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Asymmetric rate of returns and wealth distribution influenced by the introduction of technical analysis into a behavioral agent-based model

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ABSTRACT

Behavioral Finance has become a challenge to the scientific community. Based on the assumption that behavioral aspects of investors may explain some features of the Stock Market, we propose an agent-based model to study quantitatively this relationship. In order to approximate the simulated market to the complexity of real markets, we consider that the investors are connected among them through a Scale-Free network; each one of the investors has his own psychological profile (Imitation, Anti-Imitation, Random); two different strategies for decision making: one of them is based on the trust neighborhood of the investor and the other one considers a technical analysis, the momentum of the market index technique. We analyze the market index fluctuations, the wealth distribution of the investors according to their psychological profiles and the rate of returns distribution. Moreover, we analyze the influence of changing the psychological profile of the hub of the network and report interesting results which show how and when anti-imitation becomes the most profitable strategy for investment. Besides this, an intriguing asymmetry of the rate of returns distribution is explained considering the behavioral aspect of the investors. This asymmetry is quite robust, being observed even when a completely different algorithm to calculate the decision making of the investors was applied to it, a remarkable result which, up to our knowledge, has never been reported before.

1. Introduction

In the last decades many researchers have devoted their studies to understand the financial market, expecting that it behaves as a complex system. Different branches of science started researching how the behavior of the investors work in real systems as an attempt to understand it as a whole [1–15]. In particular, we have the Economic system which works as a complex system, where people, companies and markets are at the microscopic level trying to increase their profits predicting the behavior of the investors [16–21]. We already know that many situations affect the stock market, such as the value of the index which depends on the choice of the investors to either buy, sell or hold their stocks. If the decision of the investors is based only on the behavior of their trust network, psychological tendencies arise from various processes [22]. Then, the trust neighborhood and also the market index behavior are driving forces in order to influence the decision making of the investors.

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Financial Market (FM) is the place where the financial assets are traded.[1] There are some economic functions provided by the FM which show how the finance is related to the economic system. The three major functions are: the interactions among buyers and sellers determine the price of the traded asset, which means that they determine the required return on a financial asset; liquidity which is a mechanism that the FM provides to investors to sell their financial assets and it can distinguish different kinds of markets (liquidity degree); and the last one is related to reducing the search costs of transactions (the money spent to advertise the one's intention to sell or purchase a financial asset) and information costs (assessing the investment merits of a financial asset: the amount and the likelihood of the cash flow to be generated). The participants of the FM can be households, business entities, national government agencies, supranational (World Bank, European Investment Bank) *etc* [23].

A Stock market has a large number of interacting agents making decisions all the time [3,11,12,24]. Many researchers are trying to study its behavior based on the similarity with a complex system. It has no central controller and the dynamics observed from it brings some patterns which are hard to predict such as patterns of bubbles and crashes. These patterns are good examples of the capacity of the market to exhibit a self-organization behavior and then emergent properties [2,16,17,25].

Several researchers from social to computation science have shown that many social networks are Scale-Free. This complex network has been used as a tool to connect people in the real world [16,26–33]. Complex networks have been used to represent the connections among agents such as banks and financial institutions. Under a novel and natural measure of influence involving cross-correlations of stock market returns and market capitalization, the resulting network of financial influences is Scale-Free [34–41]. As stated by Samit et al. the topology of the network does matter and plays a crucial role for the dynamics of an artificial stock market [42]. In these works and many others from the literature we see how the Scale-Free network has been applied to the connections among agents for exhibiting a power-law characteristic. In this sense, complex networks are able to describe social interactions playing a central role on the social relations because they are very important to spread information, [28,32]. We have applied a Scale-Free network to represent our society of investors in a financial market which makes the most realistic connection among the investors, building their trust neighborhood [26,27,43–50]. One of the most important characteristics of the Scale-Free network is that there is almost always a shortcut connecting any two nodes. In this situation, there are many alternative routes between any two points, and it is very likely that some will involve only a few jumps (links). Moreover, a SFN feature is that highly connected nodes have a greater-than-average chance of being linked to other highly connected nodes creating hubs which are highly connected among themselves. Members of a hub trust network might, for instance, share information, quickly synchronizing their "cluster", while for the rest of network information percolates slowly by local interactions [26,28,31,32,51,52].

Duncan J. Watts e Steven Strogatz show that the average distance $\langle l \rangle$ between two nodes increases logarithmically with the size of the network. We see that $\langle l \rangle = \ln N$ [28,53]. This characteristic can also be seen in Scale- Free network (SFN). Then, we can infer that most Scale-Free networks are a kind of small world networks (SWN) [28,31,32,54]. Therefore, we can represent our society of investors in the stock market connected through a Scale-Free Network as shown in Fig. 4. In this sense, the literature has shown a lot of works which apply Scale-Free network (complex network) to the financial system such as financial market and its products. Oliver Hein et al. shows that the topology of the communication network influences the price building process [55]. Vertices of the SFN can be seen as agents, banks, stocks, companies, some sectors of the financial markets, urban growing and its network topology implies directly on the entire system due to the behavior of one node and the edges have been used as trade of goods and services between nodes [56–62].

In our previous investigations, an agent-based model grounded on behavioral stochastic Cellular Automata (CA) has been implemented in order to reproduce the main features of the Stock Market and study it as a complex system [63]. However, to approach the agents to real investors, it was mandatory to consider a technical analysis in the decision making of the agents, feature which has not been considered in the algorithm yet. As forecasting price movements is the core of the technical analysis, this methodology uses past prices, volume and/or open interest in order to bring several kinds of forecasting techniques such as chart analysis, taking into account shapes in bar charts, as gaps, spikes, flags, etc, which tests the profitability of visual chart patterns, cycle analysis and computerized technical trading systems [11,64–68]. Technical analysis is widely used among traders and financial professionals (i.e. the participants of the FM), and is very often used by active day traders and market makers [68].

Thus, in this work we improve the original model [63], exploring the decision making algorithm which is now combining two strategies to help the investor to make an investment. At each time step, the investor will consider his trust neighborhood and the trend of the stock market index with different weights. In order to study the stock market index tendency, we are going to apply a technical analysis methodology called momentum. This indicator warns about latent strengths or weaknesses in the tendency by monitoring the price [64–66]. Yet, it will be taken into account the psychological behavior of each investor when applying these two strategies. In this way, the investor will take a decision of either buying, holding or selling stocks based on combinations of his trust neighborhood and the momentum technique choices.

Next section, we present the methodology developed to implement the rules through the CA, the Complex Network and the algorithms to simulate every scenario analyzed. We show how these algorithms work with the decision making of the investors. We also discuss the role of the hub of the system (SFN) over the wealth distribution. Eventually, we present some results from our simulation where we explain the effect of both strategies over the wealth distribution of the investors and their profitable return. In the conclusion section, we state the impressive result that we have obtained when comparing the rate of returns of the anti-imitators with the rate of returns of the imitators.

[1] Although, the assets do not, necessarily, have to be traded in a market.

2. Methodology

In a previous work [63], we presented a Hybrid Cellular Automata (HCA) model and studied four different kinds of networks (Regular, Random Conservative, Random Non-Conservative and Scale-Free Network) and their influence in the Stock Market Index oscillations. This Agent-Based Model consists of the HCA which is able to apply a Monte Carlo process. Each node is as an investor (agent) having a psychological profile (Imitator, Anti-Imitator and Random Trader), a state (buying, holding, selling) and a number of links (connections). By using a complex network, we construct the trust neighborhood of the investors which is given by the connections that each of them has through the SFN. The states and psychological profiles are placed at random into the trust network. The stock market index was initially set to 100 and updated at each time step considering the net balance between the number of investors buying and selling stocks, divided by the size of the system [63].

Being an imitator means that an investor will perform the same state as the majority in his neighborhood. Anti-Imitator profile means that an investor will perform the same state as the minority of his neighborhood. Random Trader profile means that an investor will take his decision randomly.

Thus, by setting up this new algorithm, we are going to give the system a dynamic process where all the investors still keep their psychological behavior, but they will not necessarily rely on their trust neighborhood. They are also going to take into account a technical analysis based on momentum technique [64–66,69]. Accordingly, we have as the first strategy (strategy 1) the trust neighborhood and as the second strategy (strategy 2) the technical analysis. The model is built by setting the trust network of the investors (strategy 1) in order to establish an initial time series (100 time steps). The index experiences a fluctuation due to the dynamics of the system during these first 100 time steps. After that, the algorithm starts performing a technical analysis over the time series which was just constructed. In this way, from the 101th time step, this new algorithm runs both two strategies.

Since we are using a Scale-Free network, we know that there are some nodes without any links. In this case, these nodes (investors) are going to behave as stubborn ones when considering the strategy 1 [63]. Therefore, those investors who do not have any connections might change their states by considering only the technical analysis (strategy 2). We can see that at every time step all the investors will look at their neighborhood (except the ones who do not have any links) and will analyze the trend of the index. The HCA, then, will give the rules for choosing a new state considering the psychological profile of the investors. By doing so, every node (agent) will be updated synchronously. At every time step we compute the index that was, initially, set to 100 as an initial condition. The algorithm starts running, updating the index considering the number of buyers and sellers. If there is more buying than selling, the net balance is going to be positive and it makes the index increase; on the other hand, if there is more selling, the net balance is negative and it makes the index decrease [63].

The implementation of a particular technical analysis, which is used in real markets to study the trend of the index, follows the momentum (MOM) technique [64,66,69]. The value of the momentum, $M_\tau(t)$, will be given by the following three equations:

$$\begin{aligned} M_1(t) &= I(t-1) - I(t-2) \\ M_2(t) &= I(t-2) - I(t-6) \\ M_3(t) &= I(t-6) - I(t-11) \end{aligned} \tag{1}$$

where M, t, τ and I stand for Momentum, Time, Time-Lag and Index, respectively.

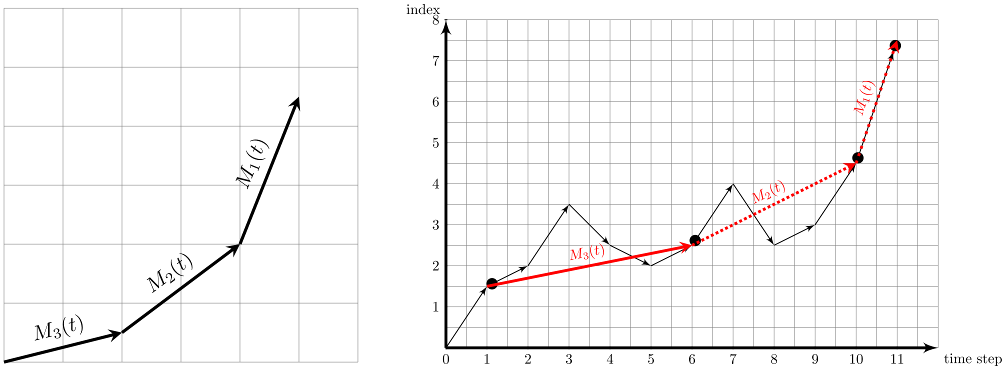
In our model, this process (MOM) consists of computing the difference between the value of the index of the three different windows: $M_1(t)$, $M_2(t)$ and $M_3(t)$. We, then, have three different measures in a given trading interval (days - time steps, for instance). From Eq. (1), computing $M_\tau(t)$, we can assume either positive or negative values, which can be seen as an expectation index of going up or down, respectively. Consequently, the traders expect an increase of the index for the next time step when $M_\tau(t) > 0$; on the other hand, if $M_\tau(t) < 0$ they expect a decrease. Based on technical analysis, the simulations will consider the value of the momentum as being the difference of the values of the indices at different time-lags (windows).

We can think about the steepness of the slope of the index: As $M_\tau(t)$ can assume either negative or positive values, we measure how positive or negative it is for each given τ. It means that the higher a positive/negative value of the ($M_\tau(t)$) is the steeper the index becomes. Thus, the value of the $M_\tau(t)$ obtained for each time-lag proposed is going to be used to set a probability weight on the process of buying, holding or selling, as shown on the Table 2. This table shows several patterns which depend on how steep the slope is, either increasing or decreasing. The probabilities that have been applied to this process are heuristic weights based on combinations of the three slopes, ($\tau = 1, 2, 3$), which are going to be interpreted as a trend of the index.

Let us consider, for instance, if the slope gets steeper with smaller time-lag, see Fig. 1, it will be interpreted as the stock price getting more expensive. This scenario sounds like the investors should buy stocks, once there is a high probability that the stock price will increase in the next time step. In this scenario, we have set a probability weight of $(1, 0, 0)$ (although this example is a deterministic decision, meaning that every investor will buy stocks) - (Case-1) - for (buying, holding, selling) respectively, see row 2 on the Tables 1 and 2. Basing on the Table 2 and applying a Monte Carlo process, we set a stochastic process in order to determine whether the investor is going to decide to buy, hold or sell stocks.

From the neighborhood and technical analysis strategies, an investor can experience either the same decision making to buy, hold or sell his stocks or a different one, see Fig. A.15 and Algorithm-1. In order to study the system dynamics, we have implemented a stochastic process where we will consider some different probabilities from a normal distribution. It will be set a probability to be: $1\%, 5\%, 30\%, 50\%, 70\%, 95\%$ and 99% to follow the decision making from the trend of the index (MOM) and, at the same time, it will be considered the behavior profile of the investors in order to follow the decision making given from the MOM.

Considering a scenario where the investor has the imitator profile, he will perform his decision as following: he analyzes his trust neighborhood and then performs the technical analysis: if he gets from strategy 1 and strategy 2 the same decision making, he will



($Trend\ of\ the\ Index$) ($Computing\ M_1(t), M_2(t)\ and\ M_3(t)$)

Fig. 1. Left: Trend of the Index where $M_1(t) > M_2(t) > M_3(t) > 0$ to which can be applied the probabilities from the 2nd row of the Table 1; Right: Picture shows how the values of $M_1(t), M_2(t)$ and $M_3(t)$ are computed.

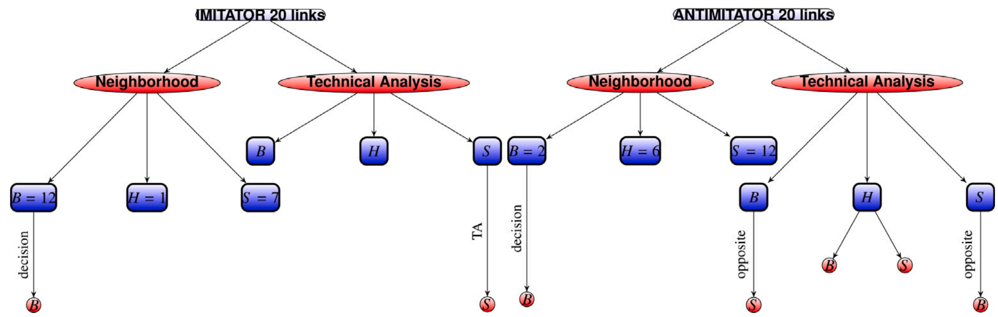


Fig. 2. Left: Flowchart shows the imitator investor and how he determines his decision based on two strategies. In this case, as an example, most of your neighbors is buying. Strategy 2 tells him to sell. So, a stochastic process is implemented in order to make a decision. TA stands for Technical Analysis. Right: Flowchart shows the antimitator investor and how he determines his decision based on two strategies. In this case, as an example, the minority in your neighborhood is buying. From TA, he makes the opposite decision.

just follow the provided decision. If the strategies (1 and 2) show a different decision making, a stochastic process is set to decide which one will be taken. For example: strategy 1 (neighborhood) comes up to buy stocks; strategy 2 (technical analysis) comes up to sell stocks, thus the imitator investor will have to decide if he will be influenced by the external factors (technical analysis) or by his neighborhood (trust network). By doing so, a probability will be set in order to follow the decision from strategy 2.

An interesting scenario occurs when an investor has an anti-imitator profile: he will always take the opposite decision which comes from the strategy 2, once the algorithm which runs the strategy 1 takes already into account the psychological profile of the investor. This situation is interesting, because we have to realize which is the opposite for holding stocks: buy or sell? Then, we set a stochastic process in order to decide which decision making he will make. See Fig. A.15 and Algorithm 2.

The decision making rules can be summarized as the following: consider that an investor has an imitator profile and has 20 connections. The code shows to him how many investors are buying, holding and selling stocks from his neighborhood. Then, at the next time step, he will make a decision to either buy, hold or sell depending on what the majority of his neighborhood was performing at that given time. Suppose that: buy = 12, sell = 7 and hold = 1, the strategy 1 tells the investor to buy at the next time step. On the other hand, if the decision making from the strategy 2 is the same as the one he already has, he will then buy stocks at the next time step, see Fig. 2 (left). But, if the strategy 2 gives him a contradictory decision, he will have a probability to follow the decision making from the technical analysis (strategy 2). Now, consider that this investor has an anti-imitator profile: if the decision making from the strategy 2 is the same as the strategy 1, it there will be three situations: first one - if both strategies show buy, he will then sell; second one - if they show sell, he will then buy; and the last one - if they show hold, he will decide between buy or sell. On the other hand, if the decision making from both strategies are contradictory, a stochastic decision is set to decide which one he is going to take: if the decisions from the strategy 1 and strategy 2 are respectively: (1) buy-sell: he is going to buy stock; (2) buy-hold or sell-hold: he is going to decide between buy and sell; (3) hold-buy or hold-sell: he is going to decide between hold and sell or hold and buy, respectively; (4) sell-buy: he is going to sell stock, see Figs. 2 (right) and 3.

We decided to study the system deeper after getting data from running the case-1, see Table 2, and getting statistical results which can be seen on Figs. 9 and 13. Once we realized that the rate of returns show an asymmetric distribution between the anti-imitators and the imitators investors, Fig. 9, and then analyzing the wealth distribution provided by Fig. 13 which shows that

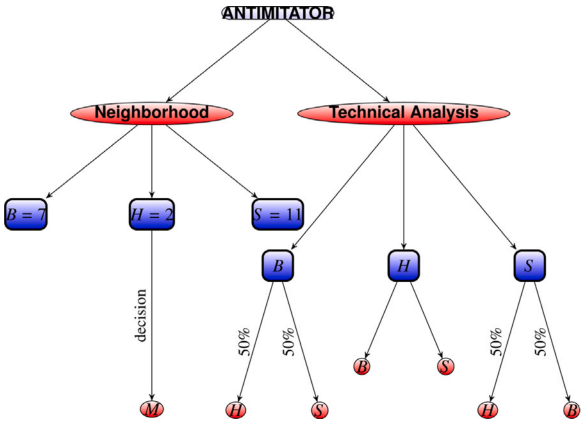
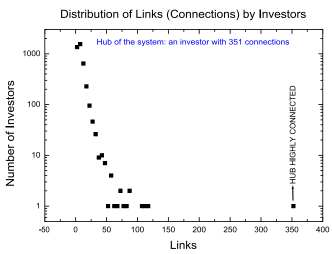
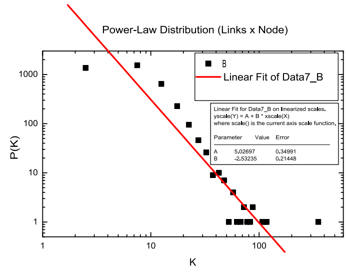


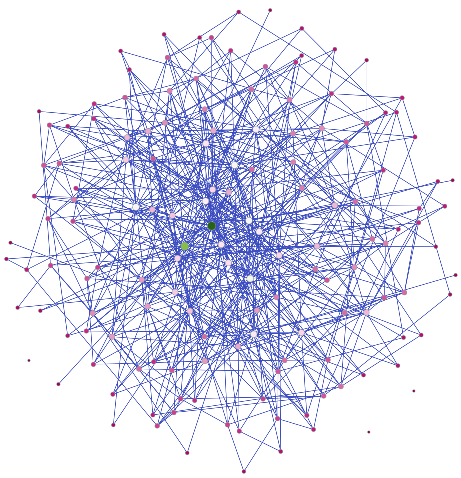
Fig. 3. Flowchart shows the antimitator investor and how he determines his decision based on two strategies. In this case, as an example, the minority in your neighborhood is holding. Therefore, when the option to buy comes from AT, he will decide between holding or selling. On the other hand, if AT's option is to sell, the investor will decide between holding or buying.



(a) The graph shows that the most connected hub of the system has 351 connections followed by the one which has 116.



(b) Linear Fit for the power law distribution presenting $\gamma \sim -2.504$.



(c) Figure shows a low density where the hubs can be seen from inside out following the proportion of its connectivity degree

Fig. 4. Scale-Free Network.

the anti-imitators investors take an advantage over the imitators ones we set the system to work on other different scenarios. These results about the wealth distribution combined to the rate of returns made us to think: what if we reversed the system by changing the probabilities to either buy, hold or sell? Then, we created the case-2, see the Table 2. This case-2 has the opposite probabilities

Table 1
The header of the table: $M_1(t)$, $M_5(t)$ and $M_{10}(t)$ stand for the momentum considering the difference for 1 time-lag, 5 time-lag and 10 time-lag, respectively. The rows are filled in with the boolean variable(1:true; 0:false) and are used to build up the probabilities.

Trend of the index					
ROW	$M_1(t) > M_5(t)$	$M_5(t) > M_{10}(t)$	$M_1(t) > 0$	$M_5(t) > 0$	$M_{10}(t) > 0$
A	0	0	1	1	1
B	1	1	1	1	1
C	0	1	1	1	1
D	1	0	1	1	1
E	0	1	1	1	0
F	1	0	1	0	1
G	1	1	1	1	0
H	1	1	0	0	0
I	1	1	1	0	0
J	0	1	0	1	0
K	1	0	1	0	0
L	0	0	0	0	1
M	0	1	0	1	1
N	1	0	0	0	0
O	1	0	0	0	1
P	0	0	0	0	0
Q	0	0	0	1	1
R	0	1	0	0	0

Table 2
The header of the table: Case-1 - We follow the tendency of the index of going up or down; Case-2 - We invert the tendency of the index of going up or down; Case-3 - We bring the system to the balance when the sum of those probabilities of buying, holding and selling has the same result. P(Buy), P(Hold) and P(Sell) stand for the probability given for buying, holding and selling. Case-4 shows the system inverted comparing it to Case-3.

ROW	Case-1			Case-2			Case-3			Case-4		
	P(Buy)	P(Hold)	P(Sell)	P(Buy)	P(Hold)	P(Sell)	P(Buy)	P(Hold)	P(Sell)	P(Buy)	P(Hold)	P(Sell)
P_A	0.8	0.1	0.1	0.1	0.1	0.8	0.6	0.3	0.1	0.3	0.6	0.1
P_B	1.0	0.0	0.0	0.0	0.0	1.0	0.7	0.3	0.0	0.3	0.7	0.0
P_C	0.8	0.1	0.1	0.1	0.1	0.8	0.6	0.3	0.1	0.3	0.6	0.1
P_D	1.0	0.0	0.0	0.0	0.0	1.0	0.7	0.3	0.0	0.3	0.7	0.0
P_E	0.6	0.2	0.2	0.2	0.2	0.6	0.4	0.4	0.2	0.4	0.4	0.2
P_F	0.6	0.2	0.2	0.2	0.2	0.6	0.4	0.4	0.2	0.4	0.4	0.2
P_G	0.6	0.2	0.2	0.2	0.2	0.6	0.4	0.4	0.2	0.4	0.4	0.2
P_H	0.1	0.1	0.8	0.8	0.1	0.1	0.1	0.3	0.6	0.3	0.1	0.6
P_I	1.0	0.0	0.0	0.0	0.0	1.0	0.7	0.3	0.0	0.3	0.7	0.0
P_J	0.2	0.2	0.6	0.6	0.2	0.2	0.2	0.4	0.4	0.4	0.2	0.4
P_K	1.0	0.0	0.0	0.0	0.0	1.0	0.7	0.3	0.0	0.3	0.7	0.0
P_L	0.2	0.2	0.6	0.6	0.2	0.2	0.2	0.4	0.4	0.4	0.2	0.4
P_M	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.3	0.7	0.3	0.0	0.7
P_N	0.1	0.1	0.8	0.8	0.1	0.1	0.1	0.3	0.6	0.3	0.1	0.6
P_O	0.2	0.2	0.6	0.6	0.2	0.2	0.2	0.4	0.4	0.4	0.2	0.4
P_P	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.3	0.7	0.3	0.0	0.7
P_Q	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.3	0.7	0.3	0.0	0.7
P_R	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.3	0.7	0.3	0.0	0.7
SUM	$\Sigma 8.2$	$\Sigma 1.6$	$\Sigma 8.2$	$\Sigma 8.2$	$\Sigma 1.6$	$\Sigma 8.2$	$\Sigma 6.0$	$\Sigma 6.0$	$\Sigma 6.0$	$\Sigma 6.0$	$\Sigma 6.0$	$\Sigma 6.0$

to the case-1. As expected, the system inverted the results, see Figs. 9 and 13 for the case-2, surprisingly, these results were not as strong as the case-1. We, then, set up the case-3 which brings the system to the balance, see Table 2, and once again the results came up, statistically, with the same results as we had from case-1. Finally, we set up the case-4 which is the opposite probabilities of the case-3. We showed only the results from the simulation of the case-4, see Fig. 13. Results from all these cases are discussed in the conclusion section where we state that the anti-imitator profile has an excellent rate of returns and wealth distribution compared to the imitators profile.

2.1. Complex network

In this section we show the properties of the trust network which connects the investors. We set a matrix whose size is 63×63, where the 3969 nodes (vertices) represent all the investors (each node is an investor) Fig. 4(c). Fig. 4, shows an example of the trust network of the investors which is a Scale-Free network (SFN). As expected, it happens to have hubs highly connected which can be realized by exhibiting the distribution of investors by links, see Fig. 4(a).

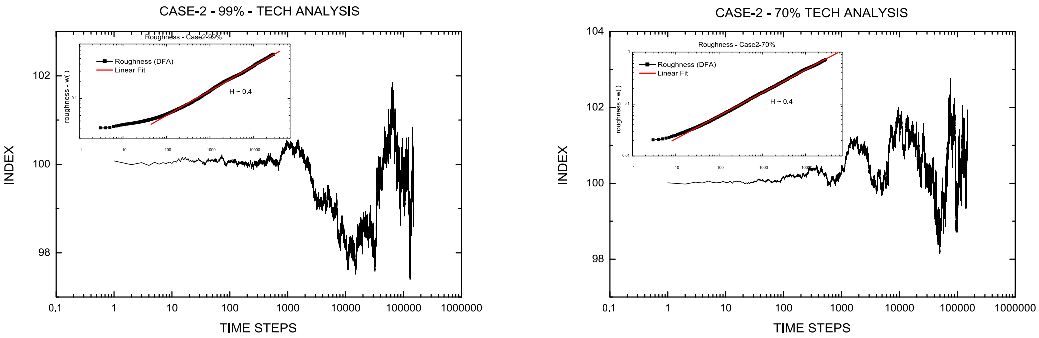


Fig. 5. Figures show the index oscillations depending on the probabilities to follow the technical analysis and the specific case from the Table 2 applied to set the probabilities. We verify the stochastic feature of the model by seeing the characteristic behavior of the stock market index quantified by the HE. Left: 99% ($H_{99\%} = 0.4375 \pm 0.001$) and Case-2; Right: 70% and Case-2 ($H_{70\%} = 0.4342 \pm 0.002$).

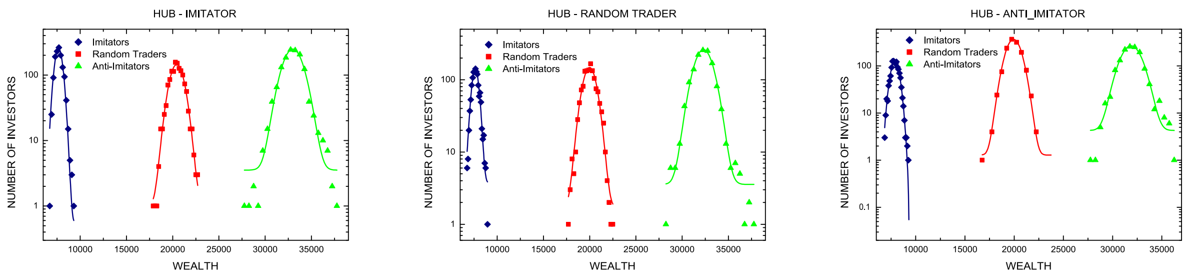


Fig. 6. Profit of the system as function of the hubs - 99%. Left: Hub - Imitator; Center: Hub - Random Trader; Right: Hub - Anti-imitator. For all of the three scenarios we can see straightaway that the anti-imitation profile has a remarkable perform over the stock market. The results for the whole system are: $\mu_{\text{anti}} = 31878.00 \pm 23.35$ $R^2 = 0.99345$; $\mu_{\text{random}} = 19937.00 \pm 16.44$ $R^2 = 0.99562$; $\mu_{\text{imit}} = 7886.00 \pm 11.41$ $R^2 = 0.98123$.

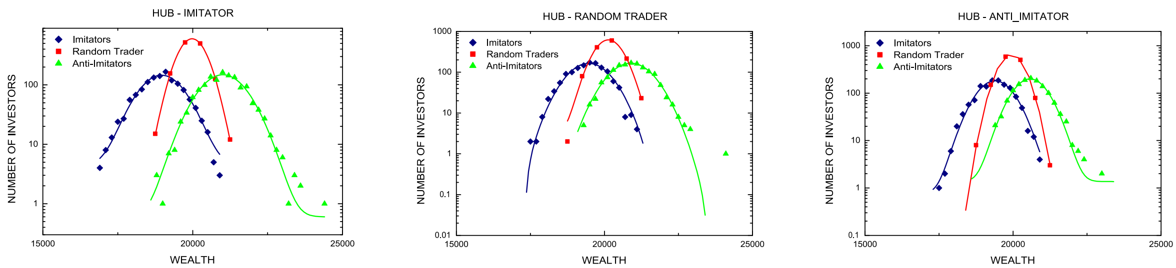


Fig. 7. Profit of the system as function of the hubs - 50%. Left: Hub - Imitator; Center: Hub - Random Trader; Right: Hub - Anti-imitator. Even though their profit is concentrated around 20 000.00, we can see that the anti-imitation strategy has a better perform than the other ones. The results for the whole system are: $\mu_{\text{anti}} = 20577.95.00 \pm 6.64$ $R^2 = 0.99738$; $\mu_{\text{random}} = 20134.00 \pm 5.49$ $R^2 = 0.99967$; $\mu_{\text{imit}} = 18963.00 \pm 20.64$ $R^2 = 0.98197$.

In case of a SFN, we consider the Barabàsi–Albert algorithm [43,70] to build it. Basically, the code considers a preferential attachment of the links in such way that, the greater the number of links of a node (investor), the higher the probability of a new node to be connected to it: the 'rich-gets-richer'! Thus, we are able to generate SFN up to N nodes and $8N$ links, whose distribution by node follows a Scale-Free power-law distribution: $\mathcal{N}(\ell) \sim \ell^{-\gamma}$, where $\mathcal{N}(\ell)$ is the frequency and ℓ is the degree. The characteristic exponent measured, $\gamma \sim 2.5$ 4(b), agrees with the characteristics expected such as a hub highly connected as in the interval proposed by Barabàsi–Albert model for Scale-Free networks [43,70]. We see $\gamma \sim 3.0$ and considering $\gamma > 2.0$ ("winner-takes-all"), it can be said that this configuration makes the earliest nodes become super hubs and all subsequent nodes link to them [43,71]. This is the main characteristic we want our trust network of investors to exhibit. For many Scale-Free networks the degree exponent γ is between 2 and 3 [43,71].

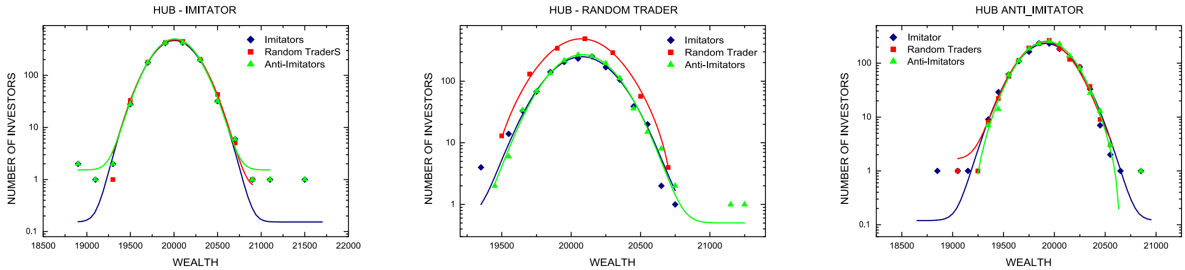


Fig. 8. Profit of the system as function of the hubs - 1%. Left: Hub - Imitator; Center: Hub - Random Trader; Right: Hub - Anti-imitator. They all present, statistically, the same results. Therefore, the choice for a specific psychological profile has no impact over the stock market. The results for the whole system are: $\mu_{\text{anti}} = 20081.95.00 \pm 2.50$ $R^2 = 0.9981$; $\mu_{\text{random}} = 20073.00 \pm 7.16$ $R^2 = 0.99644$; $\mu_{\text{imit}} = 20077.00 \pm 5.17$ $R^2 = 0.99325$.

We can realize that this trust network (SFN) presents a power-law distribution, explaining such a highly connected investor that we are calling by hub of the system. In this case the hub has 351 connections followed by other hubs which have, roughly, less than 125 connections. This behavior of having hubs highly connected is characterized by the power-law distribution as a Scale-free networks are characterized by a power-law distribution of a node's degree [31].

3. Results

We have extended a behavioral finance model in the stock market, as seen in our previous work [63], in order to study the distribution of the richness among the investors. Combining two different techniques which are the neighborhood with their psychological profile and the table which studies the oscillation of the index for different time-lags (technical analysis), this complex system suggests that when taking a probability greater than 50% to apply the technical analysis, there will be a huge chance of getting richer even though having a risk of getting the least profit which is still not too bad when comparing it to other probability scenarios.

We present in this section some results for those two combined strategies. Firstly, we show the temporal series analysis of the stock index considering those three cases from the Table 2. Secondly, we are going to consider some scenarios for these combined strategy 1 and strategy 2 where we are going to discuss the wealth distribution of the investors and the rate of returns based on influence of the hub (investor) according to his psychological profile.

3.1. Index oscillation

In this section we show some results for the Case-2, from Table 2. In Fig. 5 we can verify that the Hurst Exponent (HE) for this case is $H_{99\%} = 0.4375 \pm 0.001$ and $H_{70\%} = 0.4342 \pm 0.002$. These measures mean that that there are no strong tendencies on the fluctuation of the indices to move down or up due to the values provided by the HE which shows that the index oscillations approach to a random walk and it then agrees with the efficient market hypothesis. The Cases 1 and 2 show two slopes for the HE which are going to be explored with another methodology in order to explain their role in this scenario.

3.2. Wealth distribution

This section presents some results considering different probabilities to follow the technical analysis (MOM), strategy 2. From Fig. 6, we can realize how strong the MOM is by impacting on the decision making of the investors. Pictures on the left, middle and right show the hub of the system set to be an imitator, random-trader and anti-imitator, respectively. It is notorious that, statistically, the three of them present the same results. We can see that the anti-imitation is the best psychological strategy adopted to work over this scenario as we have $\mu_{\text{anti}} = 31878.00 \pm 23.35$ $R^2 = 0.99345$; $\mu_{\text{random}} = 19937.00 \pm 16.44$ $R^2 = 0.99562$; $\mu_{\text{imit}} = 7886.00 \pm 11.41$ $R^2 = 0.98123$. This result has been highlighted by the study of the rate of returns as it is shown in Fig. 9 on the next part of this section, 3.3, for each one of them.

From Fig. 7, we can realize that the anti-imitation still have a better profit than the other profiles, but not as good as the previous scenario from Fig. 6. We do mean profit as we compare it to the amount that all the investors started (money + asset = 20 000). Again, there is no difference if the hub of the system changes his psychological profile: the system response is, statistically, the same. Now, we have results from Fig. 8 which show that the wealth distribution of the investors is the same for all of them. So, it does not matter their psychological profile when setting the probability of 1% to follow the MOM. Simulations from several scenarios with different probabilities to follow the MOM technique have provided us such a remarkable result where all the investors who are anti-imitators obtained an excellent rate of returns by following strictly the MOM.

Considering Fig. 14, we see how the whole system displays the wealth distribution as we increase the probabilities from 1% to 99%. For each probability, we run the system with the hub set to be an imitator and we got the average of the wealth from all the imitators in the system. After we did the same by setting the hub to be a random-trader and then an anti-imitator. We can see straightaway from the simulations that all the anti-imitators got very rich, not only the hub of the system, but all the anti-imitators

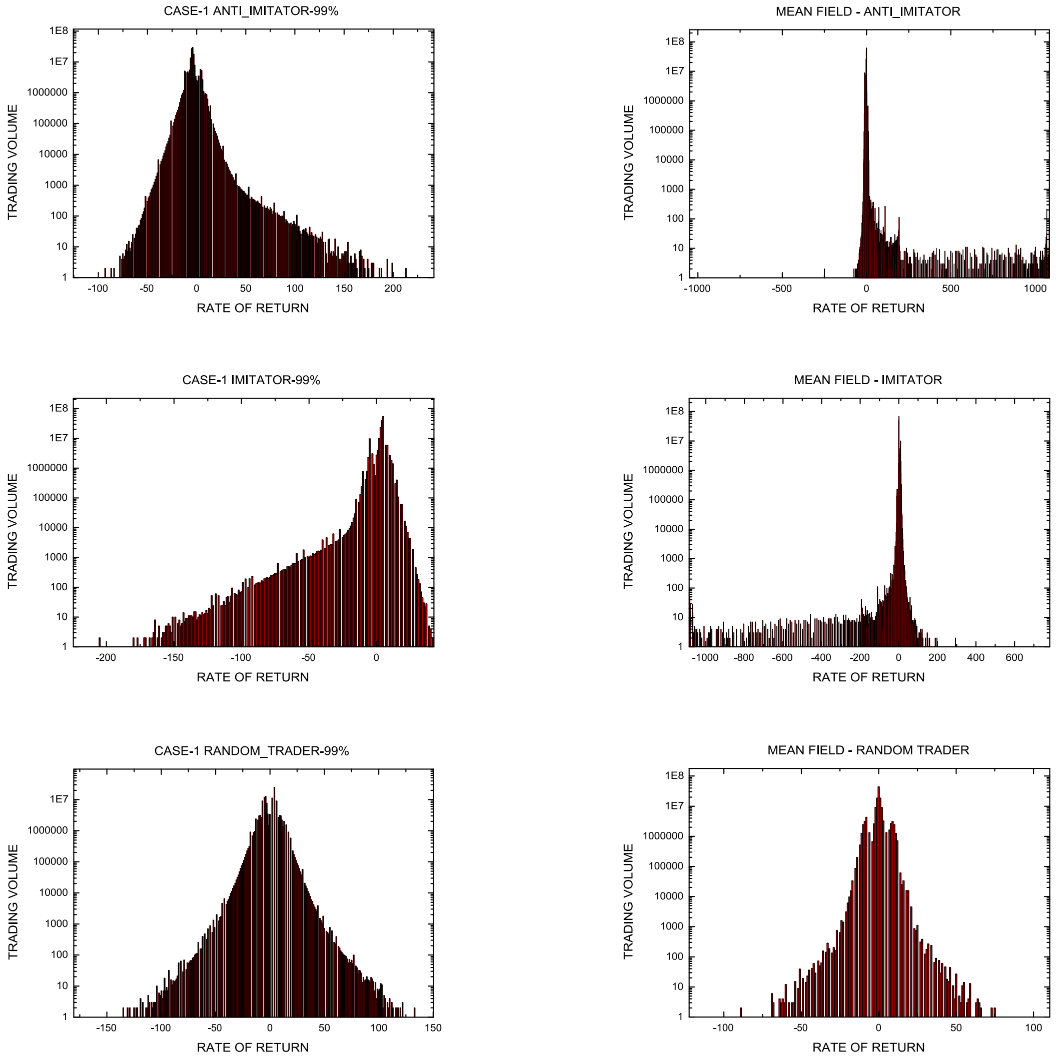


Fig. 9. Rate of returns. Left side: Applying the Case-1 from the Table 2 and a probability of 99% to follow the technical analysis - Top-anti-imitators investors which is concentrated on the positive returns side; Middle-imitators investors which is concentrated on the negative returns side; Bottom-random-trades investors which is symmetric around the origin. Right side: figures show, statistically, the same results as the ones shown at the left side when applying another technique to compute the decision making.

while the imitators got very poor. As for the random-traders, their richness remains statistically the same as confirmed by the literature [2,69,72], bringing robustness to our model. Although, statistically they all had the same profit (Figs. 7 and 8). Fig. 14 gives an exact idea of how the anti-imitator , performing a technical analysis, is far more profitable than the other two ones.

3.3. Returns distribution

This section presents results about the distribution of the rate of returns considering the probabilities set to follow the technical analysis (MOM). We build a probability density distribution (PDF) computing the value of the stock for every single trading that the investor performs. We set the algorithm-1 and algorithm-2, see Fig. A.15, to cumulate all the operations over the stock market for all the investors. From Fig. 9 and Fig. 12 we can see an asymmetry of the rate of returns as a function of the psychological behavior. They show us the histograms for the rate of returns distribution. On the top-left we can see that the anti-imitator profile has a better return than the other profiles. The imitator profile, middle-left, has the worst one, which can be seen by getting negative returns. As it was to expect, on the bottom-left, we see that the random profile has a normal distribution. The remarkable result is this asymmetric distribution between the anti-imitator and imitator investors. In order to compare it to the scenario where we set the probability to follow the MOM to be 5%, we plotted Fig. 10. We see that there is no impact when choosing a specific profile, because they all have a Gaussian distribution. Fig. 11 gives an exact idea of what is going on in case-2 (as we inverted the probabilities

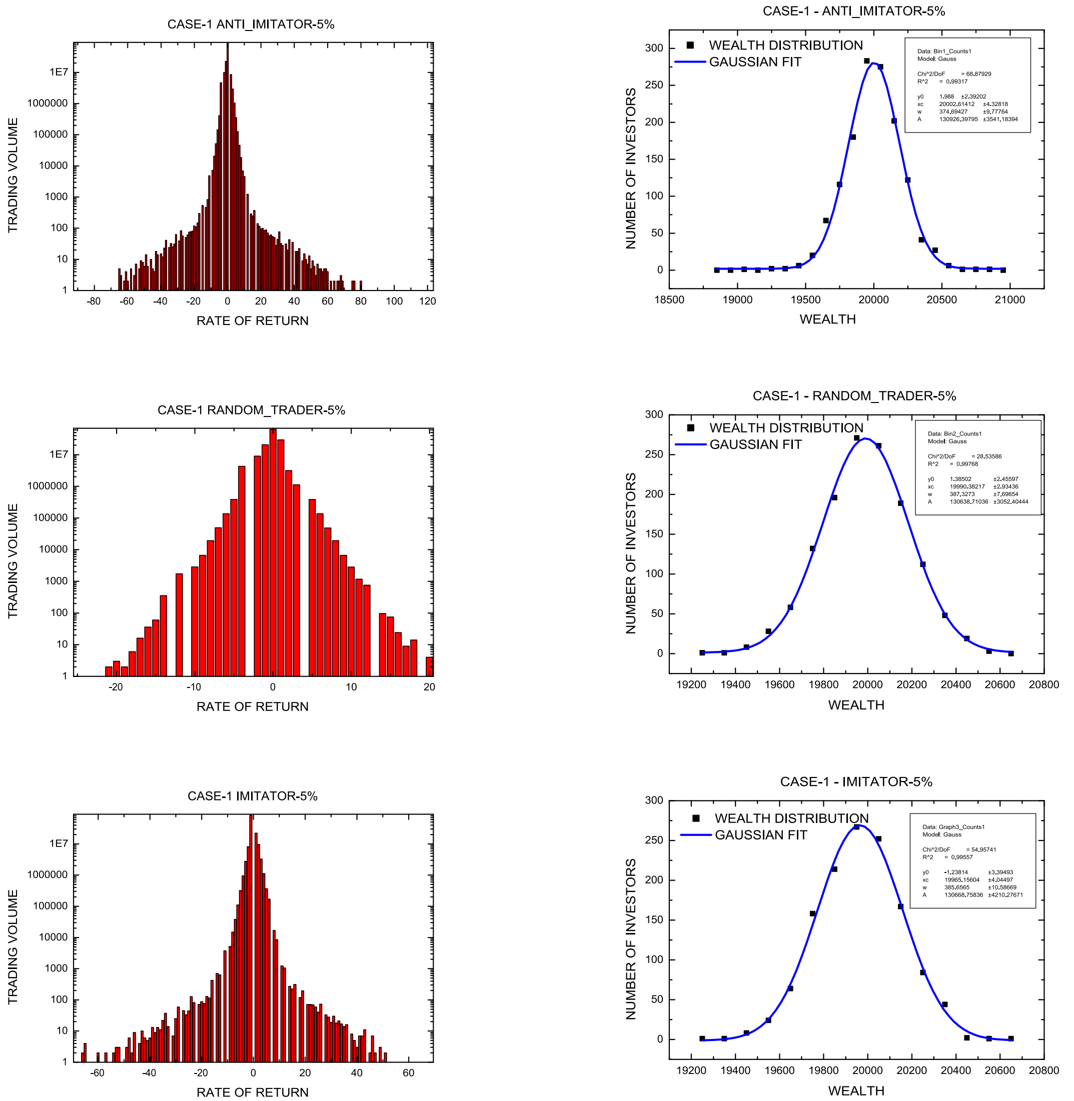


Fig. 10. Rate of returns x Wealth distribution. Figures show the results when we apply the Case-1 from the Table 2 and a probability of 5% to follow the technical analysis. Left side - Rate of returns: top-anti-imitators; middle-random-traders; bottom-imitators. Right side - Wealth distribution: top-anti-imitators ($R^2 = 0.99317$); middle-random traders ($R^2 = 0.99768$); bottom-imitators ($R^2 = 0.99557$).

applied to the case-1) showing the results for the rate of returns on the left side and the wealth on the right side. As expected, it inverted the system results obtained on case-1.

In order to verify the robustness of this result we considered a different algorithm for investor's decision making. Instead of comparing between two options from trust network or technical analysis, we include both strategies in a single index. For example, if the trust network of a given investor composed of 10 agents, and 6 are holding (value +1), 3 holding (0) and 1 selling stocks (−1), the weight of the trust network for the index will be $(6 + 0 - 1)/10 = 0.5$. Supposing that technical analysis indicates a set of probabilities of $(0.8, 0.1, 0.1)$ to buy, sell or hold respectively, it would contribute with $0.8 - 0.1 = 0.7$ to that index, obtaining the value 1.2. Thus, this investor will buy stocks, since the result was larger than one. Otherwise, if the result was smaller than −1, the investor would sell stocks. If the value remained between −1 and 1, the investor would sell (or buy) stocks with a probability equal to the modulus of the index, or holding otherwise. Fig. 9 and Fig. 12, on the right side, exhibit the results obtained with this alternative algorithm, and displays, statistically, the same results as we had on the left side which is the previous algorithm. However, the range of the distribution was considered enlarged,

This asymmetry can be explained as following: when the result from the (MOM) is to buy stocks, all the imitators follow that decision which makes them spend their money on a high price. As the amount of money is limited, they hold their stocks when they do not have enough money to buy more stocks. On the other hand, the anti-imitators will sell their stocks on a high price. As the stock just gets either more expensive or cheaper, the quantity of stock does not vanish at the same rate as the money of the imitator

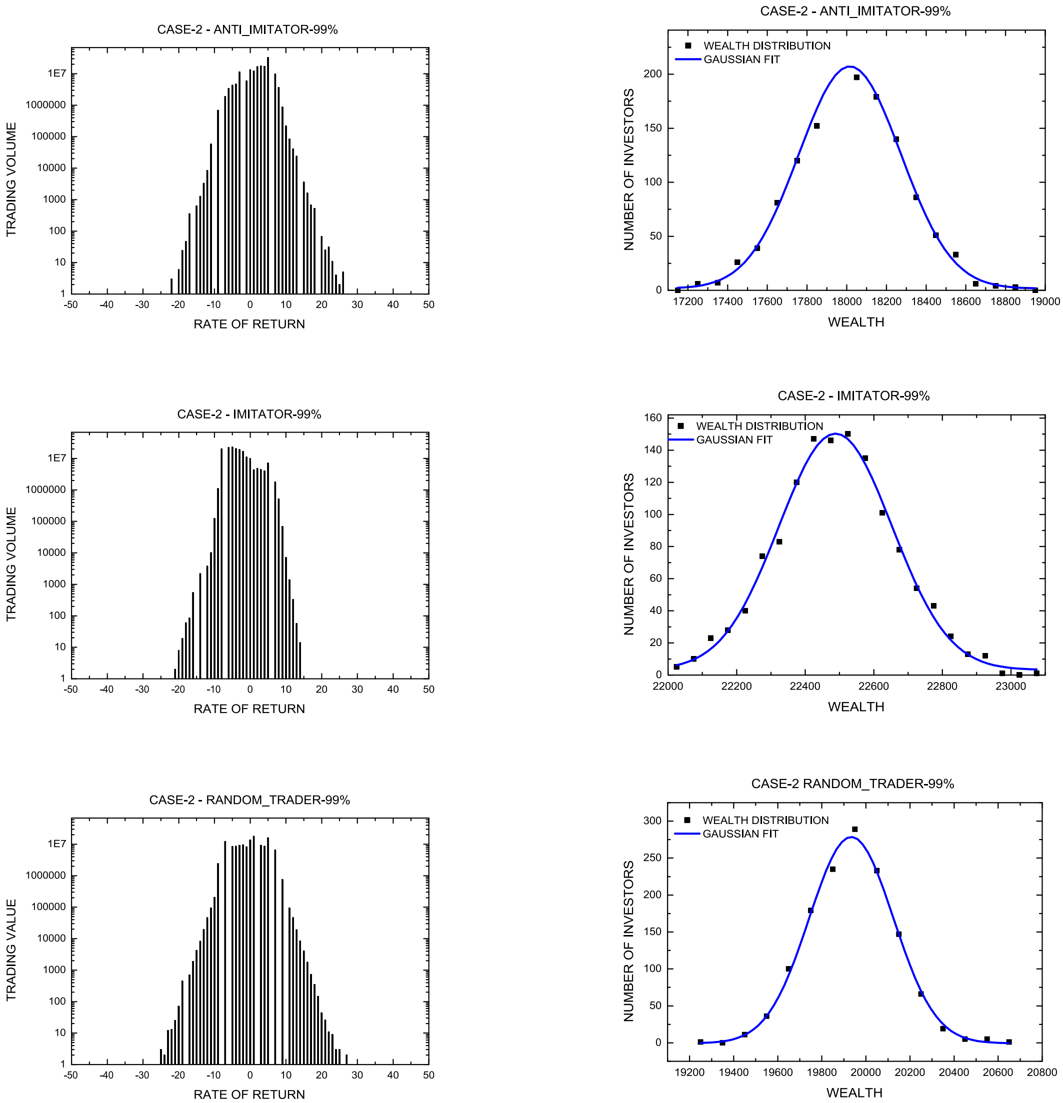


Fig. 11. Rate of returns x Wealth distribution. Figures show the results when we apply the Case-2 from the Table 2 and a probability of 99% to follow the technical analysis. Left side - Rate of returns: top-anti-imitators; middle-imitators; bottom-random traders. Right side - Wealth distribution: top-anti-imitators ($R^2 = 0.99566$); middle-imitators ($R^2 = 0.99877$); bottom-random traders ($R^2 = 0.99676$).

investors. Then, the imitators will have few stocks on a high price and the anti-imitators will have a lot of money in function of the stocks which were sold. The same mechanism happens when the trend of the index is decreasing and the MOM says to sell. Thus, the imitators sell and the anti-imitators buy stocks at a lower price they have paid for. Over a period of time we have results from simulation showing that asymmetric rate of returns depends on the behavior of the investors (see Fig. 12).

3.4. System wealth distribution

Now taking into account the results from Fig. 13, we see the comparison among those four scenarios as already explained above: wealth of the hub of the system as a function of the probability adopted to follow the technical analysis strategy for each psychological profile of the Hub. Case-1 13(a) and case-3 13(c) happens to show that the anti-imitator profile has ended up with a better performance and how the hub imitator lost their wealth over the simulation considering how we increase the probability greater than 50% to follow the technical analysis. Case-2 13(b) and case-4 13(d) are the results obtained by inverting the system probabilities. Even though we inverted the system, the imitator hub did not have the same success as the anti-imitator one. Considering the results from Fig. 14 (left side), which shows that the whole system follow the results obtained by the hub, we decided to perform a new set of simulations to make this influence clearer. We create one copy of a given realization of a Scale-Free network with one third of each behavioral profile from which we chose the 300 less connected investors (5 links) to change their

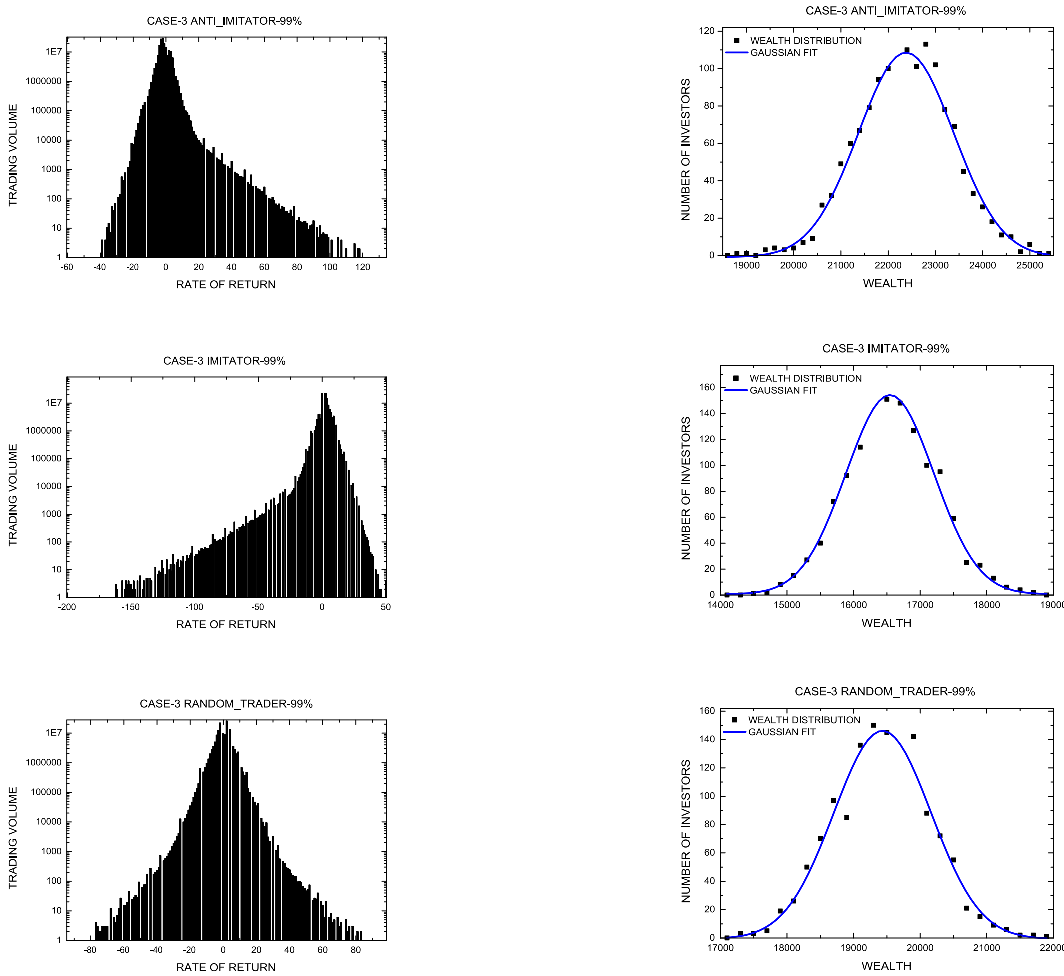


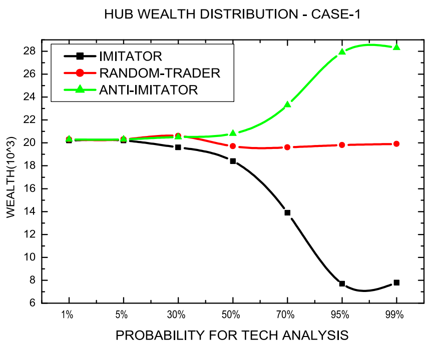
Fig. 12. Rate of returns x Wealth distribution. Figures show the results when we apply the Case-3 from the Table 2 and a probability of 99% to follow the technical analysis. Left side - Rate of returns: top-anti-imitators; middle-imitators; bottom-random traders. Right side - Wealth distribution: top-anti-imitators ($R^2 = 0.99448$); middle-imitators ($R^2 = 0.99867$); bottom-random traders ($R^2 = 0.99788$).

psychological profiles and compare the evolution of wealth distribution to the original one. We can observe in Fig. 14 (right side) that the difference between the realizations is marginal (comparing it to Fig. 14 - left). Then, we take again both realizations and now we changed the behavioral (psychological) profile of only one link – the hub – we compared the results for wealth distribution. It is clear that the influence of changing is given only by the hub which is much stronger than changing provided by those 300 less connected investors (5 links each), evincing that the hub can alter significantly the market.

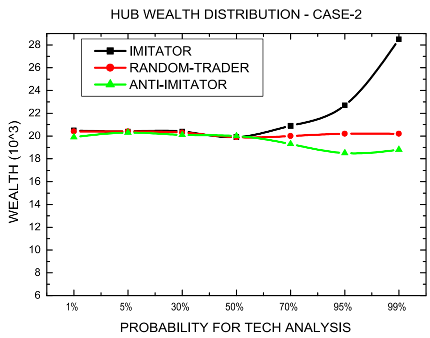
4. Conclusion

In this paper we present a behavioral finance model considering two strategies at the same time. In this sense we developed an algorithm to perform a technical analysis over the index oscillation. The simulations results have shown us how the behavior of the investors and the technical analysis (MOM) can bring an asymmetric rate of returns where the anti-imitators investors had a profitable wealth comparing with the imitators ones. Moreover, as much as they tend to follow MOM technique as much as we can see how profitable anti-imitators investors become. From Figs. 13 and 14, we can clearly see how the anti-imitator improve his profit along the period of investment. The results from simulations, considering the random-traders investors, just confirming the results from the literature [2,69], which make the model robust.

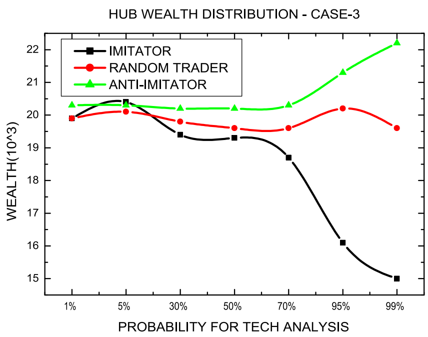
We still need a deeper study of the weight probability given for the slope between the time-lags. Furthermore, we are considering to extend the amount of the resources, a relative risk aversion and make each investor to buy and sell from each other instead of trading straight from the stock market.



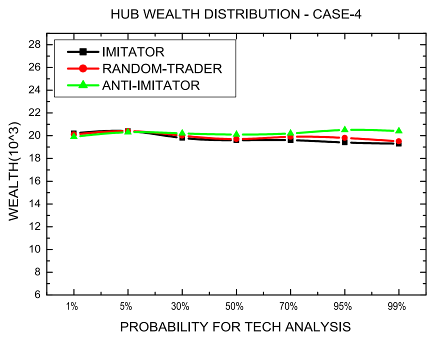
(a) Case-1.



(b) Case-2.

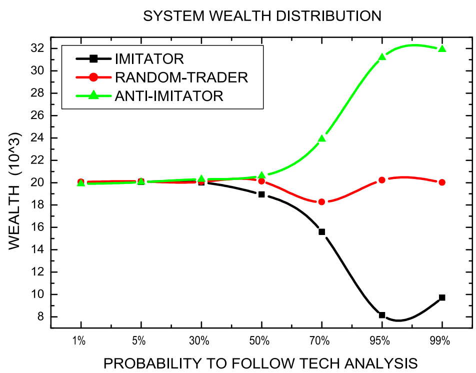


(c) Case-3.



(d) Case-4. (Inverted tendency of the Case-3)

Fig. 13. Graphics show the wealth of the Hub of the system as a function of the probability adopted to follow the technical analysis strategy for each psychological profile of the Hub.



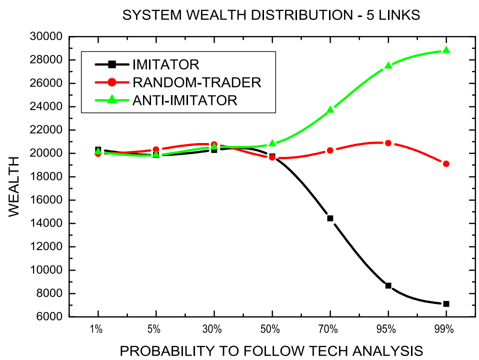


Fig. 14. Left: Graphic shows the average wealth for every kind of psychological behavior as a function of the probability adopted to follow the technical analysis strategy applying the Case-1 from Table 2. Right: Graphic shows the wealth of the whole system as a function of the probability adopted to follow the technical analysis strategy for each psychological profile of the investors applying the Case-1 from Table 2. Each one of them shows the average value of the system when the hub was set to be anti-imitator, imitator, then random-trader.

Algorithm 1: Strategy's results, all the investors who are linked look at their neighborhood. At the same time, all the investors perform a technical analysis and the value of the index is updated.

```
Result: a ← follow neighborhood or
        b ← follow MOM
Data: N = 63 × 63
begin
    for t = 0 to t = 150000 do
        for i = 0 to i = N do
            Setavaluefromneighborhood(vec, max, min, i)

            UpdateInvestor(Investidor[i], max, min)

            a ←
            ActionInvestor[i](buy, hold, sell)

            b ← a
            if Investor ↚ Random then
                TechAnalysis(Indices, t, buy, hold, sell)

                UpdateInvestor(Investor[i], buy, hold, sell)

                b ← ActionInvestor[i]
                Decision(i, a, b)
            end
            else
                Investor[i] ← a
            end
            aux =
            aux + (1.0 − actionofInvestor)
        end
        aux ← aux/N
        INDEX ← INDEX + aux × 1.0
    end
    INDEX ← 100
end
return aorb
```

Algorithm 2: Decision-make strategy, this algorithm takes the choices from the trust neighborhood and the technical analysis and perform a stochstic process to decide which one the invesor will follow.

```
Result: a ← followneighborhood or b ← followMOM
; Data: Decision ← a or b, μ = 0, σ = 1
; begin
    for i = 0 to i = N do
        y = generateGaussianNoise(μ, σ)
        if (y < μ − σ) or (y > μ + σ) then
            if a! = b and InvestorImitator then
                Investor[i] ← b
            end
            else
                Investor[i] ← a
            end
            if a == b and InvestorImitator then
                Investor[i] ← a
            end
            if a! = b and InvestorAnti − imitator then
                if (a ← hold) and (b ← buy) then
                    sortMontecarlo
                    Investor[i] ← hold or sell(50%)
                end
                else if (a ← hold) and (b ← sell) then
                    sortMonteCarlo
                    Investor[i] ← hold or sell(50%)
                end
                else if (a ← buy) and (b ← hold) or (a ← sell) and
                (b ← hold) then
                    sortMonteCarlo
                    Investor[i] ← buy or sell(50%)
                end
                else if (a ← buy) and (b ← sell) then
                    Investor[i] ← buy
                end
                else if (a ← sell) and (b ← buy) then
                    Investor[i] ← sell
                end
            end
            else if a == b and InvestorAnti − imitator then
                if a ← buy then
                    Investor[i] ← sell
                end
                else if a ← hold then
                    sortMontecarlo
                    Investor[i] ← buy or sell(50%)
                end
                else
                    a ← sell
                end
                Investor[i] ← buy
            end
        end
        else
            Investor[i] ← a
        end
    end
end
return a or b;
```

Fig. A.15. Left: The algorithm shows the strategy's results. All the investors who are linked look at their neighborhood. The investors perform a technical analysis and the value of the index is updated at the same time. Right: Decision making strategy, this algorithm takes the choices from the trust neighborhood and the technical analysis and perform a stochastic process to decide which one the investor will follow.

CRediT authorship contribution statement

F.M. Stefan: Conceptualization, Software (Algorithms and Coding), Data curation, Writing – original draft, Formal analysis, Validation, Investigation, Visualization. **A.P.F. Atman:** Methodology, Resources, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix. Algorithm

The Algorithm-1, from Fig. A.15, shows how we have set the process of verifying what is the state of the trust neighborhood, that means, what every single investor is performing (buying, holding, selling) at a current time and, at the same time, making each investor to perform a technical analysis over the temporal series of the index (MOM). The Algorithm-2 from A.15 shows how the stochastic process works in order to decide if an investor should either follow the MOM result or his trust neighborhood.

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