyze the influence of different characteristics on various phenomena.

In this paper, an agent-based model of stock market is developed. The goal is to understand to the effect of endogenous variables and traders characteristics such as imitation, learning and switching strategies on the macro-level behaviors and patterns in stock markets. Furthermore, we are interested to investigate different parameter settings that would replicate some of the characteristics of real financial time series.

The reminder of this paper is organized as follows: In Section 2,the literature on agent-based models of financial markets is reviewed. Section 3 presents our approach. Statistical analysis of the model's results and BAC time series, along with the investigation of the stylized facts are given in Section 4. Summary and conclusions are presented in Section 5.

2. BACKGROUND

In this section, some of the previous agent based financial market models are reviewed. In try to categorize different agent-based models, it is helpful to classify them based on their agent's complexity. This can range from simplest settings with only two-types of agents learning with imitation and reinforcement algorithms all the way to many type agents with complex learning algorithms such as genetic programming and neural networks.

The two-type design is the simplest kind with respect to heterogeneity. There are generally two different types of trading strategies that financial agents follow, fundamental and technical. Fundamentalists and chartists (technical, trend- follower) have very different views on price dynamics. The former make decisions with the assumption that the price of an asset returns to its fundamental value in the long run, while the latter are mostly concerned about the trends and patterns observed in the past prices.

Zeemans's model [Zeeman 1974] is a pioneer in financial market models with fundamentalists and chartists, and a large number of the literature was developed following the lead of him. He proposed a qualitative description of the stylized facts observed in short-term bull and bear markets. In the model, fundamentalists are assumed to know the intrinsic value of the stock and they only buy (sell) when the observed price is below (above) that value. Chartists, on the other hand, believe that prices move in trends so they buy when price rises and sell when it falls.

Another example of the two-typed design is the model developed by Westerhoff [2008]. The agents could select one of the technical or fundamental trading rules or they could stay inactive. The choice of traders is based on past performance of the trading rule and the price adjustment process depends on the excess demand in the market. The model was very successful in reproducing some of the important stylized facts of financial markets.

Three-type design, which is an extension of two-type design, adds to the heterogeneity of the agents. With the risen capability of observing the behavior of financial agents due to large amount of proprietary trading data, it can be confirmed that chartists can be further divided into optimists and pessimists. Optimist traders are the same as previously defined chartists, whereas pessimists act completely opposite to that. They still look at the past movements of the price to predict the future, but act against the trend, anticipating that the trend will soon be finish and reversed. Lux and Marchesi [2000] developed a model with these three types of agents, either an optimistic or a pessimistic chartist or fundamentalist. Traders can switch between chartist and fundamentalist and within chartist, between optimistic and pessimistic strategies and the price is determined based on the aggregated excess demand.

Many-type designs introduce new approach that let artificial agents become more real by learning and creating new strategies on their own. They use artificial intelligence to model evolution and learning. One of the interesting characteristics of many of these models is that agents start with very homogeneous features and evolve in their features and rules endogenously over time. The Santa Fe Artificial Stock Market (SFI-ASM) [Arthur, Holland, LeBaron, Palmer, & Tayler 1996] is a pioneer and most influential work in this area.

3. AGENT-BASED MODEL

In this paper, the methodology of two-typed design suggested by Westerhoff [2008] is followed to model the stock market. The two typed design is chosen to allow for a less complicated validation process and better tractability of the model's parameters. The proposed approach to model the stock market differs from the original model, mainly in the interaction and learning behavior of the agents and the level of heterogeneity among traders. To make every fundamentalist and chartist unique, different memory length and reaction intensity to price and fundamental changes are assigned to each agent, which will be described in details later in this section. This added heterogeneity provides a better approximation of the reality of financial markets and traders. In addition, in order to gain a broader global insight to trading strategies and evolution of the agents, local interactions are introduced instead of general fundamentalist to chartist communication.

3.1 The Asset

The model describes daily stock trading with only one risky asset of the price P_t at time t. The fundamental value of the asset F_t is publicly available to all traders. It is assumed that the fundamental price of the risky asset is given exogenously as a random walk process:

$$F_t = F_{t-1} + \eta \tag{1}$$

where, the current value of the variable is comprised of the previous period's value and a white noise element. η is a normal noise process with zero mean and constant standard deviation σ_η, added to take the fundamental shocks into account.

3.2 The Market Maker

In this model, two types of agents are introduced: the market maker and traders. At the end of each trading day, the market maker sets the price at which a trader can buy or sell the asset. Following

[Day & Huang 1990], a simple price adjustment scheme based on the excess demand is used as,

$$p_{t+1} = p_t + a(1 + D(t) - S(t)) + \delta \tag{2}$$

where, a is a positive coefficient, which can be explained as the speed of price adjustment, $D(t)$ is the number of buy and $S(t)$ is the number of sell orders at time t. A random term (a normal, IID noise process with zero mean and constant standard deviation σ_δ) is also added to the equation to account for more variety and unknown facts, contributing to price change.

3.3 The Trader

There is a fixed number of N traders in the market. At the beginning of each simulation, all traders are assigned the same amount of cash and shares of a single stock. At each time step t, a given trader can choose between three actions $\{+1, -1, 0\}$: +1 if he decides to buy one unit of the stock, -1 if he decides to sell one unit of the stock, or 0 if he remains inactive.

Traders can pick any of two general belief systems, technical or fundamental trading rules at the start of each trading period. Fundamentalists make decisions with the assumption that the price of an asset returns to their fundamental value in the long run. Therefore, they try to buy (sell) the asset when the price is below (above) its fundamental value. Their expectation of the next period price can be written as:

$$E_t^f[p_{t+1}] \ = \ p_t + f * (F_t - p_t) + \alpha \tag{3}$$

where, p_t is the current price and f is a positive coefficient that describes fundamentalist mean-reverting belief. The parameter f is basically specifying the speed with which fundamentalists expect the price to return to its fundamental value. The random variable α (a normal, IID noise process with zero mean and constant standard deviation σ_α) is included in the equation to account for perception errors or uncontrollable elements.

On the other hand, chartists are mostly concerned about the trends and patterns observed in the past prices so they buy when price rises and sell when it falls. Their expectation of the next period price can be written as:

$$E^c_t[p_{t+1}] \;=\; p_t + c * (p_t - p_{t-1}) + \beta \tag{4}$$

where, c is a reaction coefficient, conveying the sensitivity of chartists to price change, and $p_t - p_{t-1}$ indicates the trend. Chartists extrapolate and predict the price change rate to be proportional to the latest observed change. The random term β is a noise process (a normal, IID noise process with zero mean and constant standard deviation σ_β) that captures the diversity and uncontrollable elements in technical analysis.

In order to account for individual heterogeneity, fundamentalists and chartists are assigned with different mean-reverting and reaction intensities. Each fundamentalist and chartist is assigned a random f and c coefficients derived from a random normal distribution with mean μ_f and μ_c and standard deviation σ_α and σ_β.

3.4 Interaction and Learning

The approach used to model social interactions and learning among agents is based on local interactions. The attractiveness of each trader's rule is represented by past myopic profitability of the rules and can be formalized as:

$$S^f_t \;=\; (\exp[p_t] - \exp[p_{t-1}]) * (f(F_t - p_t) + \alpha) + mS^f_{t-1} \tag{5}$$

$$S^c_t \;=\; (\exp[p_t] - \exp[p_{t-1}]) * (c(p_t - p_{t-1}) + \beta) + mS^c_{t-1} \tag{6}$$

where, S^f_t and S^c_t are the fitness of fundamentalist and chartist trading strategies respectively. In order to account for the past performance of each rule, a memory parameter m is introduced. Each agent is assigned a unique memory length at the beginning of the simulation. $m = 1$ results in the fitness to be the sum of all past observed profits, while $m = 0$ indicates that agent has no memory and the fitness is the current profit.

In the two-type fundamentalist/chartist model, agents can only choose between two rules, therefore modeling the switch is typically done using a binary choice model, particularly, the logit model [Luce 2005]. At the end of each trading day, every agent meets agents on its neighboring patches. Given the uniqueness of each fundamentalist and chartist, the average utility associated with each type in the neighborhood is calculated and compared. Agent then chooses the more profitable rule with the probability that the gained profit is larger than the other rule:

$$P(X = f) = \frac{\exp[\lambda \bar{S}_t^f]}{\exp[\lambda \bar{S}_t^f] + \exp[\lambda \bar{S}_t^c]} \tag{7}$$

where, $P(X = f)$ is the probability that the agent chooses fundamental trading rule, $\bar{S}_t^f$ and $\bar{S}_t^c$ are the average profit made by neighbor fundamentalists and chartist, and the parameter $\lambda \geq 0$ is the intensity of choice. If $\lambda = 0$, no switching is going to take place between strategies, while all agents instantaneously switch to the best strategy when $\lambda = +\infty$.

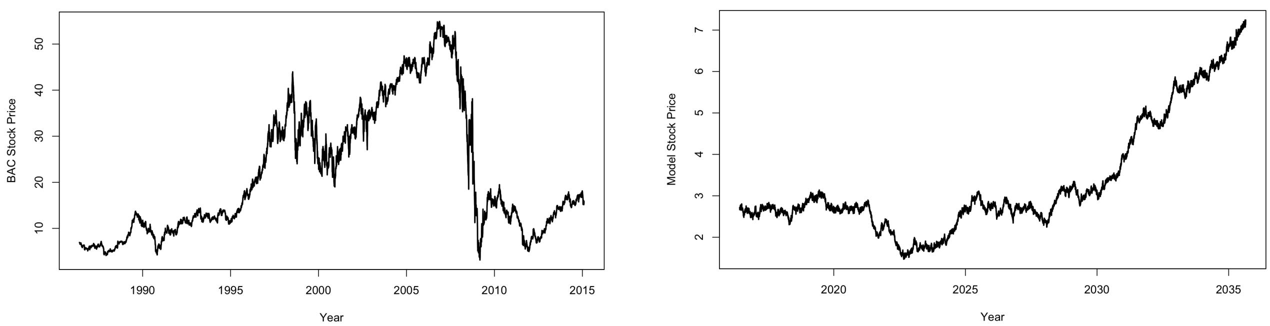
4. SIMULATION RESULTS

The Bank of America (BAC) stock is used as benchmark for model validation. The data of the BAC covers the period between May 1986 to February 2015 of 7230 daily observations. The data is collected from the [*Yahoo Finance* n.d.]. We have performed statistical analysis on BAC and the model generated time series with 7000 observations. The focus of analysis is on statistical properties of the distribution of stock returns, random walk price dynamics, and the volatility clustering in the market. The parameters of the model have been adjusted to reproduce some of the stylized facts in the market. Table I provides the values of the parameters used in the simulation.

First, we are going to look into the random walk price dynamics in financial markets. The graphs in Figure 1 shows the daily development of prices for BAC and the model. Both series appear to have an

Table I. : Parameters of the Stock Market

Parameter	Definition	Value
N	Number of traders	1000
a	Price adjustment	0.2×10^4
c	Reaction coefficient	$N(\mu_c : 0.05, \sigma_c : 0.01)$
f	Reverting coefficient	$N(\mu_f : 0.04, \sigma_f : 0.01)$
σ_η	Standard deviation of random factor in fundamental price process	0.026
σ_δ	Standard deviation of random factor in price process	0.025
σ_α	Standard deviation of random factor in fundamental trading	0.01
σ_β	Standard deviation of random factor in technical trading	0.05
λ	Intensity of choice	90
m	Memory of traders	$m \in [0, 1]$



(a) (b)

Fig. 1: Time series of stock prices (a) BAC (b) Model.

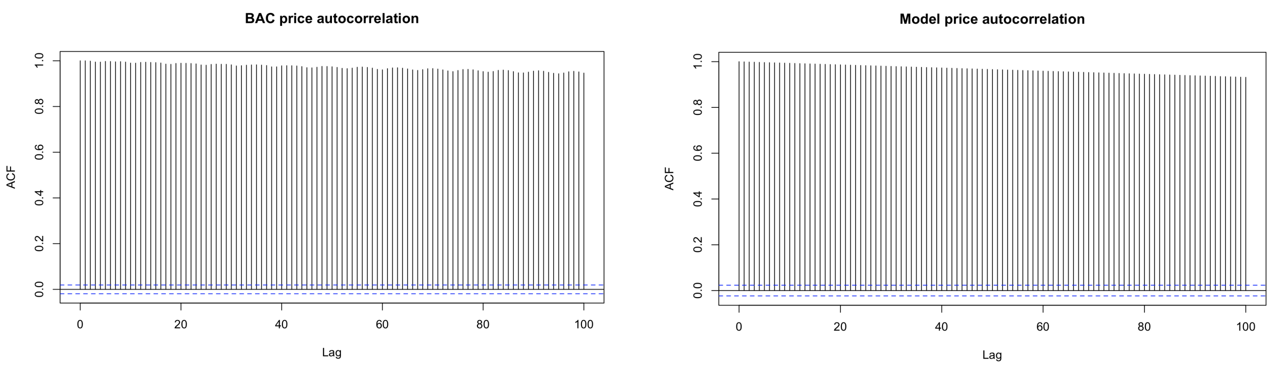
obvious upwards trends. In non-stationary time series, the mean and variance change over time and prices do not have tendency to come back towards their average, which appears to be the case here, too. Following the standard econometric practice, an augmented Dickey-Fuller [Dickey & Fuller 1981] unit root test is conducted on the price time series to examine for stationarity. Tables II and III and Figure 2 represent the results of the tests, which examines the null hypothesis of non-stationarity. ACF plots demonstrate that the correlation between the time series and its lags fall outside the 95% of confidence interval of no auto correlation for 100 lags. Also, the P-values of zero-mean Dickey-Fuller test statistic,

Table II. : Augmented Dickey-Fuller unit root test for BAC price

Type	Lags	Rho	P < Rho	Tau	P < Tau
Zero Mean	0	-0.0703	0.6671	-0.09	0.6529
	1	-0.0784	0.6653	-0.10	0.6497

Table III. : Augmented Dickey-Fuller unit root test for model price

Type	Lags	Rho	P < Rho	Tau	P < Tau
Zero Mean	0	1.3832	0.9588	1.63	0.9755
	1	1.5068	0.9681	2.25	0.9946



(a) (b)

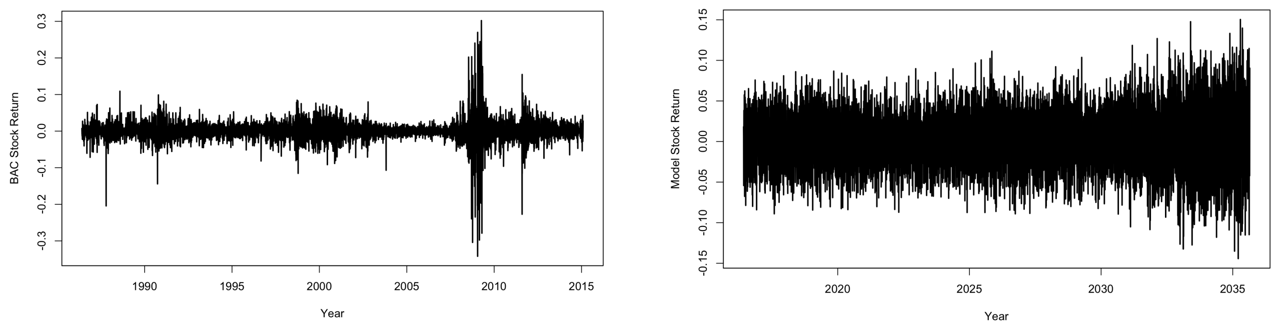
Fig. 2: The autocorrelation function for price (a) BAC (b) Model.

which tests for random walk with no trend and drift, cannot reject the null hypothesis that the series are non-stationary. The results confirm that both prices are in fact random walk and the model price resembles the dynamics of the prices in real market.

Non-stationary data are unpredictable, therefore they cannot give us meaningful sample statistics and correlations with other variables. In order to induce stationarity, first differences of logs of the price series, also know as the stock returns, are derived as:

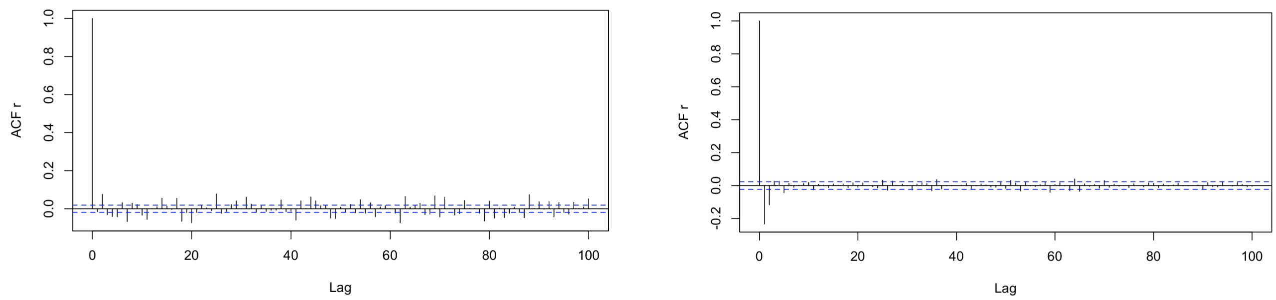
$$r_t = \ln[p_t] - \ln[p_{t-1}] \tag{8}$$

Figure 3 shows the plots of stock returns for both BAC and the model time series. They appear to have constant mean and variance change over time. the Dickey-Fuller test is repeated on the return



(a) (b)

Fig. 3: Time series of returns (a) BAC (b) Model.



(a) (b)

Fig. 4: The autocorrelation function for raw returns (a) BAC (b) Model.

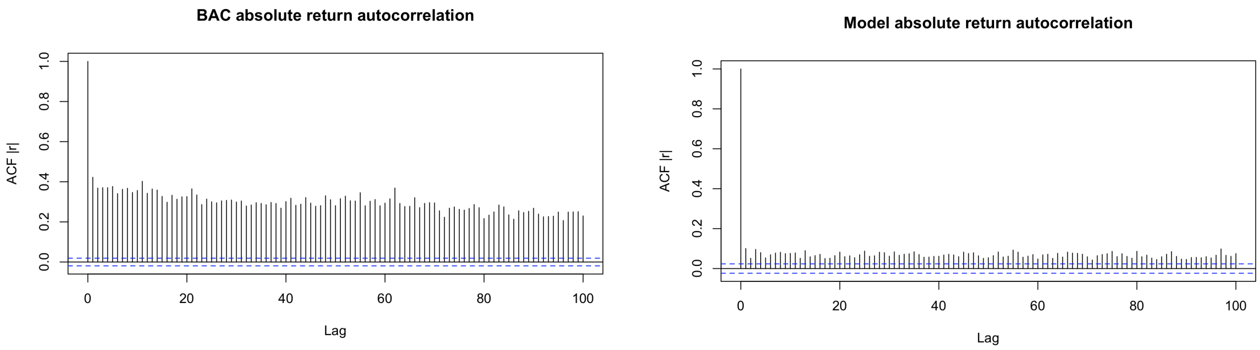
time series and the results are shown in Figure 4 and tables IV and V. ACF plots demonstrate that there is no correlation between the time series and its lags after the first few lags. In addition, the P-values of Dickey-Fuller test statistic for both time series reject the null hypothesis that the series are non-stationary.

Table IV. : Augmented Dickey-Fuller unit root tests for BAC return

Type	Lags	Rho	P < Rho	Tau	P < Tau
Zero Mean	0	-7150.46	0.0001	-84.09	<.0001
	1	-6803.75	0.0001	-58.31	<.0001

Table V. : Augmented Dickey-Fuller unit root tests for model return

Type	Lags	Rho	P < Rho	Tau	P < Tau
Zero Mean	0	-8657.28	0.0001	-106.19	0.0001
	1	-12486.6	0.0001	-78.95	<.0001



(a) (b)

Fig. 5: The autocorrelation function for absolute returns (a) BAC (b) Model.

The next property we are going to investigate is volatility clustering phenomenon, which describes the fact that high-volatility events tend to cluster in time. Empirical analysis on financial markets shows different measures of volatility display a positive autocorrelation over several days.

A common proxy for volatility is given by the absolute return. Figure 5 displays the autocorrelation of absolute returns in both BAC and model stock returns. The dotted lines specify the 95 percent confidence intervals. Notice that for both cases, despite the absence of autocorrelation in raw returns, the autocorrelation of absolute returns are positive and significant. This is a clear evidence of volatility clustering.

Finally, table VI presents some of the basic statistics of the return time series.

Excess kurtosis is an indicator of departure from normality. For a normal distribution, the excess kurtosis should be 0. However, in financial data, the excess kurtosis of return time series is larger than 0, indicating that the distribution of returns displays a heavy tail [Lux & Alfarano 2016].

Table VI. : Basic statistics of stock returns for model and BAC

Model				
a	Mean	Variance	Skewness	Excess Kurtosis
0.00002	0.000647	0.001328	0.084513	0.197373
0. 0001	0.000642	0.001005	2.307299	15.32734
BAC				
	Mean	Variance	Skewness	Excess Kurtosis
	0.000115	0.000711	-0.359977	26.81

The kurtosis of 26 for the returns on BAC stock is a strong evidence against normality and existence of fat tail. It has been observed that the kurtosis of the returns in the model is sensitive to the speed of price adjustment, a. As it is demonstrated in table VI, the increase in a from 0.00002 to 0.0001 results in excess kurtosis, hence the fat tail in return distribution.

5. CONCLUSION

Viewing financial markets as a large number of boundedly-rational, heterogeneous agents makes it possible to explain social phenomena and macroscopic properties by micro behaviors of traders and market. This paper developed a two-type agent-based model of the stock market, where traders can choose between either fundamental or technical trading rules. The two-typed design was chosen to allow for tractability of the model's parameters.

Local interactions and heterogeneity among fundamentalists and chartists has been introduced to provide a better approximation of the reality of financial markets and traders. The model was able to reproduce some of the important stylized facts of financial time series, such as random walk price dynamics and volatility clustering, solely from interaction and learning between traders. Additionally, it has been observed that the kurtosis of return distribution is sensitive to the price adjustment coefficient. By increasing the speed of price adjustment, the fat tail in return distribution could be achieve.

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