Using agent-based artificial financial market to analyse market manipulation

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Abstract. *This work aims to evaluate price manipulation provided by investors with great amount of capital and its overall effect in the stock market. In order to do so, we have created an artificial financial market using NetLogo. The experiments were carried out in a closed environment, with technical analysis speculators and other three different groups of agents, each one with a unique investment strategy. This work provides inputs for the creation of an artificial financial market, in which other diverse agent strategies could be added, and evidences of a market manipulation caused by excess demand.*

Resumo. *Este trabalho visa estudar a manipulação de preços por grandes investidores e seu efeito geral no mercado de ações.. Para isto, criou-se um mercado financeiro artificial utilizando NetLogo. Foram efetuados experimentos em um ambiente fechado, com especuladores que utilizam análise técnica e outros três diferentes perfis de agentes com estratégias de investimento únicas. Este trabalho provê insumos para a criação de um mercado financeiro artificial, no qual poderiam ser adicionadas outras diversas estratégias para seus agentes, e evidências de uma manipulação de mercado causada por excesso de demanda.*

1. Introduction

Financial markets are highly volatile. They consist of a heterogeneous environment, in which each investor has distinct interests and investing profiles. Furthermore, markets are strongly affected by unexpected news. Since it represents a complex environment, financial market modeling becomes extremely attractive for a multi-agent approach.

Financial markets are defined as markets where investors can buy and sell securities (stocks, bonds), commodities (agricultural products, precious metals) and currencies (dollar, euro…). They are divided in different types, such as [CVM, 2013]:

- Capital markets;
    - Stock markets, which consist of financing common stocks; a single share of stock represents fractional ownership of a corporation in proportion to the total number of shares; stock owners receive dividends equivalent to organization's profit;

    - Bond markets, which consist of financing private and public bonds, such as Debentures or Public Treasure Titles; its securities are known to have a fixed income and refer to a debt issued by its participants;
- Commodity, derivatives, future, foreign exchange and other markets.

Our work is focused in stock markets, where trades are intermediated by a centralized exchange authority. These markets are increasingly being conducted by electronic exchanges.

Electronic trading has promoted an important increase in high-frequency trading and in using complex algorithms that attempt to predict the market behavior. It enhanced speculative trading and market manipulation as well [Angel and Mccabe, 2013]. Spoofing and layering, which creates artificial demand conditions, insider trading and other abusive actions are reduced by market regulation. An organization called CVM (Comissão de Valores Mobiliários) was created in 1976 in order to supervise, regulate, discipline and develop the Brazilian securities market. The responsibility to supervise and prevent fraudulent and abusive transactions, though, belongs to the exchangers, brokers and other organizations involved.

Financial markets are political and economic thermometers for a nation. When they are down, it strongly indicates that the country's economy is not performing as it should , and the opposite indicates that its performance is considered by the market as positive. Similarly, a poor political administration may reflect in a financial crisis. In a coordinated move, investors could create a false perception of economic and/or administrative issues within companies and the nation itself.

In this work, our objective is to analyse how investors with great amount of capital could influence asset pricing. We created an agent-based artificial financial market using NetLogo to this goal. We believe that it is possible to manipulate the market only by excess demand, and having more capital facilitates this intention. We designed a strategy used by "big" investors, i.e., institutional investors that can strongly influence the asset price and manipulate the market. Three other groups of investors were designed with distinct strategies. We observed the performance of the strategy used by big investors alongside the other investors' strategies.

In the next section, we present the market environment, its transaction mechanism and some other important concepts discussed throughout this work. In section 3, we show some literature concerning the discussion of essential features used to build the artificial market. Section 4 presents the simulation framework, detailing the four different groups of investors, other system parameters, algorithms and the logic behind the functioning of the artificial financial market. Finally, the simulation results are presented and discussed in Section 5, and we describe our conclusions and future work in Section 6.

2. Stock Exchanges

Trading in stock markets can basically occur following two types of trading systems, which are executed mainly electronically: *Agency Markets*, such as New York Stock Exchange (NYSE), Toronto Stock Exchange or BOVESPA (Brazil), or *Dealer Markets (Over-The-Counter)*, such as BM&F (Brazil), where the trading occurs via a dealer network [Vishwanath and Krishnamurti, 2009]. In 2008, BM&F merged with BOVESPA creating BM&FBOVESPA and in 2017 with CETIP (entity responsible mainly for the Brazilian private bonds) creating the B3 organization, which now coordinates most of the Brazilian financial market.

The stock markets' transaction mechanism of a single asset works as follows: (i) the investor sends a market or limit order to buy a certain quantity of a stock to an electronic platform that belongs to a brokerage firm; (ii) the broker then sends the order to the centralized exchange that have all the orders organized in an *order book*; (iii) the exchange intermediates the transaction through a *clearing* procedure, finding another investor which is willing to sell the stock at the same price, if it is a limit order, or execute it immediately at any price, if it is a market order; and (iv) the exchange finally executes both transactions, sending the results back to their specified brokers [Vishwanath and Krishnamurti, 2009]. This mechanism follows a simple supply and demand rule: when there is excess demand, the asset price tends to rise, and vice-versa.

The value of a stock can be estimated by two different approaches. *Fundamental analysis* considers macroeconomic (overall economy) and microeconomic (company's financial conditions and management) factors to determine the intrinsic asset value. On the other hand, *technical analysis* attempts to forecast the market behavior based on the statistics of the trading activity, such as price returns and trading volume. This analysis is commonly used in combination with charts of the asset price to find past patterns [Reilly and Brown, 2011]. Investors who use technical analysis of financial data to predict future market trends are called *chartists*.

Multiple indicators have been developed in an attempt to better predict the assets' future price movements, such as moving averages, trend lines and momentum indicators. Some of them are primarily focused on identifying the current market trend, and others determine its strength and the probability of its continuation.

The *risk* of an asset is strongly dependent on the volatility of its expected return. Investments can be classified as low, medium and high-risk investments. The lower the risk, the safer the bet, but the lower the return, and vice-versa. Investors have different preferences regarding acceptable risk for their investments. These preferences originate different investor's profiles.

3. Related Work

In the literature, we can find some research about financial market manipulation through multi-agent simulation. Regarding transaction taxes, there is a contradiction between models found in the literature. As [Marchesi et al. 2008] noted, the introduction of transaction taxes may increase asset price returns volatility and reduce market volume, mostly when there are chartist/technical traders present on the market. However, a different result was found by Buss et al.[Buss et al. 2016] and Westhoff and Dieci [Westhoff and Dieci 2006]. In our experiments, we used technical traders and no taxes, as there is no conclusion about its effect. [Moore et al., 2018] identified a price manipulation in the bitcoin market through suspicious trading activity in the Mt. Gox Bitcoin currency exchange. The bitcoin market is known for having no regulations at all and, thus, it is a golden pot for market manipulation. In our work, there were no regulatory measures or transaction taxes modeled. We consider an environment that is optimal for speculators, like those observed in cryptocurrencies.

[Immonen 2017] proposed a robust and complex agent-based framework, based on dynamical systems models, contributing with agents that use both technical and fundamental strategies. We created a simple model by applying only technical analysis, as shown in Section 4.

A model based on partially cooperative agents in a world of risks was designed by [de Castro and Sichman 2012]. It assumes that investors have different preferences concerning their investments' risks and minimal returns, which were represented by an investor description model. Our traders agents were inspired by these representation of investor description models. A multi-agent architecture, named COAST, was proposed, where coaches negotiate with each other in order to define the best money allocation among different assets. The model used a financial market simulator called AgEx, that uses real data from NASDAQ stock exchange.

[Reis et al. 2016] used NetLogo integrated with R, a language and environment for statistical computing, along with machine learning techniques, to select the best feature or group of features that could better predict the market behavior using empirical data from BOVESPA stock exchange. Their results were used to select the technical indicators to use in our chartist agents. We applied in our work the exponential moving average (EMA), which is commonly used by chartist and chartist traders.

[Raberto et al. 2001] built the Genoa model, in which the clustering effect between investors was studied. As well as Genoa's, there is no money-creation in our model, the investors have a finite amount of cash and a finite quantity of assets, and the asset pricing is guided by simple supply and demand rules.

For more information regarding agent-based artificial financial markets, [LeBaron 2000] and [Cavalcante et al. 2016] reviewed and commented the existent literature and included a discussion about the future directions of this research field.

4. Framework

4.1. Environment and Design

We designed intelligent agents assigned with the role of investors and divided them into four groups with distinct investment profiles: (i) chartist traders, that use exponential moving average (EMA), (ii) random walkers, traders that will randomly send buy or sell orders) and (iii) "buy-and-hold" traders, that buy the assets in the beginning and just hold them until the end of simulation, as we focus on the effect caused by the asset price manipulation.

Each of them is capable of sending either buy or sell orders of a single asset and have a unique trading strategy. Limiting the trading to one asset only makes it simpler to observe these strategies without losing efficacy of the study. The investors can only send one order at a time: the investor must wait until its execution or expiration to send another order.

We assume a closed environment, in which there is no money creation and the agents start with a finite amount of cash and quantity of the asset. Thus, an agent can only buy the asset with its available cash. These assumptions impose some constraints on our model and makes it more realistic.

The model is guided by simple trading rules, following the mechanism of an ordinary order book. The clearing price was determined using the methodology described by [Wurman et al. 1998], which modeled a double auction mechanism that admit multiple buyers and sellers. Let L be the total amount of active single-unit orders, M is the amount of sell orders and $N = L - M$ is the amount of buy orders. Wurman determines the *Mth-price* as Mth highest price among all L orders, which plays the role as the clearing price of our order book.

We also designed a mechanism to simulate orders sent at the market price, i.e. orders sent at the lowest ask price or at the highest bid price. They are prioritized and executed before the others in the order book and do not influence the asset's price. This is useful when simulating the market reaction to a sudden drop or rise in the asset's price.

4.2. Strategies

As described in Section 4.1, we designed four different strategies assigned to four different groups of investors, which are described below. *Chartists* have been prioritized in relation to investors who follow a fundamentalist analysis, since in a speculative scenario the macroeconomic and microeconomic factors are neglected and the investment decisions are strongly influenced by the price trends. *Random-walkers* were designed to provide stock liquidity to the system and the *buy-and-holders* form the control group when compared to the others. These three are usually the common groups found in the market and their design is the simplest way to analyse market manipulation by a big investor.

Each strategy tells the investors whether they must send buy or sell orders, at which price and frequency of trading. With the exception of the *big-investor*, the quantity of stocks of each order sent by the investors was fixed to 1. By fixing this value, we assume a uniform order sending, reducing the standard deviation of the average wealth of each group of investors. Then, the rate of orders sent by one group of investors relies on the total number of investors present on this group and their trading countdown defined in Section 4.3.

4.2.1. Buy-and-holders

The buy-and-holders start with the predetermined cash and asset quantity and keep them until the end, without sending any buy or sell order during the entire period. The results of this group are used as a control group compared to the others.

4.2.2. Random-walkers

The random-walkers have an equal chance of either sending a buy order, sell order or holding its position. Thus, random-walkers tend to create a white noise in the asset's price return series, as noted by [Raberto et al. 2001] in their work. They also provide liquidity to the asset, by supplying the system with enough buy and sell orders, then allowing the other groups to apply their strategies.

The order's price definition considered a volatility factor. The price $p(t+1)$, at the time $t+1$, considers the value obtained by a random-normal function $N(\mu, \sigma_t)$, where μ is the distribution mean value and σ_t is the standard deviation of the asset's price calculated within the range of the 20 previous time steps. The price $p(t+1)$ is then defined as follows:

Buy orders:

$$p_b(t+1) = P(t) * N(\mu_b, \sigma_t) \quad (1.1)$$

Sell orders:

$$p_s(t+1) = P(t) * N(\mu_s, \sigma_t) \quad (1.2)$$

Where $P(t)$ is the asset's price at time *t*.

We set $\mu_b = 1.01$ and $\mu_s = 0.99$. By forcing the mean value of $p_b(t+1)$ to be slightly greater than $P(t)$ and the mean value of $p_s(t+1)$ to be slightly lower than $P(t)$, we are stimulating the trading environment and consequently increasing the volatility of the system. A similar volatility factor in the price formation is also found in [Raberto et al. 2001].

4.2.3. Chartists

A chartist sends a buy or a sell order relying on the trending denoted by the Momentum Strategy, here designed with exponential moving averages to predict the market behavior through moving average crossovers.

As the purpose of a chartist is to react to the changes of the market's behavior, all the orders sent by this group are at the market price and, thus, are prioritized against the others. The strategy employed with this indicator is described in Section 4.4.

4.2.4. Big-investor

The *big-investor* strategy is more complex than the others', though it is still simple: he buys in the lower prices to sell in the higher ones. This strategy relies on the Trend Indicator as well, but have a different duration than the one used by the chartists.

As the Momentum Strategy changes, the *big-investor*'s strategy starts. If it tends to the buying position, the *big-investor* sends a high share of buy-orders (85-95% of all sell-orders in the order book) until reaching 50% of the strategy duration time. There is then a small pause in which only *chartists* and *random-walkers* trade, and when it reaches the last 25% - when the prices are even higher, the big-investor starts sending sell-orders in smaller portions (20-30% of all buy-orders in the order book), until all the orders bought are sold or the asset's price reaches the value when the strategy was initiated.

In this way, the investor buys at a low price, starts a high trend and sells later, when it reaches higher prices. This strategy makes the speculation profitable for the investor.

4.3. Trading Countdown

The Trading Countdown was designed to control the market volatility, i.e., in order to control the frequency in which orders are sent by the investors. Each investor starts with a countdown at its maximum value. The countdown is then decreased by 1 for each time step. When the countdown reaches 0, the investor is enabled to send another order.

The maximum value varies accordingly to each group of investors. The big-investor, as well as the *chartists*, have a maximum countdown value of 5 time steps. After a few trials, this value was found to be the optimal for a proper market reaction, volatility control and strength of the *big-investor's* manipulation. On the other hand, the random-walkers have a countdown with a random maximum value of one of the following prime numbers: 2, 3, 5, 7 and 11. By setting the trading countdown of the *random-walkers* randomly to prime numbers, they provide the stock with enough liquidity for every time step, enabling the stock trading.

4.4. Moving Average Crossovers

The moving average crossover strategy denotes the market's tendency of buying, selling or holding the investors' position. It can assume three different values: -1 (selling position), 0 (holding position) and 1 (buying position). Exponential moving averages are calculated for long and short historical periods. When they cross each other, the indicator changes.

The exponential moving average (EMA) at time t is defined as [Kirkpatrick II and Dahlquist, 2010]:

$$EMA(t) = (P(t) - EMA(t-1)) * WM + EMA(t-1) \qquad (2.1)$$

$$WM = \frac{2}{N_{EMA}-1} \qquad (2.2)$$

Where $P(t)$ is the asset's price at time t, WM is the weighting multiplier, N_{EMA} is the period covered by the moving average and $EMA(t-1)$ is the exponential moving average at time $t-1$. The strategy holds the buying or selling position for a determined period before going back to the holding position. This period is set by a system parameter.

When the ascending short term EMA intersects the long term EMA from below, the strategy assumes the buying position (1), and when the descending short term EMA intersects the long term EMA from above, it assumes the selling position (-1). **Algorithm 1** describes the implemented logic in NetLogo. We called it a Momentum Strategy and it is indicated as MS, since it compares the current price in relation to the past price.

As the Momentum Strategy changes its value, it resets the *chartists'* and *big-investor's* countdown, as they promptly react to the market movement.

Algorithm 1 Calculate Momentum Strategy

to **calculate-momentum-strategy**
if $EMA_{short}(t\text{-}1) < EMA_{long}(t\text{-}1)$ and $EMA_{short}(t) > EMA_{long}(t)$
[**set** *MS* 1
ask *chartists* [**set** *countdown* 0] ;resets the chartists' countdown
if *big-investor-active?* ;system parameter that indicates whether the big-investor is enabled to send orders
[**set** *big-investors-buy* **true**] ;initialize the big-investor's buying strategy
set *duration MS-duration* **]** ;system parameter that sets the duration of the tendency
else if $EMA_{short}(t\text{-}1) > EMA_{long}(t\text{-}1)$ and $EMA_{short}(t) < EMA_{long}(t)$
set *MS* -1
ask *chartists* [**set** *countdown* 0] ;resets the chartists' countdown
if *big-investor-active?* ;system parameter that indicates whether the big-investor is enabled to send orders
[**set** *big-investors-sell* **true**] ;initialize the big-investor's selling strategy
set *duration MI-duration* **]** ;system parameter that sets the duration of the tendency
if *duration* = 0
[**set** *MS 0* ;after reaching duration 0, updates MS to the neutral position
set *duration MS-duration*]
if *duration* > 0
[set *duration duration* – 1] ;updates tendency duration
end

4.5. Order Expiration

As in real markets, investors don't let an order linger for too long. They tend to cancel and update their bets by sending another order. This is controlled by an Order Expiration parameter. As the orders reach the lifespan limited by this parameter, they are removed from the system and the investors are free to renew their bets.

4.6. Parameters and Interface

Chartists, *random-walkers* and *buy-and-holders* start with 80 shares of asset and $1000 amount of money. The *big-investor* starts with 100.000 times more wealth than the other investors, i.e., 8.000.000 shares of the asset and $100.000.000 amount of money. Thus, if the asset's starter price is 10, then the initial wealth of the *big-investor* is 180 million and the others' is 1.800.

When investors run out of stocks, they have 25% chance of sending a buy-order and 75% of holding their position. Similarly, when they run out of money, they have 25% chance of sending a sell-order.

The total number of investors, with the exception of the big-investor, is 200. The ratio of the *chartists* is 0.05, *random-walkers*' is 0.90 and *buy-and-holders*' is then 1 - 0.90 - 0.05 = 0.05. The more *chartists* present in the market, the higher the volatility of the stock price. Analogously, the more *random-walkers* in the market, the higher the liquidity of the stock. The order expiration time is set as 15 ticks. Every tick is defined as an increase of one time step: $t+1$.

The short term N_{EMA} is 15 ticks and the long term N_{EMA} is 100 ticks. The duration of the tendency set by the Momentum Strategy is 150 ticks. Regarding the big-investor, there is a switch that turns on/off his strategy, whose duration is parameterized as 100 ticks.

The screen interface is divided in 4 quadrants. The top quadrants are occupied by the *chartists*. In the bottom-left quadrant are the *random-walkers* and in the bottom-right are the *buy-and-holders*. The big-investor lies on the middle line. When sending an order, the investors hatch a turtle-agent that holds the order attributes and links it to them. Then, the orders are sent to the middle of the screen, where the asset lies. The orders are matched and, after updating the wealth of their respectively investors, they are deleted. The orders that do not match with any other stay in the middle until they are resolved or expired.

The initial exponential moving averages and initial asset price are calculated based on the historical closing prices of the Brazilian stock PETR4, from Petrobras, obtained from BOVESPA between the periods of 1st June 2017 to 3rd August 2017.

4.7. Meta-algorithm

For every time step, the **algorithm 2** is executed.

Algorithm 2 Go

to **go**
    ask *orders* [**expire**] ;orders expiration procedure
    ask *chartists* [**send-order**] ;regular order sending procedure
    ask *random-walkers* [**send-random-order**] ;random-order sending procedure
    ask *big-investor* [**send-big-order**] ;big-investor's order sending procedure
    ask *orders* [**move-to** *stock*] ;moves all the orders to the middle of the screen
    ask *stock* [**close-trades**] ;matches the orders and execute the trades
    ask *investors* [**update-wealth**] ;updates the wealth of all investors
    ask *stock* [**update-stock-price**] ;updates the stock-price
    calculate-indicators ;calculates mean wealth sd, EMAs and momentum strategy
    update-labels ;updates stock, investors and other interface labels
    tick
end

5. Results and Discussion

We ran 20 trials for 3 different scenarios: in the first one, there were only random-walkers trading. Next, we added the *chartists* and finally the big-investor, when all of three groups traded. Wealth variation, stock price, standard deviations and stock returns where observed and recorded.

Random-walkers send buy or sell orders arbitrarily, increasing or decreasing the stock price with equal probability. Thus, they make the time series unpredictable. By definition, a white noise process has serially uncorrelated errors with expected mean equal to zero. A random walk time series is non-stationary because its covariance is time dependent. In **Figure 1,** we observe the logarithmic plot of the price returns of Scenario 1 (when only random-walkers are trading). In Scenarios 2 and 3, it is possible to observe some trends created by the *chartists* and the *big-investor*, especially around timestep 375.

Table 1. Description of the scenarios and its participants.

	Buy-and-holders	Random-walkers	Chartists	Big-investor
Scenario 1	Active	Active	Inactive	Inactive
Scenario 2	Active	Active	Active	Inactive
Scenario 3	Active	Active	Active	Active

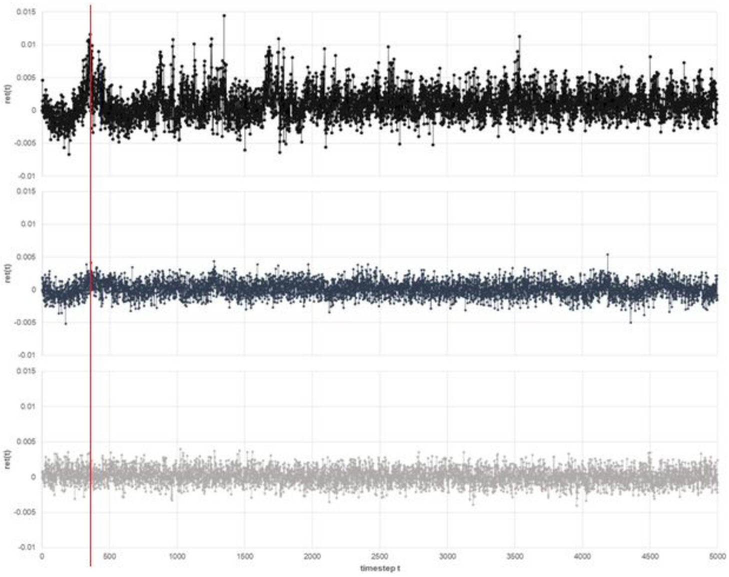

Figure 1. Logarithmic plot of price returns function $ret(t) = log(P(t)) - log(P(t-1))$ **. The black dots concerns the Scenario 3, the blue gray dots are from the Scenario 2 and the light gray dots are from the Scenario 1.**

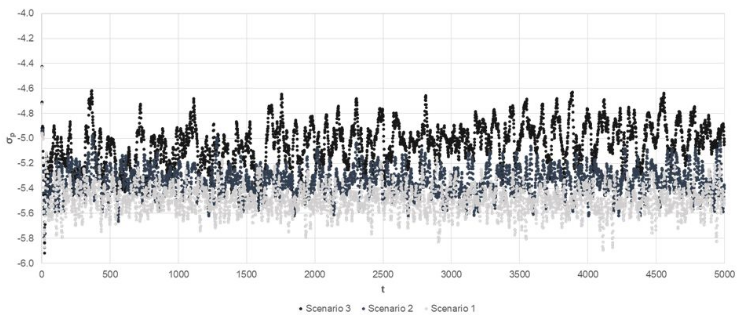

Figure 2. Logarithmic plot of the stock prices' standard deviation for the three different scenarios.

The introduction of the strategies from the *chartists* and the random-walkers enhanced the volatility of the time series and, thus, the risk of the stock returns. In **Figure 2**, the standard deviations $\sigma_p(t)$ of the three different scenarios are logarithmic plotted. The standard deviation $\sigma_p(t)$ of the price $P(t)$ is calculated based on the previous 20 timesteps. As observed, the time series standard deviation rises with the introduction of the other market players.

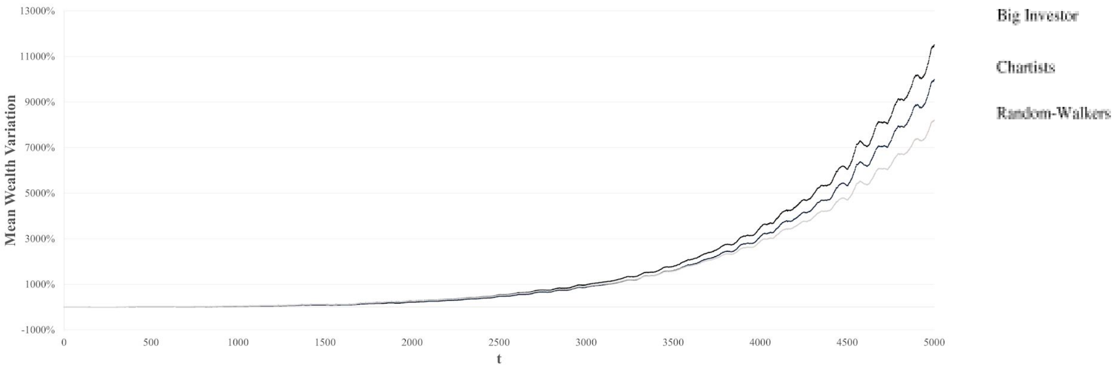

Figure 3. Overall performance of three groups in Scenario 3: big-investor, chartists and random-walkers.

The overall performance of the three different groups is observed in **Figure 3** – the curve for the *buy-and-holders* was suppressed since it is very similar to the *big-investor*'s curve, and final results after 5000 time steps are shown in **Table 2**. The *big-investor* and the *buy-and-holders* had the most profitable returns as the stock price rose significantly. Both multiplied their wealth by 115. After them, the *chartists* were able to grow their fortune by almost 100 times and the random-walkers by 82 times, this one with a standard deviation of 27 times. The stock price rose from 13.3 to 2985.1, 22384% higher.

Table 2. Final results after 5000 time steps on the Scenario 3.

	Buy-and-holders	Random-walkers	Chartists	Big-investor
Mean Wealth Variation	**11506.5%** ± 0.0%	**8203.3%** ± 2658.4%	**9991.5%** ± 241.2%	**11512.6%** ± 0.0%

As discussed in section 3, there were no regulatory measures introduced in our system, which is a perfect environment for speculation. In a regulated market, the manipulation would be more subtle. The strength of our artificial market manipulation relies on the period of the EMAs (velocity of the market response) and other parameters, such as how much *chartists* are trading on our artificial market (volatility) and the total number of investors (liquidity). It is possible to observe the fat tails formed in the time series in **Figure 4** and the exponential growth that market manipulation created on the stock price time series.

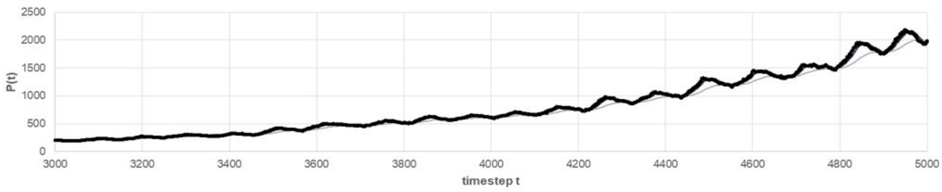

Figure 4. Price P(t) time series from one of the Scenario 3 trials starting at time step 3000.

6. Conclusions

An artificial market was successfully built using NetLogo. It was possible to emulate different investment profiles and introduce technical analysis within its strategies. The financial market is unpredictable, but it can be manipulated to a certain level by investors with a great amount of capital in the absence of regulation. During our research, we identified scenarios that are very close to real situations, such as cryptocurrencies markets, in which no regulatory measures are applied.

The big investor is able to manipulate the market by injecting a great amount of capital in one stock, giving an artificial sensation of growth in this particularly stock, which is followed by the investment of other market players and creating a chain reaction. Since big investors hold a large amount of stock shares, they can handle its price negatively as well, by selling a huge amount of shares of this same stock in a short time span.

The *buy-and-holders,* compared to *chartists* and *random-walkers,* take advantage on the market manipulation because the stock price was rising. However, on an opposite manipulation, i.e., forcing a price decrease, their strategy could be the worst one. The different reaction timing to the market changes from the *chartists* could explain why this group underperformed when compared to the *big-investor* strategy.

Furthermore, NetLogo seems a great tool for the construction of our artificial financial market, enabling the creation of several intelligent agents, with an easy and concise programming language and meeting system performance.

Future steps of our work include defining better-designed big-investor strategies, introducing new investor profiles based on expected risk and return, applying different technical analysis indicators, as well as a fundamentalist approach, and inserting multiple stocks in our artificial market.

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