Modelling an Artificial Financial Market: Agent Based Approach[1]

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Abstract

A primitive agent-based artificial financial market is created based on the Genoa market model introduced by Raberto et al., (2001). We aim to replicate the stylized fact of financial asset returns to assure validity of model. Agents are endowed with prespecified cash and assets amount. Agents based simulation is run under different scenarios and results are examined. Agents differ when trading as being noise trader or an agent using technical trading. The model was able to replicate leptokurtic shape of probability density function, absence of autocorrelation and volatility clustering.

Key words: Artificial Financial Market, Agent Based Model, Heterogenous Agents

JEL Classification: C63, G1, G20, G11, D31

Yapay Finansal Market Modelleme: Ajan Temelli Yaklaşım

Öz

Raberto ve diğerleri (2001) tarafından sunulan Genoa piyasa modeline dayanarak, ilkel bir ajan tabanlı yapay finansal piyasa yaratılmıştır. Modelin geçerliliğini sağlamak için finansal varlık getirilerinin

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"stylized fact" olgusunu tekrarlamayı hedefliyoruz. Ajanlara önceden belirlenmiş nakit ve varlık tutarı atanır. Ajan tabanlı simülasyon farklı senaryolar altında yapılarak sonuçlar incelendi. Ajanlar, alım satım yaparken gürültücü yatırımcı veya teknik indikatörleri kullanan bir ajan olarak farklılık gösterir. Model olasılık yoğunluk fonksiyonunun leptokurtik şekli, getirilerin otokorelasyon yokluğu ve uçuculuk kümelenmesi özelliklerini tekrarlamıştır.

Anahtar kelimeler: Yapay Finansal Piyasa, Ajan Temelli Model, Heterojen Ajanlar

JEL Sınıflandırılması: C63, G1, G20, G11, D31

1. Introduction

The idea of representative agents with rational expectation has been challenged by findings that cannot be explained with these assumptions. In this sense, alternative approaches have been suggested to overcome with these limitations and to propose a model that can mimic real market findings. The representing agents with rational expectations is shifted to boundedly rational agents with heterogenous expectations.

As it is investigated, it is not easy to explain some financial time series features, the so-called stylized facts, with paradigm of homogenous agents and rational expectations. Besides, agents have heterogeneous beliefs and behavioural rules, and it may change over time because of social interaction and evolutionary selection (see Lux, 1995, Arthur et al., 1997b, and Brock and Hommes, 1998). In this regard, alternative approaches are to be considered such as agent-based and behavioural economics. Jean-Claude Trichet, the former ECB president, writes "We need to deal better with heterogeneity across agents and the interaction among those heterogeneous agents" (Dieci, 2017).

This study focuses on Agent Based Models (ABM) with its applications in finance, its aim is to model an artificial financial market resulted from the interaction of heterogeneous investors with different behavioural rules, such as fundamental and technical trading rules. As a first model of this study, a primitive agent-based artificial financial market is created based on the Genoa market model introduced by Raberto et al., (2001). In this model, heterogenous agents trade one single asset and asset price formation is based realistic trading mechanism. Agents are endowed with cash and assets, agents make buy and sell decisions based on their trading tool with constraint of available resources. The decision is not totally random since it depends on clustering of agents and previous periods volatility. The model was able to replicate some the stylized fact of financial asset returns namely leptokurtic shape of probability density function and volatility clustering.

Satisfying the stylized facts serves as a benchmark for ABM models as assures the success of the model. If ABMs show common stylized facts, they can be used to get insights of the real market through experiments. These models make it possible to understand the forces that drive trader behaviour and the market dynamics, especially when it is hard to find analytical solutions mathematically (LeBaron, 2001).

There are several ABM studies that exhibit the stylized facts observed in the market (Brooks, 1996; Levy and Solomon, 1996; Arthur et al., 1997; Lux and Marchesi, 2000; LeBaron, 2001; Farmer and Joshi, 2002; Iori, 2002; LiCalzi and Pellizzari, 2003; Cincotti et al., 2005; Alfi, 2009; Martinez-Jaramillo and Tsang, 2009; Lux and Alfarano, 2016; He and Li, 2017). Although an agent-based financial markets have great advantages when modelling markets, it has been criticized for its complexity (calibration problem) and its requirement for numerous parameters (Winker and Gilli, 2001; LeBaron, 2003; LeBaron, 2006).

This study has three main contribution to the agent-based financial market modelling literature: (1) we have re-implemented Genoa market model (Raberto et al., 2001) and we present similar results; (2) we have diversified agent types and equipped agents with realistic technical trader tools for decision making and a similar extension was applied by Llacay and Peffer (2018) to Farmer and Joshi (2002) market model; (3) we have analysed wealth dynamics of agent types and questioned if intelligent traders outperform noise traders.

This study is structured as five parts, the literature review is given in the second part, the model description and model parameters setting are given in the third part, simulation results are given in fourth part and the study is concluded in the last part.

2. Literature Review

Financial Markets are institutions where financial securities, commodities and other assets are exchanged. Some well-known financial markets could be categorized as stock market, commodity markets, bond markets, derivatives market, and foreign exchange markets.

Financial data reveal some common properties which are not in line with Efficient Market Hypothesis (EMH). These statistical properties are called "stylized facts" (Dacorogna, 2001). These stylized facts are independent of time and considered important for evaluating ABMs since they are taken as benchmark. Certain stylized facts commonly observed in financial markets and referred in literature are as follows:

- Absence of linear autocorrelation (in foreign exchange market by Hsieh (1989), in Sterling market by Brooks (1996)).
- Heavy tails (fat tails)
- Volatility clustering (Mandelbort 1963; Engle 1982; Bollerslev, 1986))
- Volume/volatility correlation
- Aggregational Gaussianity

Under EMH, these stylized facts are supposed not to emerge. In this regard, alternative approaches for modelling financial markets was inevitable. LeBaron (2001) puts forward the necessity of computational tools for understanding and exploring financial markets since analytical models have limitations in modelling. Hence, ABMs have been an essential tool in describing trading patterns in financial markets (Farmer and Foley, 2009). They gave birth to simulation programs that emulate real market. This is a growing area. A review of ABMs and its simulations in financial markets could be found in LeBaron (2001), LeBaron (2006), Samanidou (2007) and Cristelli et al. (2011).

There are number agent-based financial market models mentioned in introduction part. These models differ with those choice of design, and benchmark and validation.

Developing an ABM requires an appropriate design. Four main design elements are market mechanism, trading strategies, traded assets and trader types. LeBaron (2001) provides a good review about the choices of ABM design.

Market mechanism is an important part of ABMs. In the literature, it is handled in four ways. First way is about determining prices that result from excess supply and demand (Martinez-Jaramillo and Tsang, 2009; Cont and Bouchaud, 2000; and Chen and Yeh, 2001). Some advantages of this method are tractability, speed and allowance the market to be in disequilibrium. On the other hand, it is sensitive to changes in parameters. Secondly, an equilibrium price could be found in the market (Levy et al., 1994; Arthur et al., 1997). This has the advantage of being easy in generating demand function for agents. The third approach to market mechanism is about modelling actual market trading system. According to LeBaron (2001), this method is suitable for high-frequency world. However, applying this model requires a good knowledge of market structure. The last method is about figuring out a continuous double auction mechanism with limit orders and other real market features. This very method is widely used in literature (Cliff and Bruten, 1997; Iori and Chiarella, 2002; Roberto and Cincotti, 2005).

Agent trading strategy is another crucial part of building a financial market model (LeBaron, 2001). Trading strategies of agents in an ABM ranges from budget constraint zero intelligence agents (Arthur, 1991; Gode and Sunder, 2004) to intelligent agents (Cliff, 1997; Lux and Schornstein, 2005; LeBaron, 2002). Llacay and Peffer (2018) used agents with real market trading strategies.

Forecasting future price is part of decision making for intelligent agents who use evolutionary techniques such as genetic programming, genetic algorithms, artificial neural network, and learning classifier system. Agents can change their forecasting strategy as they adapt to new market conditions. Studies using learning agents with evolutionary techniques include Amilon (2008), Arthur et al. (1997) and Chen and Yeh (2001).

Agents can be allowed to have a certain *objective function* used in decision making process. This objective function can be of two types: implicit and explicit. *Implicit* objective function is indirectly incorporated into decision making process while in *explicit* objective function, agent's performance is evaluated directly via a utility function (Chen and Yeh, 2001; Arthur et al., 1994)

In social learning, agents observe other agents' trades in the market and can change their strategy (LeBaron, 2006; Lux, 1998; Alfarano et al., 2005). For instance, Hott (2009) shows that herding behaviour is the reason for price bubbles in the market.

Choosing for traded assets in ABMs constitute another part of design. This can be in terms of number of assets, asset properties and asset types. In literature, ABMs with one risky asset and one risk-free asset are preferred most of the time (LeBaron, 2001). ABMs with multi-assets are employed by Cincotti et al. (2005), Westerhoff, F. (2004), and Hommes and LeBaron (2018).

Time is another design issue since ABMs learn from previous information in the market. LeBaron (2001) conduct experiments to explore the effect of different memory lengths on market prices. ABM trading is mostly synchronized by the designer (LeBaron, 2001). At each step, agents update their strategies. The choice can be between discrete-time or continuous-time trading. However, doing trading computation at each step is time costly.

Validation of an ABM is vital since it ensures the appropriateness of the model for capturing real financial markets. In the literature, this validity is obtained by the capacity of the model to reproduce the stylized facts witnessed in the market. The constituents of modelled market need to be well defined (LeBaron, 2001). Alternatively, real market parameters can be used as benchmark (Lux, 1998; Chen and Yeh, 2001; LeBaron, 2003). The reason why these studies prefer this parameterization is to avoid complexity and reaching tractability. Therefore, the minimal parameter selection is possible with experiment to get right value of parameters.

3. Artificial financial market

There are number of artificial financial stock markets and in this study Genoa Artificial Stock Market (Genoa ASM) is extended by adding new type traders called technical traders. Every simulation was run with two type traders and one of which is noise trader who randomly decide. Technical traders could be named by the indicator they use to trade. We employ two different commonly used indicator named Rate of Change (ROC) and Bollinger Bands (BOL).

3.1. Extended Genoa artificial financial market

The market is consisting of N traders and i refers i^{th} trader. Simulation time evolves in discrete steps. A trader's amount of cash at time t is denotated as $C_i(t)$ and the amount of assets trader owned is $A_i(t)$. The price of the stock at time t is denotated as $p(t)$. Every agent in market is assigned as noise or technical trader with a random process. Every agent is assigned to be noise or technical trader with a predetermined share of technical trader in market. There are two different market exercises, in both exercises there are noise traders and technical traders which are named by the tool they use to trade. In the first exercise there are there are noise traders and rate of change (ROC) traders and in the second exercise, there are noise traders and Bollinger Bands (BOL) traders.

Noise trader has a buy probability of p_i and sell probability of $(1-p_i)$ while technical traders are to be buyer or seller based on the indicator used so it is not a random process. The p_i is set to 0.5 for agents called noise for each step of simulation.

ROC is final indicator used in this study and its calculation is simple:

$$\text{Price ROC} = \frac{\text{B}-\text{A}}{A} \cdot 100 \qquad (1)$$

where B is current price and A is price at previous time. If ROC value is positive, agents take long positions and if it is negative, they take short position.

BOL-traders takes 14-day moving average of asset price and calculates upper and lower bands by adding and subtracting two standard deviations from moving average, respectively. Formally,

$$\text{BOLU} = \text{MOV}(\text{AssetPrice}, 14) + 2 \cdot \sigma_{\text{AssetPrice}} \qquad (2)$$

$$\text{BOLD} = \text{MOV}(\text{AssetPrice}, 14) - 2 \cdot \sigma_{\text{AssetPrice}} \qquad (3)$$

where:

BOLU=Upper Bollinger Band

BOLD=Lower Bollinger Band

MOV=Moving Average

If asset price is higher than upper Bollinger band, agent takes short position while agent takes long position if asset price is lower than lower Bollinger band. If none of these conditions satisfies, there is no trade.

Suppose i^{th} trader is seller at time t+1 and the quantity it offers to sell is a_i^s, which is a random fraction of assets owned at time step t+1. Formally, a_i^s=$[r_i\ A_i(t)]$ where r_i is a randomly generated number from a uniform distribution in the interval [0,1] and [w] denotes the truncated part of w.

Sell limit price is stipulated as s_i= $p(t)\ / N_i(\mu, \sigma_i)$ to assure that sell orders are not executed at prices below the limit price. $N_i(\mu, \sigma_i)$ is a random draw from a Gaussian distribution with average $\mu = 1.01$ and standard deviation σ_i.

The σ_i is proportional to historical volatility $\sigma(T_i)$ of the price $p(t)$ with the equation $\sigma_i = \mathrm{k}\,\sigma(T_i)$ where k is a constant and $\sigma(T_i)$ is standard deviation of price log-returns. Raberto et al. (2001) found that optimal values as $k = 3.5$ and time window $T_i = 20$. Setting a link between limit orders and volatility helps to catch a realistic aspect of trading behaviour: the higher volatility the more uncertainty.

The amount of buy and sell orders are symmetrical. If agent i is buyer at time $t+1$, the amount of cash the agent employs to buy stock, C_i, is a random fraction of its available cash at time t; C_i=r_i $C_i(t)$.

Buy limit orders are stipulated like sell orders, b_i= $p(t) * (\mu, \sigma_i)$ to assure that buy orders are not executed at prices higher than the limit price. $N_i(\mu, \sigma_i)$ is a random draw from a Gaussian distribution with average $\mu = 1.01$ and standard deviation σ_i. Suppose i^{th} trader is buyer at time t+1 and the quantity of assets ordered is a_i^b, which is a random fraction of assets owned at time step t+1. Formally, a_i^b=$[c_i/b_i]$ where [w] is the integer part of w. It is to note that b_i can be higher than limit price and s_i could be lower than limit price since $N_i(\mu, \sigma_i)$ is a random draw from a Gaussian distribution with average $\mu = 1.01$ and standard deviation σ_i.

The price formation is set as intersection of supply and demand function. The computation of these functions at $t+1$ is as follows. Let limit price at $t+1$ is p and agents issue U sell order and V buy order. The pair (a_u^b, b_u) indicates, respectively, the quantity of stocks to buy and the associated limit price. The pair (a_v^s, b_v) indicates, respectively, the quantity of stocks to sell and the associated limit price. Thereby, the functions are defined as:

$$f_{t+1}(p) = \sum_{u|b_{u \geq p}} a_u^b \tag{4}$$

$$g_{t+1}(p) = \sum_{v|s_{v \leq p}} a_v^s \tag{5}$$

$f_{t+1}(p)$ represent the total amount of stock would buy at price p (demand function) and it is a decreasing step function of p. If p is greater than the maximum value of b_u then $f_{t+1}(p)$ =0. If p is lower than the minimum value of b_u then $f_{t+1}(p)$ is the sum of all stocks to buy. Conversely, supply function $g_{t+1}(p)$ is an increasing step function of p and its properties are symmetric to $f_{t+1}(p)$.

The clearing price p* is where supply and demand function intersect. The limit price for next step is p(t+1) =p*. The aggregate amount f(p*) is the number of stocks for which there is a demand at a limit price higher or equal than p*. The aggregate amount g(p*) is the number of stocks which is offered at a limit price lower or equal than p*. Since same aggregate quantities can be executed the minimum of { $f_{t+1}(p)$, $g_{t+1}(p)$} is to be trade volume at p*. After execution, the cash and asset of agents are updated.

The clustering among agents is an aspect of behavioural finance, opinion propagation, based on study of Cont and Bouchaud (2000), is tool to model this aspect. All noise traders have an initial probability of placing a buy order of 0.5. This probability is updated with the function of clustering effect as below. At each step of simulation, pairs of traders are randomly chosen with probability of P_a, if a pair is chosen, they form a pair. Thereby, cluster of traders are progressively formed, grow in that way, and eventually merge. That means they all are either seller or buyer. At each time steps, a cluster could be activated with probability of P_c and inactivated with probability of $1 - P_c$. If a cluster is activated, all traders belonging to chosen cluster update their probability of either buy order to 1 or sell order 0. After order placed, the cluster is destroyed, and traders belong to the cluster update their probability of buy order of p_i to 0.5. Cont and Bouchaud (2000) gives that cluster size follows inverse power law distribution.

Agents total wealth is calculated as of agents at timestep *t* of market run, agent *i*'s wealth at time t is calculated as $w_{it} = C_i(t) + A_i(t) * p(t)$, where $C_i(t)$ is agent's cash amount at time *t*, $A_i(t)$ is asset amount of agent *i* at time *t* and $p(t)$ is asset price at time *t*. And the average wealth of agent types at the end of market simulation can be calculated as

$$\bar{w} = \frac{\sum_{i=1}^{N} w_{iT}}{N} \tag{6}$$

where T is simulation time, N is number of traders considered and w_{iT} is total the wealth of agent i at the end of trading period.

3.2. Simulation model

The simulation has market parameters and agent parameters to set before running the market. These parameters are initialized at the beginning of market run and may subject to change based on the market to replicate. Market initial parameters are given on **Table 1.**

Table 1: Market Parameters

N	Number of agents in the market
timeSteps	number of trading phases
clusPairProb	probability for an agent to pair with another agent to form clusters. Each agent can pair with any other agent during each timestep
clusActivateProb	at each time step a cluster is randomly chosen and activated with this probability
globalBuyProb	probability that an agent is a buyer during a time step in which being seller and buyer is equiprobable.
sellMu	expectation value for the price factor of a seller
sellSigmaK	standard deviation for the price factor of a seller
buyMu	expectation value for the price factor for a buyer
buySigmaK	standard deviation for the price factor of a buyer
technicalFraction	The population share of technical trader in market

Agent parameters need to be initialized are given on **Table 2.**

Table 2: Agent Parameters

cash	the agent's amount of money
assets	the agent's number of assets
buyProb	probability that the agent is a buyer
isBuyer	indicates whether the agent is a seller
isSeller	indicates whether the agent is a buyer
buyCash	the amount of money a buyer is willing to pay for assets
buyQuant	the quantity of stocks a buyer wants to buy
buyUpLimit	determines the highest price a buyer is willing to pay for assets
sellQuant	holds the quantity of stocks a seller wants to sell
sellLowLimit	determines the lowest price a seller is willing to sell his assets
cluster	holds the index of the cluster which the agent is a member of
type	type of agent: noise or technical

The flow chart of code structure for market simulation is given at **Figure 1.**

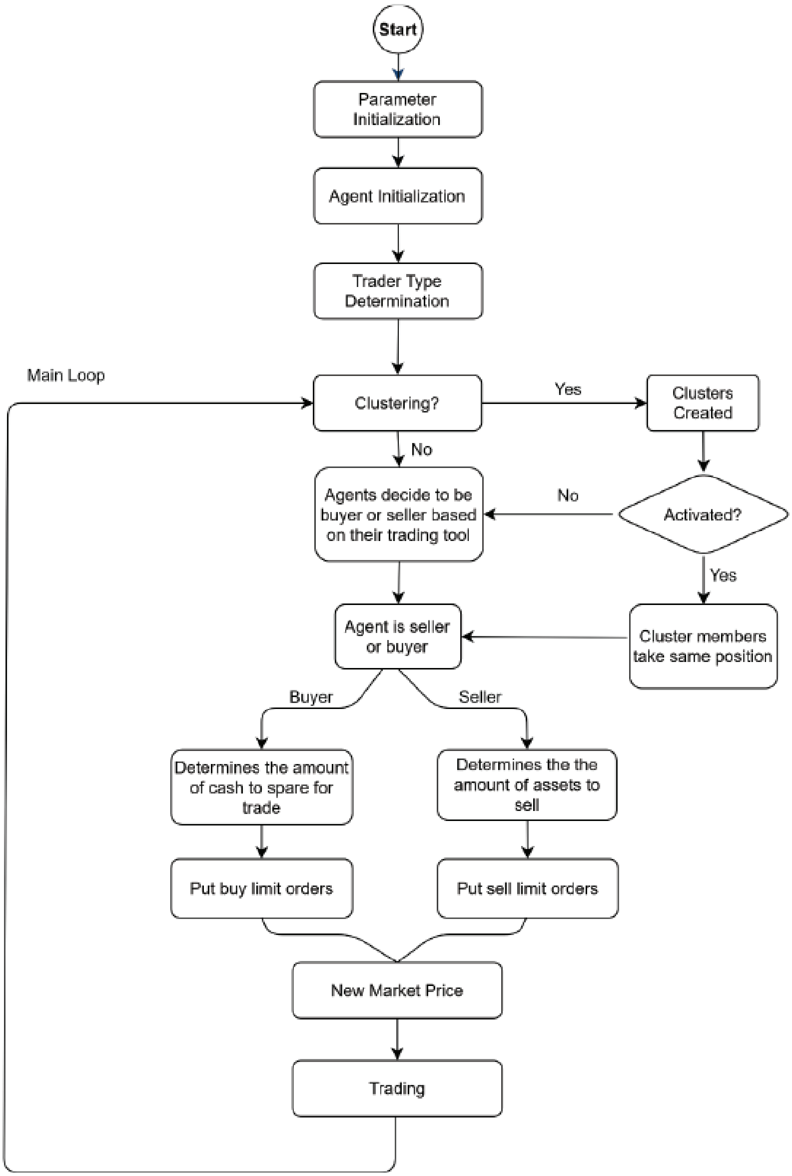

Figure 1: Extended GASM Simulation Code Structure

4. Simulation results

In this section, the results of simulation will be presented. The market is 3000-time steps long and the number of agents (N) is 300; $P_a = 0.0002$; P_c=0.1. The initial price of the stock has been 1$ as standardized. Every trader is endowed with 1000 assets and 1000$ cash.

For our simulation we have run two main simulation, each simulation was exercised under four different scenarios in terms of fraction of traders in the market. These two market simulations are noise traders and technical traders who is named by indicator they use to trade. The first simulation run is consisting of noise traders and rate of change (ROC) traders and the second one is noise traders and Bollinger Bands (BOL) traders.

In these two simulations, four scenarios were obtained: the base model pure noise with no technical traders (0%), technical trade fraction of 5% and technical trader fraction of 10 %, technical trader fraction of 15 %. Based on these scenarios, price formation, price volatility, return features and wealth distribution were analysed.

The simulation initial parameters for market are given in **Table 3.**

Table 3: Market parameters initial values (Raberto et al., 2001)

Market Parameters	Initial values
N	300
timeSteps	3000
clusPairProb	0.001
clusActivateProb	0.002
globalBuyProb	0.5
sellMu	1.01
sellSigmaK	3.5
buyMu	1.01
buySigmaK	3.5
technicalShare (%)	0, 5, 10, 15, 20

4.1. Simulation exercise I: a market with noise traders and ROC-traders

In this setting, two type of agent is employed noise traders and traders using rate of change (ROC) indicator to trade. The market is set to have **300 agents** and **3000 timesteps**. Four different scenarios are applied in terms of population fraction of trader in the market. These scenarios are a market with 0%, 5%, 10% and 15% fraction of ROC-type traders. Every single setting has its own price features and wealth distribution. The main results from this simulation will be presented in the following part. Price features will be analysed as a first step.

4.1.1. Asset price

The graph for price from four scenarios is given in **Figure 2**; and descriptive statistics in **Table 4**. The initial asset price is set to be 1$, it is taken as 100$ for ease of visualisation.

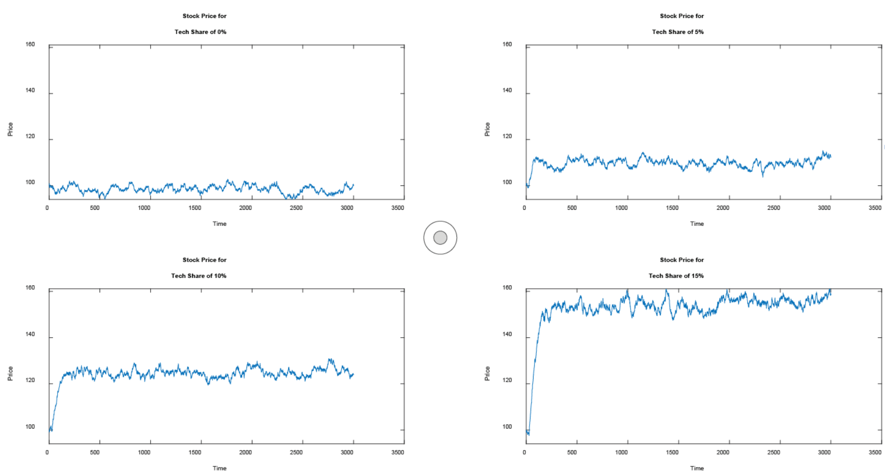

Figure 2: Asset prices under different population fraction of ROC-traders in the market. The price start-at value of 100 for each market settings scenario. Upper left panel: asset price under the pure noise trader. Upper right panel: asset price under the population fraction of 5% ROC-traders. Lower left panel: asset price under the population fraction of 10% ROC-traders. Lower right panel: asset price under the population fraction of 15% ROC-traders.

Table 4: Summary statistics for asset price emerged under markets settings with different population fraction of ROC-traders

	Population fraction of ROC-traders in the market			
	0%	5%	10%	15%
Mean	98.5	109.7	124.1	152.6
Median	98.4	109.9	124.5	154.0
Standard Deviation	1.6	2.1	3.8	8.3
Skewness	-0.2	-1.2	-3.8	-4.7
Kurtosis	2.7	7.2	23.1	27.9

The descriptive statistics of asset prices indicates the more ROC-trader in the market the more price volatility.

4.1.2. Asset price returns

Asset price returns from four different scenarios is given in **Figure 3** and descriptive statistics are given in **Table 5.**

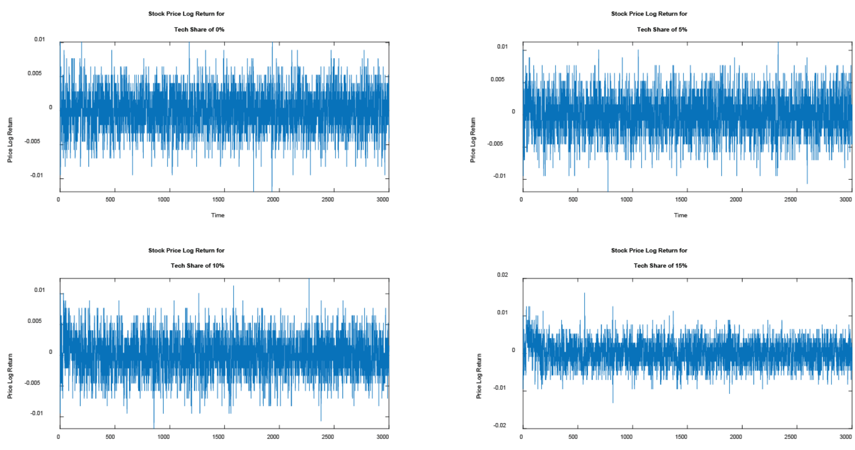

Figure 3: Log returns of asset prices under different population fraction of ROC-traders in the market. Upper left panel: log returns under the pure noise trader. Upper right panel: log returns under the population fraction of 5% ROC-traders. Lower left panel: log returns under the population fraction of 10% ROC-traders. Lower right panel: log returns under the population fraction of 15% ROC-traders.

Table 5: Summary statistics for log returns of asset prices emerged under markets with different population fraction of ROC-traders

	Population fraction of ROC-traders in the market			
	0%	5%	10%	15%
Mean (%)	0.00	0.00	0.01	0.02
Median (%)	0.04	0.04	0.04	0.04
Standard Deviation (%)	0.32	0.33	0.34	0.36
Skewness	-0.01	-0.05	0.00	0.05
Kurtosis	2.96	2.88	2.90	2.93

As it is observed, the mean return of asset price is about zero which is a real financial asset return feature. The statistics support the more ROC-trader the more volatile market.

4.1.3. Volume

The traded volume through the four different scenarios is given in **Figure 4.**

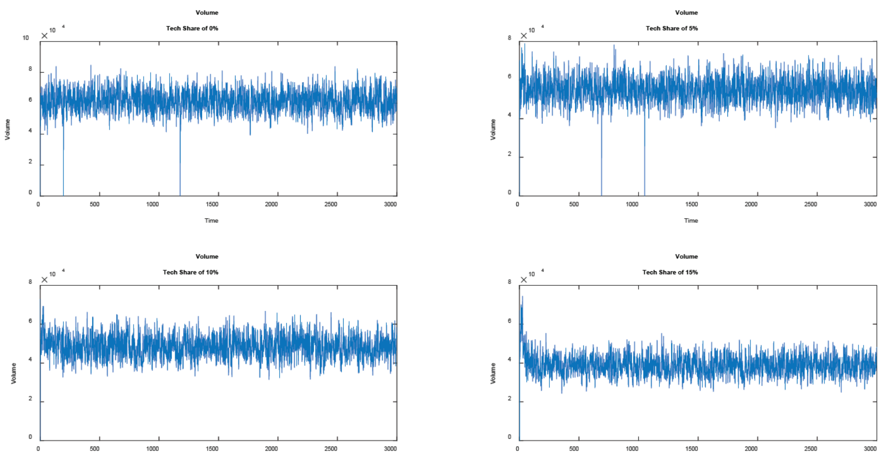

Figure 4: The traded volume under different population fraction of ROC-traders in the market. Upper left panel: traded volume under the pure noise trader. Upper right panel: traded volume under the population fraction of 5% ROC-traders. Lower left panel: traded volume under the population fraction of 10% ROC-traders. Lower right panel: traded volume under the population fraction of 15% ROC-traders.

4.1.4. Autocorrelations

Asset log returns have some stylized facts in real world market. These features are taken as threshold for artificial financial market since it could be use if only can replicate some of these stylised facts. In this regard, autocorrelation in returns will be tested by Ljung-Box approach for different lags and results are given in **Figure 5.**

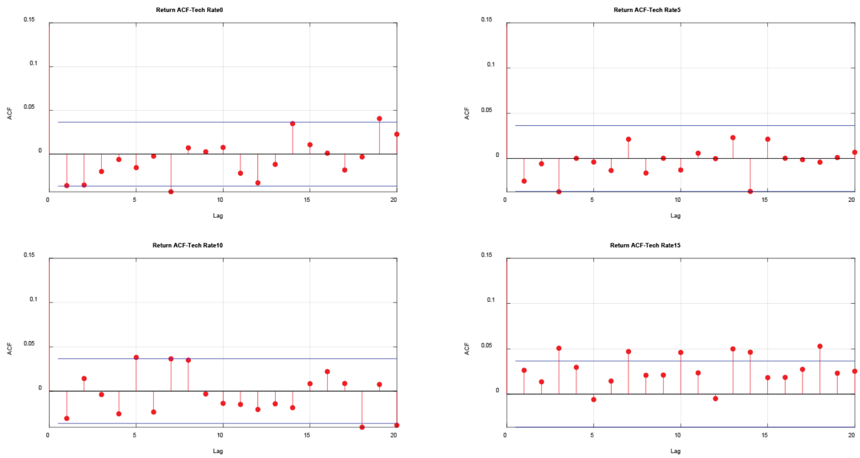

Figure 5: The autocorrelation function (ACF) log returns under different population fraction of ROC-traders in the market. Upper left panel: ACF under the market with the pure noise trader. Upper right panel: ACF under the population fraction of 5% ROC-traders. Lower left panel: ACF under the population fraction of 10% ROC-traders. Lower right panel: ACF under the population fraction of 15% ROC-traders.

Absence of return autocorrelation is assumed to be a return stylized fact, however in our simulation setting that is not valid for all scenarios since increasing technical trader fraction may lead co-movements so the autocorrelation. Another stylized fact for asset returns is volatility clustering, in other words ARCH effect is to be tested. To test this, autocorrelation in squared returns is analysed and test results for this is given in **Figure 6.**

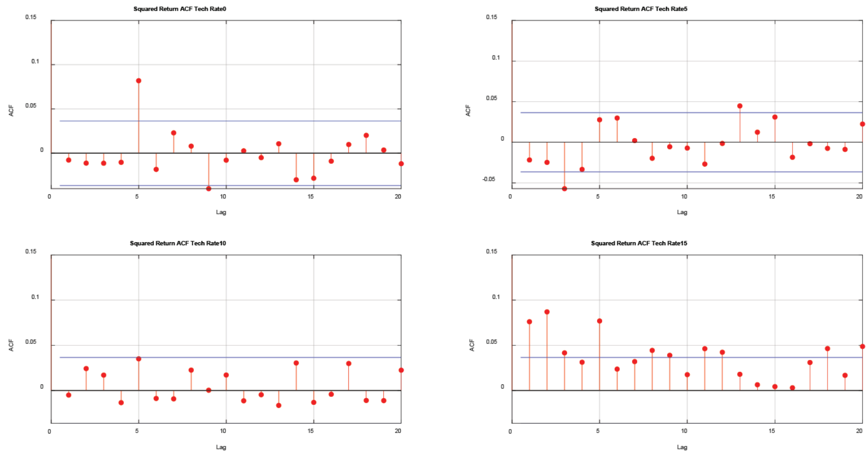

Figure 6: The autocorrelation function (ACF) squared returns under different population fraction of ROC-traders in the market. Upper left panel: ACF under the market with pure noise. Upper right panel: ACF under the population fraction of 5% ROC-traders. Lower left panel: ACF under the population fraction of 10% ROC-traders. Lower right panel: ACF under the population fraction of 15% ROC-traders.

For most of scenarios, ARCH effect in squared returns is a replicated real market stylized fact.

4.1.5. Wealth

One of the main goals of study in this part is to analyse the wealth of agent types throughout simulation. In this regard, *i.* agent's wealth at time t is calculated and averaged for whole simulation period for both agent type. The wealth distribution of noise trader and ROC-traders is compared.

The total wealth of an agent at timestep *t* is calculated as $w_{it} = C_i(t) + A_i(t) * p(t)$, where $C_i(t)$ is agent's cash amount at time *t*, $A_i(t)$ is asset amount of *agent i* at time *t* and $p(t)$ is asset price at time *t*.

Every trader has total wealth of 2000$ at the beginning of simulation and throughout the trading period their wealth is change depending on their actions. To understand the wealth dynamics of trader types, Gini coefficient is calculated before and after market run. It is given in **Figure 7.**

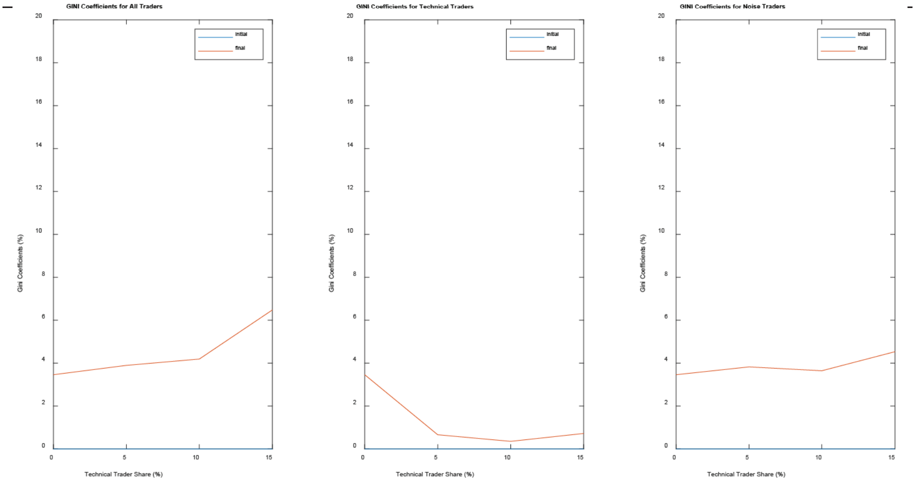

Figure 7: The blue line indicates Gini coefficients before trading and the red line shows after trading. Left panel: Gini coefficients for four scenarios for all traders. Mid panel: Gini coefficients for four scenarios for ROC- traders. Right panel: Gini coefficients for four scenarios for noise traders.

Every single agent was endowed with equal wealth at the beginning of trade; therefore, their wealth has zero Gini coefficient. However, wealth has non-zero Gini coefficients after trading. **Table 6** is given to see if ROC-trader outperforms noise trader.

Table 6: The blue line and the red line in all panel states Gini coefficient of wealths at the beggining and at the end of market run, respectively. Left panel: all traders initial and final wealth's Gini coefficients for four scenairos. Mid panel: ROC-traders initial and final wealth's Gini coefficients for four scenairos. right panel: noise traders initial and final wealth's Gini coefficients for four scenairos.

	Population fraction of ROC-traders in the market							
	0%		5%		10%		15%	
	Noise	ROC	Noise	ROC	Noise	ROC	Noise	ROC
Initial Average Wealth ($)	2000	-	2000	2000	2000	2000	2000	2000
Final Average Wealth ($)	2021	-	2133	2322	2250	2569	2442	3066

It is clear that both agent types are able to increase their wealth; however, ROC-traders outperforms noise traders.

4.2. Simulation exercise II: a market with noise traders and BOL-traders

A market with noise traders and Bollinger Band (BOL)-traders is another simulated market for this study. The results of this setting are similar our first simulation run; therefore, they are summarized in **Figure 7** and **Table 7**.

Figure 8: Asset prices under different population fraction of BOL-traders in the market. The price start-at value of 100 for each market settings scenario. Upper left panel: asset price under the pure noise trader. Upper right panel: asset price under the population fraction of 5% BOL-traders. Lower left panel: asset price under the population fraction of 10% BOL-traders. Lower right panel: asset price under the population fraction of 15% BOL-traders.

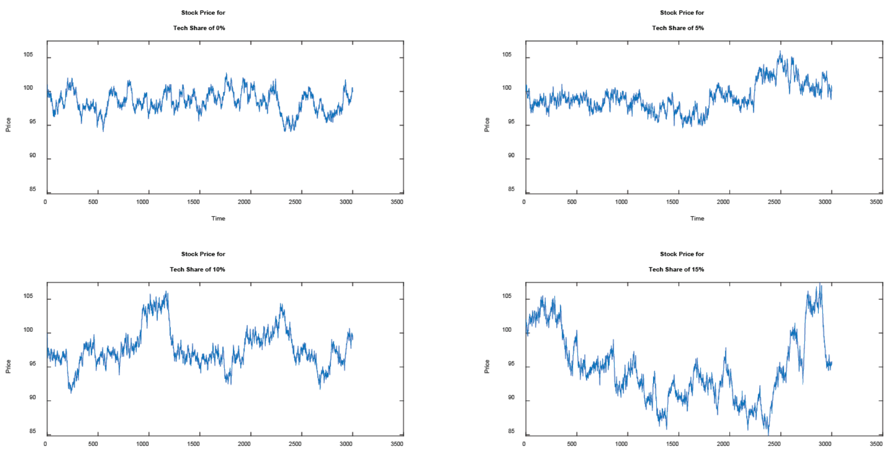

Table 7: Summary statistics for asset price emerged under markets settings with different population fraction of BOL-traders

	Population fraction of BOL-traders in the market			
	0%	5%	10%	15%
Mean	98.46	99.16	97.73	94.73
Median	98.43	98.87	97.15	94.09
Standard Deviation	1.60	2.10	2.80	4.97
Skewness	-0.17	0.63	0.73	0.52
Kurtosis	2.68	3.18	3.45	2.42

Asset price returns has shown similar pattern to our first run and they satisfy leptokurtic distirubiton, absence of autocorrelation and autocorrelation in squred returns so the ARCH-effect. They are not given here for the sake of shortness.

However, since it is an extension, wealth distribution of agents are given in detail.

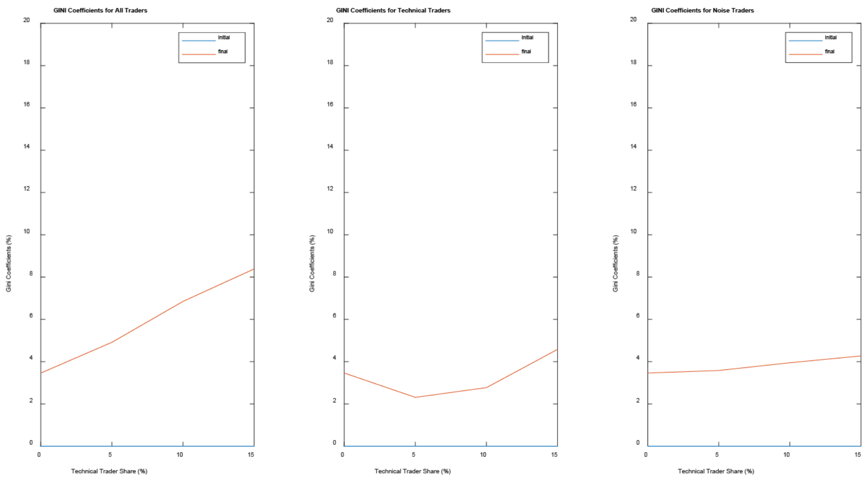

Figure 9: The blue line indicates Gini coefficients before trading and the red line shows after trading. Left panel: Gini coefficients for four scenarios for all traders. Mid panel: Gini coefficients for four scenarios for BOL- traders. Right panel: Gini coefficients for four scenarios for noise traders.

Every single agent was endowed with equal wealth at the beginning of trade; therefore, their wealth has zero Gini coefficient. However, wealth has non-zero Gini coefficients after trading. **Table 7** is given to see if BOL-trader outperforms noise trader.

Table 7: The blue line and the red line in all panel states Gini coefficient of wealths at the beggining and at the end of market run, respectively. Left panel: all traders initial and final wealth's Gini coefficients for four scenairos. Mid panel: BOL-traders initial and final wealth's Gini coefficients for four scenairos. right panel: noise traders initial and final wealth's Gini coefficients for four scenairos.

	Population fraction of BOL-traders in the market							
	0%		5%		10%		15%	
	Noise	BOL	Noise	BOL	Noise	BOL	Noise	BOL
Initial Average Wealth ($)	2000	-	2000	2000	2000	2000	2000	2000
Final Average Wealth ($)	2001	-	1965	2735	1908	2758	1823	2450

It is clear that only BOL-traders are able to increase their wealth while noise traders have in a market, they compete with BOL-traders.

5. Conclusion

In this study, we have introduced an Agent-Based stock market model as an extension of Raberto et al., (2001) model. We have populated market with two types of traders and equipped them with real market technical trader strategies, namely, rate of chance (ROC) and Bollinger Bands (BOL). We have run our simulation under different scenarios of population fraction of technical traders. Llacay and Peffer (2018) did a similar extension to Farmer and Joshi (2002) market model and traders in their model applied real market trading strategies for their decisions.

Since the validity of financial markets is verified by stylized facts, we have tested well-known market features and we were able to replicate some stylized facts such as absence of autocorrelation and ARCH effect in returns, in other words, the volatility clustering. Validity of model is subject to the features Ponta et al. (2011) had multi-asset environment model as an extension of Genoa market model (Raberto et al., 2001). They have used Random Matrix Theory and compared it with S&P 500 index to validate their model.

Co-evolutionary Heterogenous Artificial Stock Market (CHASM) (Martinez-Jaramillo and Tsang, 2009) had there types of traders fundamentalists, chartists and noise traders. Iori and Chiarella (2002) introduce a double auction agent-based market with three types of agents: fundamental analysts, technical analysts, and noise traders. In our model, in addition to the base model, we have technical and noise traders. Therefore, we analyse wealth dynamics since we have two types of agent. We have compared Gini coefficients for agent wealth's as before and after trading. Besides, we have compared initial wealth of traders to their final wealth with question of whether technical trader outperform noise traders. Under our market settings, technical traders have better performance since they have higher rate of returns.

Our model, Martinez-Jaramillo and Tsang (2009) and Iori and Chiarella (2002) model has populated market with different types of traders under different market settings. These studies were able to replicate some real market features. Based on this validation, the model we presented can give valuable information about market mechanism and wealth dynamics of market participants. The model also reveals that an agent-based market model with different type of traders works and it can be extended with more complex trading strategies and different initial wealth distributions.

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