On Agent-based Modelling for Financial Markets: The Case of Egypt

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Abstract

In this article asset pricing dynamics in artificial financial markets model is studied. The financial market is populated with two heterogeneous beliefs of the traders; technical trading rule and fundamental trading rule. The agents are loss averse over asset prices fluctuations. The loss aversion behaviour depends on previous performance of the trading strategy in terms of evolutionary fitness measure. We propose a novel application of the prospect theory to an agent-based model, and by simulation, the effect of evolutionary fitness measure on adaptive belief system is investigated. Qualitative and quantitative validation of our proposed agent-based financial markets model is performed using real financial data of the Egyptian Stock Exchange. We find that our framework can explain important stylized facts in financial time series, such as; random walk prices, bubbles and crashes, fat tails in the returns distribution, mean reversion, excess volatility, and volatility clustering.

Keywords

Stock markets, bounded rationality, loss aversion, simulation analysis, time series analysis and econometric measures, evolutionary dynamics, Monte Carlo study

1. Introduction

Artificial financial markets are models developed for understanding the endogenous variables that cause the emergent behaviours and patterns at the macro-level. These artificial markets serve as test-beds for policy makers to explore the effect of different regulatory policies which improves the decision making process.

Studying financial markets as complex adaptive systems comprised of heterogeneous agents invites for agent based modelling as the most suitable approach, as it provides more flexible tools to simulate the real world [1]. This approach implies new challenges and opportunities for policy and managing economic crisis.

Behavioural finance is a new paradigm seeks to link behavioural and cognitive psychological theories with finance to understand the bounded rational decisions of financial traders. Since 1979, Kahneman and Tversky provoked the idea of the choice under uncertainty. They spent many years to study this concept by conducting experiments and collecting data about the agents' behaviour under uncertainty [2, 3, 4, 5]. Kahneman and Tversky propose that, the outcomes of risky prospects are estimated by a value function. This function is characterized mainly by; loss Aversion, that is; the function is steeper in the negative than in the positive domain. This characteristic describes an asymmetric S-shaped value function which is concave above a reference point and convex below it.

Although the prospect theory has been developed since 1979, yet; there is no clear definition of gains and losses and how to measure them. Also, there is no clear identification of the reference point. Accordingly, its application into financial markets framework is very challenging. Our model provides a novel application of the prospect theory, where agents recognize their gains and losses in terms of the evolutionary fitness measure.

Frankel and Froot [2], Taylor and Allen [3], and Menkhoff [4] conducted different questionnaire surveys to investigate traders' main heuristics in order to model their behaviours. The studies revealed that traders rely on two trading philosophies; the technical analysis and the fundamental analysis, to determine their trading strategies. According to chartists, the ones believe that price trend will continue and follow technical analysis; they try to maximize their profits by taking advantages of asset price fluctuations [5]. Chartists compare the current price with the previous one, they buy (sell) when the asset price increases (decreases). On the other hand, fundamentalists, the ones follow fundamental analysis; believe that the asset price will revert to its fundamental value [6]. Therefore, fundamentals buy (sell) when the asset price decreases (increases) more than its fundamental value.

Many studies were developed to model the switching dynamics between fundamental analysis and technical analysis, such as; Day and Huang [7], Brock and Hommes [8], Farmer and Joshi [9], and.Westerhoff [10]. Few authors studied behavioural biases in their agent-based financial framework, such as; Feldman [11] and Lovric, et al. [12].

We explore the agent-based modelling as a tool for studying loss aversion behavioural bias introduced by the prospect theory. Our model contributes to behavioural finance research by linking the macro and the micro behaviours. This link is ignored in classical models studied behavioural finance. To our knowledge no research has been conducted to study the impact of loss aversion behavioural bias on the adaptive belief system and asset pricing dynamics, which is considered as our main contribution.

The rest of this article is organized as follows. In Section 2, we introduce an agent-based financial market model in which the chartist traders are loss averse along with the basic parameter settings and model implementation. In Section 3, we investigate the extent to which our proposed agent-based model is able to replicate the stylized facts of the real financial markets. Also, the simulation results of a large Monte Carlo analysis we performed to check the robustness of our results are presented. In Section 4, we summarize our results and conclusions.

2. An Agent-based Model under Loss Aversion

In this section we introduce an agent-based financial model populated with heterogeneous agents with loss aversion behavioural bias. At the beginning we discuss the model definition and assumptions. In Subsection 2.2, the detailed model is provided. Finally, the parameter setting is depicted in Subsection 2.3.

2.1 Model Definition and Assumptions

The main assumptions of the proposed artificial financial market can be summarized as follows;

- There is only one risky asset to be traded.

- There are two types of agents; market maker and traders.
- There are two heterogeneous beliefs of the traders; technical trading rule and fundamental trading rule. It is assumed that fundamental traders can calculate the fundamental values.
- In each time step $t, t = 0,1,\ldots,T$, each trader has three alternative actions; either to submit orders following technical analysis (chartists), submit orders following fundamental analysis (fundamentalists), or abstain from the market. It is assumed that at time t = 0, the orders are submitted without knowing the asset price.
- Beliefs adaptation rule; the agents are boundedly rational as they tend to choose the strategy performed well in the recent past, and therefore display some kind of learning behaviour. It is assumed that, the fitness of each trading strategy is available and publically known by all agents.
- The chartist agents are loss aversion so they recognize their losses more than double their recognition of gains. So they consider a value function proposed by the prospects theory to evaluate the fitness of each trading strategy.
- The fraction of traders use each strategy is determined via a discrete choice model.
- The market maker correlates the orders and adjusts the asset price according to the net submitted orders. The market maker is assumed to be a risk neutral and settle the asset prices without intervention.
- Agents in our market interact indirectly through their impact on price adjustment which affects the performance of the trading rules which affects the agent decision to select trading strategy and so on.

2.2 Model Formulation

The behaviour of the market maker is described as in Former and Joshi [9], where the price settlement is formulated as a log-linear price impact function. This function measures the relation between the quantity ordered (demand/supply) and the price of the asset. Thus, the log-price of the asset in period *t+1* is given by;

$$p_{t+1} = p_t + a\left(w_t^c D_t^c + w_t^f D_t^f\right) + \alpha_t \qquad (1)$$

where a is a positive price settlement parameter, D_t^c and D_t^f are orders submitted by chartists and fundamentalists; respectively, at time t and w_t^c and w_t^f are weights of technical strategy and fundamental strategy; respectively, at time *t*. In order to make our assumptions close to the real market, the noise terms α_t are added to catch any random factors affect the price settlement process. It is assumed that, $\alpha_t, t = 1, 2, \dots, T$ are IID normally distributed random variables with mean zero and constant standard deviation σ_α.

The goal of technical analysis used by chartists is to exploit the price changes [5]. Orders exploiting technical trading rules may be written as;

$$D_t^c = b(p_t - p_{t-1}) + \beta_t \qquad (2)$$

where b is a positive reaction parameter (also called extrapolating parameter) that capture the strength of agents' sensitivity to the price signals. The first term at the right hand side of Eq. (2) is representing the difference between current and last price is the exploitation of price changes. The second term captures additional random orders of technical trading rules. $\beta_t, t = 1, 2, \dots, T$ are IID normally distributed random variables with mean zero and constant standard deviation σ_β.

Fundamental analysis assumes that prices will revert to their fundamental values in the short run [6]. Orders generated by fundamental trading rules may be formalized as;

$$D_t^f = c(F_t - p_t) + \gamma_t \qquad (3)$$

c is a reaction parameter (also called a reverting parameter) for the sensitivity of fundamentalists' excess demand to deviations of the price from the underlying fundamental value. F_t[1] are log-fundamental values (or simply fundamental values) [7]. γ_t is introduced to capture additional random orders of fundamental trading rules. $\gamma_t, t = 1, 2, \dots, T$ are IID normally distributed random variables with mean zero and constant standard deviation σ_γ.

The evolutionary part of the model, inspired by Brock and Hommes [8], depicts how beliefs are evolved over time. That is, how agents adapt their beliefs and switching between strategies; which is mirrored in their fractions $w_t = \{w_t^c, w_t^f, w_t^0\}$, where w_t^0

[1] The fundamental value is assumed to be a constant, such that; $F_t = 0$. This assumption enables us to refer market crashes to price dynamics and eliminate the possibility of fundamental crashes.

represents the fraction of inactive agents and w_t^c, w_t^f are as indicated in Eq. (1), the strategy weights add up to one. Fractions are updated according to evolutionary fitness measure (or attractiveness of the trading rules) can be presented as follows;

$$A_t^c = (\exp(p_t) - \exp(p_{t-1}))D_{t-2}^c + mA_{t-1}^c \quad (4)$$

$$A_t^f = (\exp(p_t) - \exp(p_{t-1}))D_{t-2}^f + mA_{t-1}^f \quad (5)$$

$$A_t^0 = 0 \quad (6)$$

where A_t^c, A_t^f, and A_t^0 are the fitness measure of using chartist strategy, fundamental strategy, and no-trade strategy respectively. The inactive traders submit zero orders, so they got zero attractiveness of taking such an action. The fitness measure of the other two trading rules; technical analysis and fundamental analysis, depends on two components. The first term of the right hand side of Eq. (4) and Eq. (5) is the performance of the strategy rule in most recent time. Notice that, orders submitted in period $t-2$ are executed at the price declared in period $t-1$. The gains or losses depend on the price declared in period t. The second term of the right hand side of Eq. (4) and Eq. (5) represents agents' memory, where $0 \leq m \leq 1$ is the memory parameter that measures the speed of recognizing current myopic profits. For $m = 0$, agent has no memory, while for $m = 1$ they compute the fitness of a rule as the sum of all observed myopic profits.

However, in Westerhoff [10]; agents symmetrically perceive gains and losses in terms of fitness. Our model proposes a realistic behavioural bias, so that; chartists evaluate their strategy fitness in terms of a value function of gains and losses. The proposed value function implies that, chartists recognize losses more than twice their recognition of gains. As our focus is to study loss aversion, we follow the Tversky and Kahneman [13] and Benartzi and Thaler [14] piecewise linear value function proposed by the prospect theory. So, the value of the fitness of technical strategy is given by;

$$v_c = \begin{cases} A_t^c & \text{for} \quad A_t^c \geq 0 \\ \lambda A_t^c & \qquad\; A_t^c < 0 \end{cases} \quad (7)$$

where λ is the parameter of loss aversion that measures the relative sensitivity to gains and losses.

Following Manski and McFadden [15], the market share of each strategy can be obtained by the discrete choice model[2], as follows;

$$w_t^c = \frac{\exp(rv_c)}{\exp(rv_c) + \exp\left(rA_t^f\right) + \exp(rA_t^0)} \tag{8}$$

$$w_t^f = \frac{\exp(rA_t^f)}{\exp(rv_c) + \exp\left(rA_t^f\right) + \exp(rA_t^0)} \tag{9}$$

$$w_t^0 = \frac{\exp(rA_t^0)}{\exp(rv_c) + \exp\left(rA_t^f\right) + \exp(rA_t^0)} \tag{10}$$

The higher attractive strategy will be chosen by the agents. The parameter r in Eq. (8), Eq. (9), and Eq. (10); is named the intensity of choice and measures the sensitivity of mass of agents is selecting the trading strategy with higher fitness measure. In such adaptive beliefs, financial market prices and fractions of trading strategies coevolve over time. The steps of each simulation run are depicted in Algorithm 1.

2.3 Basic Parameter Setting

Model parameter settings are determined following Tversky and Kahneman [13], Winker and Gilli [16] Farmer and Joshi [9], and Westerhoff [10]. The values of model parameters were chosen so that the model can mimic the dynamics of real financial markets.

The main idea behind choosing specific values of the parameters can be summarized as follows. The reaction parameters of technical and fundamental trading rules (multiplied by the price settlement parameter) are between 0 and 0.1 for daily data.

To keep the autocorrelation[3] of raw returns[4] close to zero; parameters b and c are chosen as follows. The population of the chartists is matched with the population of the

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[2] A discrete choice model specifies probabilities $P(i|z,\theta)$ for each set of alternatives $\{i\}$ among which decision maker can choose. The exogenous variables *z* describe observable attributes and characteristics of the decision maker and available alternatives to her/him. The parameters θ are to be estimated from the observed choices of a sample of decision makers. The choice probabilities are determined by the multinomial logit model as follows; $P(i|z,\theta) = \frac{\exp V_i(z,\theta)}{\sum_{j=1}^{M} exp V_j(z,\theta)}$ where M is the number f available alternatives. And $V_i(z,\theta)$ is a summary statistic measuring the attractiveness of alternative i. It has the linear form of $V_i(z,\theta) = z_i.\theta, for\ i = 1,2,\dots,M$ [15].

[3] Autocorrelation Function (ACF) studies the linear dependence between r_t and its past values r_{t-l}. The correlation coefficient between r_t and r_{t-l} is named *lag- l autocorrelation* of $r_t$and it is denoted by $\mathrm{AC}_{\mathrm{r}}^{l}$,

fundamentalists, so the positive short-term autocorrelations induced by the chartists are cancelled by the negative short-term autocorrelation of the fundamentalists. Therefore, the reaction parameters of technical and fundamental trading rules are set to be the same.

Algorithm 1. Pseudo code for the proposed artificial financial market.

```
Initialize
repeat n times
    for t = 2 : T do
        submit orders use Eq. (2) or Eq. (3)
        evaluate trading rules use Eq. (4), Eq. (5) & Eq. (6)
            If [A_t^c ≥ 0] then v_c = A_t^c;
                else v_c = λ A_t^c;
            end if
        Calculate weights use Eq. (8), Eq. (9) & Eq. (10)
        Update price use Eq. (1)
    end do
end loop
```

The value of σ_β is assumed to be higher than σ_γ to reflect the level of noise associated with technical trading rule. The value of *m* is assumed to be near one, so the agents have good memory. Also, the value of *r* reflects the bounded rationality in choosing the trading rule with highest fitness measure. Finally, experiments estimate loss aversion parameter to be in the neighbourhood of 2, that is; the utility of losses is twice as great as the utility of gains [3, 17]. Experimental estimation of λ has been proposed by Tversky and Kahneman [17], such as; $\lambda = 2.25$. The values of model parameters are summarised in Table1. In the following section we study the evolutionary dynamics of our proposed model.

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which can be found by; $\mathrm{AC}_r^l = \frac{Cov\,(r_t, r_{t-l})}{\sqrt{Var(r_t)Var(r_{t-l})}} = \frac{Cov\,(r_t, r_{t-l})}{Var(r_t)} = \frac{\gamma_l}{\gamma_0}$, where the property of weak stationarity $Var(r_t) = Var(r_{t-l})$ is used. From the definition; $\mathrm{AC}_r^0 = 1$, $\mathrm{AC}_r^l = \mathrm{AC}_r^{-l}$, and $-1 \leq \mathrm{AC}_r^l \leq 1$ [28].

[4] The returns are defined as; $r_t = \log(\frac{P_t}{P_{t-1}}) = p_t - p_{t-1}$, where $p_t = \log(P_t)$, [28].

3. Evolutionary Dynamics

In this section we discuss the dynamics of our model by simulation. In Subsection 3.1 we describe the simulation design. The extent to which our model is able to replicate the

Table 1. Parameters for the simulation of the financial markets under loss aversion.

Parameter	Value	Description of parameter
a	1	Price settlement parameter
b	0.04	Extrapolating parameter
c	0.04	Reverting parameter
m	0.975	Memory parameter
r	300	Intensity of choice parameter
σ_α	0.01	Standard deviation of the random factors affect the price settlement process
σ_β	0.05	Standard deviation of the additional random orders of technical trading
σ_γ	0.01	Standard deviation of the additional random orders of fundamental trading
λ	2.25	Loss aversion parameter

statistical properties, of the real financial markets is investigated in Subsection 3.2.1. The results obtained from a large Monte Carlo analysis we performed to validate our model and investigate the robustness of our model dynamics are illustrated in Subsection 3.2.2. Finally, the micro-macro dynamics and the effect of loss aversion on the adaptive belief system and the asset pricing dynamics are investigated in Subsection 3.2.3.

3.1 Simulation Design

To implement the proposed model, an agent-based financial market simulation platform is developed using Netlogo platform. NetLogo is the environment for modelling problems or systems which have natural or social character [18]. We investigate the performance of 5000 simulation runs; each containing 4120 observations. In the initialization all parameters of the model can be defined as in Table 1, and the values of the other variables, such as; p_t, p_{t-1}, w_t^c ,w_t^f, w_t^0, D_{t-2}^c , D_{t-2}^f , D_t^c , D_t^f , A_{t-1}^c, A_{t-1}^f, A_t^c, and A_t^f are set to zero. The steps of our model implementation are summarized in Algorithm 1. In the following subsection, the simulation results are indicated.

3.2 Simulation Results

The extent to which our model is able to replicate the stylized facts of real financial markets is investigated. The Egyptian Stock Exchange (ESE) main index (EGX 30) is used for model validation purposes. The data of the EGX 30 covers the period between January 1, 1998 and November 16, 2014 of 4123 daily observations mirroring about 16 years. The financial data is collected from the Egyptian Stock Exchange website[5]. We apply time series analysis and econometrics using Excel and Eviews software.

Many researchers conducted empirical studies to identify a set of common characteristics among financial data that are known as stylized facts [21, 22, 23]. These main facts can be summarised as follows; crashes and bubbles, random-walk price behaviour, fat tail distributions of returns, excess volatility, and volatility clustering.

3.2.1 Qualitative Results

Fig. 1 compares directly a snapshot of the dynamics of a representative simulation run (the set of panels on the right) and the macro behaviour of the EGX 30 (the set of panels on the left), respectively. Fig. 1 is designed as follows. The panel shows from top to bottom; the evolution of log-prices (index prices for the EGX 30), the returns, the distribution of returns, the behaviour of extreme events in Hill plot of the left tail and the right tail, respectively [19][6], and the autocorrelation functions of raw (solid line), squared (rounded line), and absolute returns (dashed line), respectively.

Now, to check the extent to which our model is able to replicate the real financial data; we need to look closely at Fig. 1. The first panel in Fig. 1 depicts that, the prices of the model fluctuate around their fundamental values. However, our model can generate significant bubbles and crashes as those observed in the EGX 30. For example, the snapshot shows a

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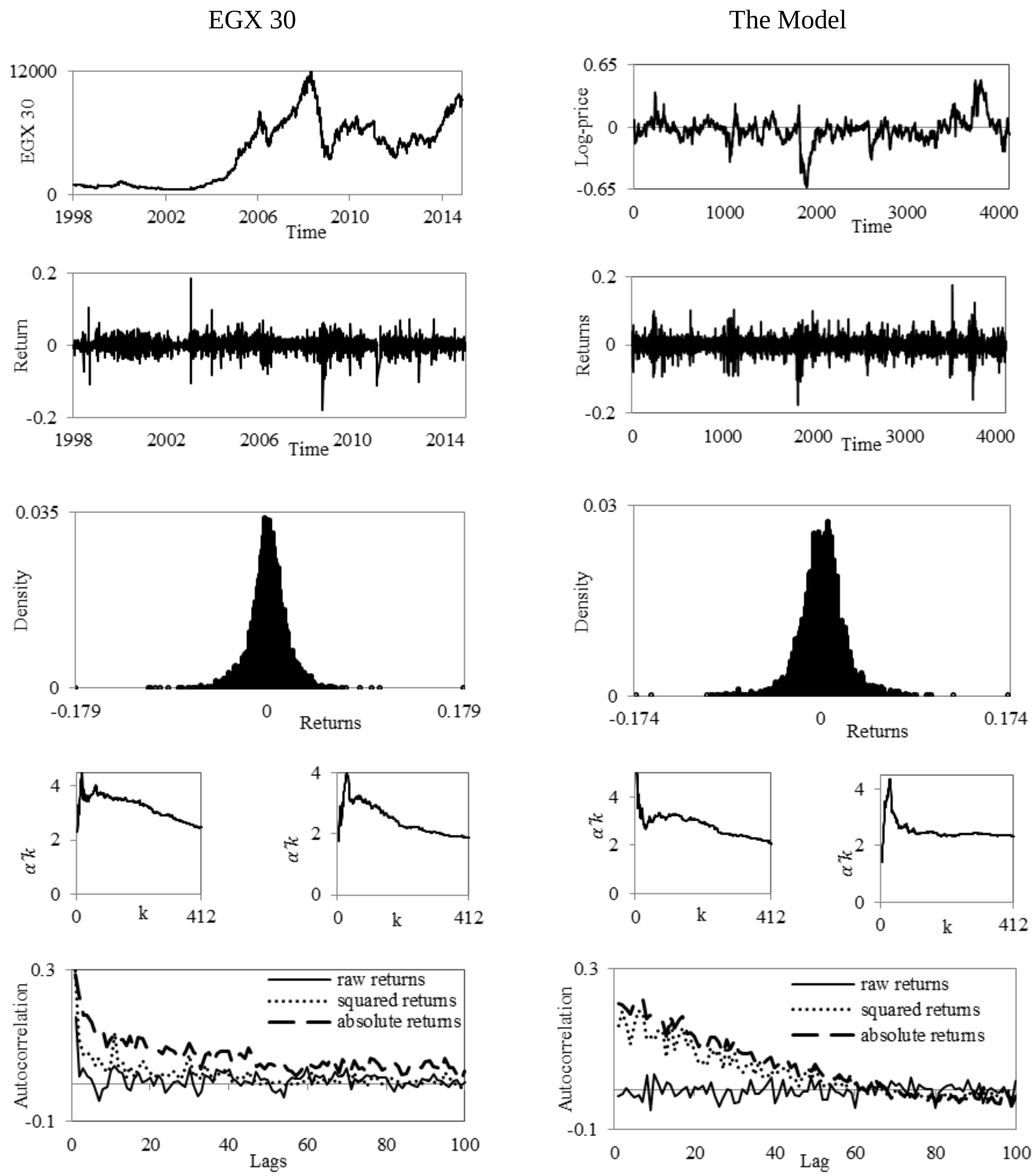
[5] http://www.egx.com.eg/english/indexData.aspx?type=1&Nav=1

[6] Hill estimate of tail-index $\hat{\alpha}_k = \left(\frac{1}{n_k}\sum_{i=1}^{n_k-1}\log R_{T-i} - \log R_{T-n_k}\right)^{-1}$, where k is the percentage of observations located in the tail and $n_k = k * T$. To apply this estimator the data elements are required to be ordered from largest to smallest; such that, $R_T > R_{T-1} > \cdots > R_{T-n_k} > \cdots > R_1$. This process is applied to the right tail and can be reversed to obtain the left tail exponent. The hill plot is obtained by plotting $\hat{\alpha}_k$ against k. However, the value of tail exponent $\hat{\alpha}_k$ is very sensitive to the choice of k. Thus, Huisman, et al. [29] recommend calculating $\hat{\alpha}_k$ for different values of k then regressing these on k; such as $\hat{\alpha}_k = c_1 + c_2 n_k + \epsilon_{n_k}$. The tail exponent estimate would be given by $\hat{\alpha}_k = c_1$, the intercept, with standard error $\sigma_\alpha = \frac{\hat{\alpha}_k}{\sqrt{n_k}}$.

Fig. 1. The dynamics of the EGX 30 and the simulated stock market



The panel shows from top to bottom; the evolution of the log-prices (prices for the EGX 30) , the returns, the distribution of returns, the behaviour of extreme events in Hill plot of left tail and right tail; respectively, and the autocorrelation functions of raw, squared, and absolute returns, respectively.

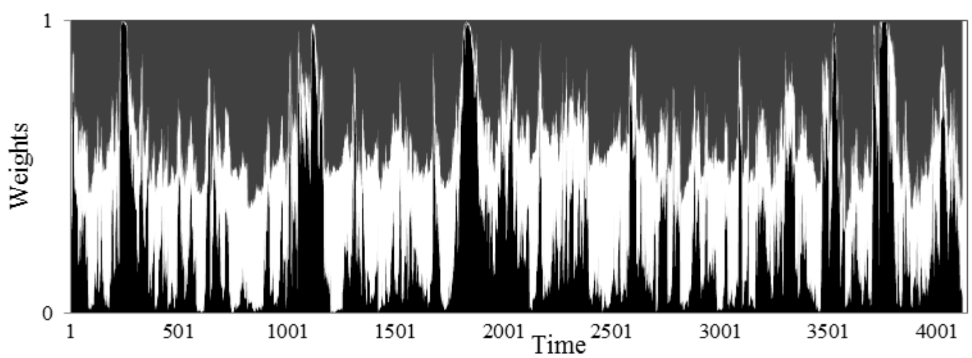
significant crash between periods 1811and 1972, were the price deviating more than 50 percent from its fundamental value. Also, we can observe a significant price bubble between periods 3600 and 3875. At this period the price deviating more than 50 percent from its fundamental value.

The second panel of Fig. 1 represents the daily returns; we can observe the clustered volatility. The negative events are more pronounced than positive ones. The extreme value of daily returns of the model reaches up to ± 17.4 percent. The extreme value of daily returns of the EGX 30 reaches up to ± 17.9 percent. The third panel of Fig. 1 indicates that, the distribution of simulated returns is fat-tail with high peak. This fact also resembles the fat tail distribution of the EGX 30. The fourth panel depicts behaviour of the smallest and largest extreme events through the Hill plot of left tail and right tail respectively from the left.

The last panel of Fig. 1 shows that; although there is almost no autocorrelation between raw returns (solid line), there is a significant positive autocorrelation between the different powers of absolute value of the returns $\{|r_t|^{\phi}, \phi = 1,2\}$, squared (rounded line) and absolute returns (dashed line) for the first 100 lags. This fact is stated by Mandelbort [20] as large returns often tend to emerge in clusters. To sum up, our model shows a remarkable capability to qualitatively replicating the stylized facts of the real Egyptian financial market and real financial markets in general.

Finally, Fig. 2 depicts the dynamics of the adaptive belief system; technical analysis (black region), fundamental analysis (grey region), and no-trade (white region). We can observe that; although there are swings between the trading strategy weights, there is no one strategy dominates the others. The average weights of this particular simulation run are; $\overline{w}_t^c \approx 27$ percent, $\overline{w}_t^f \approx 39$ percent, and $\overline{w}_t^0 \approx 34$ percent.

Fig. 2. Dynamics of the adaptive belief system



The figure displays the fraction of chartists (black region), fundamentalists (grey region), and inactive traders (white region).

The robustness of our results is investigated in Fig. 3 and Fig.4. Fig. 3 represents four repetitions of simulation model using different random seeds. The four simulation markets have significant price bubbles and crashes. The volatility clustering is obvious in all the simulation return series. It is also clear that, there is an endogenous competition between the trading strategies in all the simulation runs and no strategy can dominate the others. We can also observe that, periods of high volatility are those when the chartist traders exist significantly more than the other two types of traders.

Fig. 4 represents four repetitions of simulation model with changing some parameters values, using the same stream of random variables as in Fig. 1. We can observe that, these changes have slight effect on our model dynamics. The following section is dedicated to check the extent to which our model is able to quantitatively replicate the stylised facts of the Egyptian Stock Exchange and the robustness of these results.

3.2.2 Quantitative Results

To check the extent to which our model is able to quantitatively replicate the stylized facts and the robustness of the model results; we perform a Monte Carlo analysis on 5000 simulation runs, each containing 4120 observations. The design of all the simulation runs is the same as that described in Section 2, but with different random seeds. The descriptive statistics of EGX 30 and simulation data are reported in Table 2. Table 2 reports the mean, maximum, minimum, standard deviation, skewness, kurtosis, and Jarque-Bera (JB)[7] of EGX 30 and estimates of the mean and the 5 percent, 25 percent, 50 percent, 75 percent, and 95 percent quantiles of these statistics.

Table 2 reveals, for instance, estimates of the standard deviation hover between 0.020 percent and 0.026 percent in 90 percent of the cases. The reported standard deviation in the same table for the EGX 30 is quite close to these figures. The two very important statistics to be noticed are the normalized third and fourth central moments[8]; the skewness and the kurtosis, respectively. However, only 25 percent of the cases are

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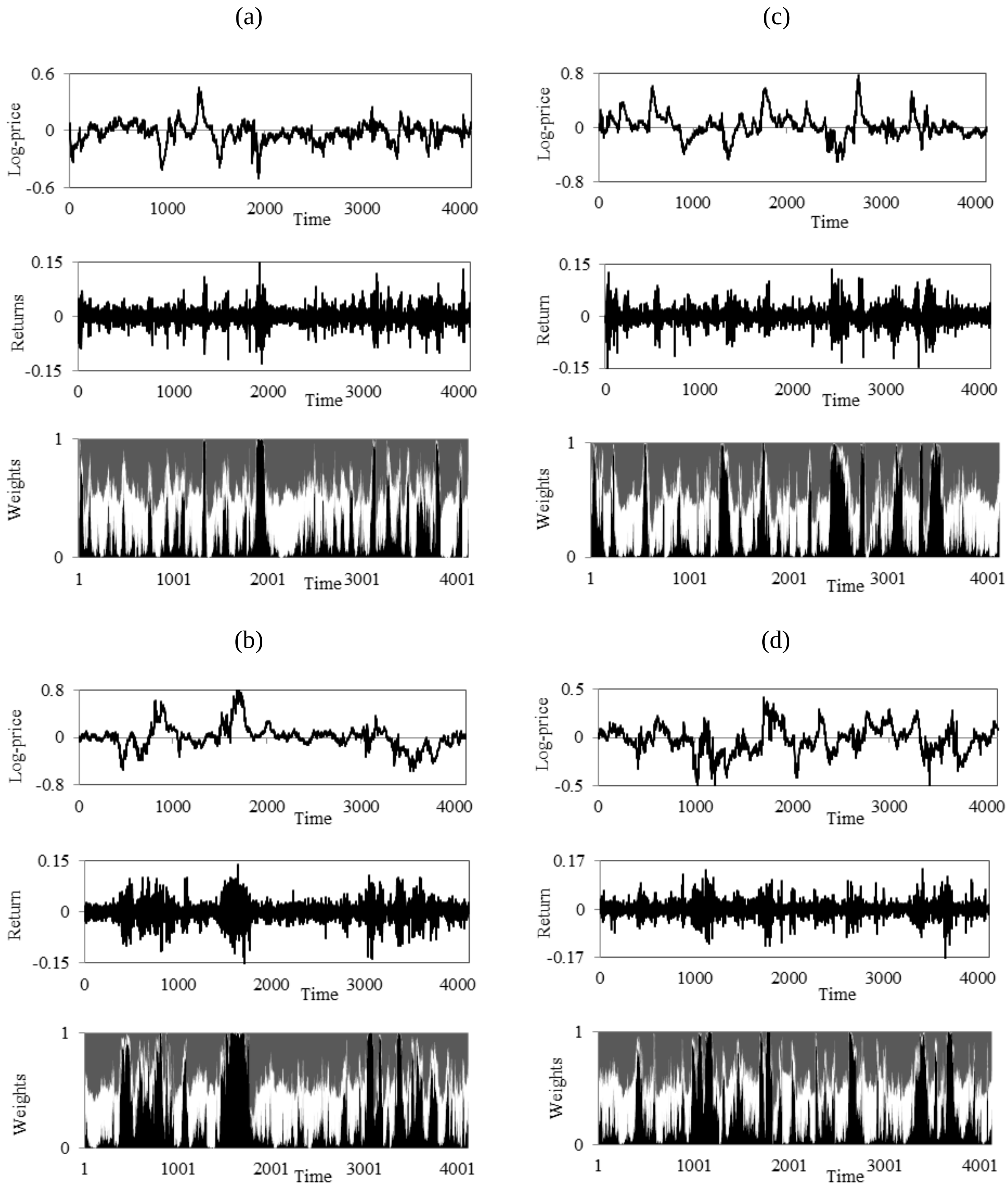
[7] The Jarque-Bera (JB) test statistic for normality is defined as follows [28];
$JB = T\left[\frac{S(r_t)^2}{6} + \frac{(K(r_t)-3)^2}{24}\right]$, where $t = 1,2,\ldots,T$, $S(r_t)$ is the skewness, and $K(r_t)$ is the kurtosis. JB is asymptotically distributed as $\chi^2(2)$.

[8] For fat-tail distributions the first and second moments are not enough to describe the data [28]. In large samples of normally distributed data, the estimators of skewness and kurtosis are asymptotically

Fig. 3. Four repetitions of the simulation using different random seeds



Each set of the four panels shows from top to bottom the evolution of stock prices, the asset returns, and the market shares of chartists (black region), fundamentalists (grey region), and no-trade (white region), respectively.

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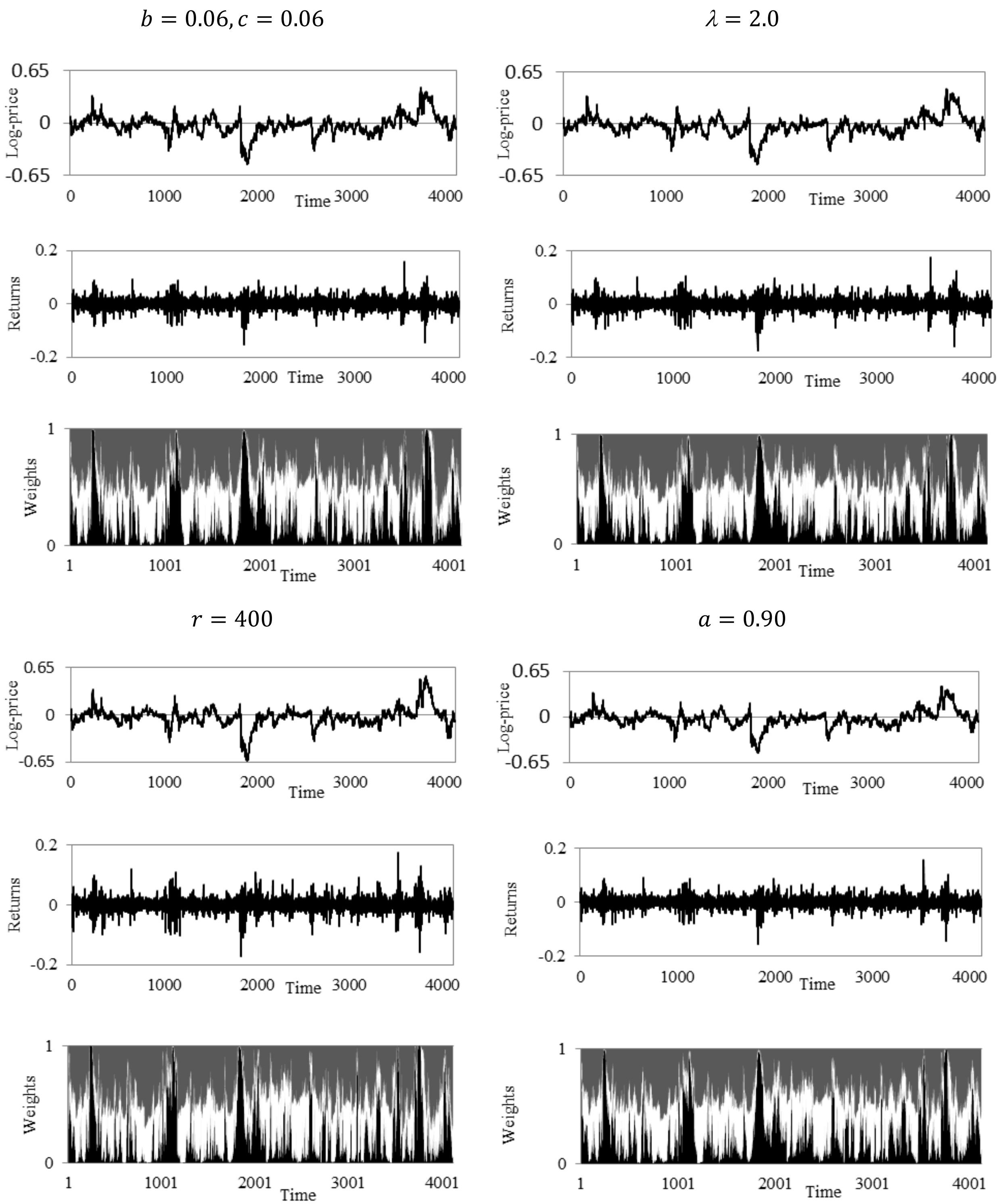
converging to normally distribution with means 0 and 3 and variances 6/ T and 24/T respectively for large samples, where T represents the daily data sample size.

Fig.4. Four repetitions of the simulation using different parameter values



Each set of the four panels shows from top to bottom the evolution of stock prices, the asset returns, and the market shares of chartists (black region), fundamentalists (grey region), and no-trade (white region), respectively.

Table 2. Descriptive statistics

	Mean/ quantile	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	JB
EGX 30		$5.39*10^{-4}$	0.18	-0.18	0.018	-0.33	12.04	14101.9
The model	Mean	$-6.19*10^{-7}$	0.14	-0.14	0.023	0.01	4.39	-
	0.05	$-6.82*10^{-5}$	0.11	-0.18	0.020	-0.25	3.28	-
	0.25	$-1.86*10^{-5}$	0.13	-0.15	0.021	-0.10	3.85	-
	0.50	$-7.31*10^{-7}$	0.14	-0.14	0.023	0.01	4.32	-
	0.75	$1.57*10^{-5}$	0.15	-0.13	0.024	0.01	4.82	-
	0.95	$6.08*10^{-5}$	0.18	-0.11	0.026	0.27	5.77	-

The table reports the mean, maximum, minimum, standard deviation, skewness, kurtosis, and Jarque-Bera (JB) of the EGX 30 and estimates of the mean and the 5 percent, 25 percent, 50 percent, 75 percent, and 95 percent quantiles of these statistics for the simulated time series. Computations are based on 5000 time series, each containing 4120 observations.

negatively skewed this may due to the fatness of the return distribution. Finally, estimates of the mean and the quantiles of the kurtosis are all greater than 3. This may give us an indication about the non-normality of all the simulated return series.

Table 3 reports the Hill estimates $\widehat{\boldsymbol{\alpha}}_{\boldsymbol{k}}$ for $\boldsymbol{k} \in \{\mathbf{2.5}, \mathbf{5}, \mathbf{10}\}$ percent of the smallest returns (left-tail) and Hill estimates $\widehat{\boldsymbol{\alpha}}_{\boldsymbol{k}}$ for $\boldsymbol{k} \in \{\mathbf{2.5}, \mathbf{5}, \mathbf{10}\}$ percent of the largest returns (right-tail) of the EGX 30 along with estimates of the mean, the 5 percent, 25 percent, 50 percent, 75 percent, and 95 percent quantiles of these Hill estimates.

From Table 3 we can notice that, the model's average Hill estimators of the tail-index for the largest and smallest 10 percent observations are in line with the EGX 30 estimators. For instance, taking the largest 5 percent of observations into account; the reported value for the EGX 30 (3.32) lays within the lower and upper quartile (3.28 and 3.74, respectively) of the estimated tail indices. Also, taking the smallest 5 percent of observations into account; the reported value for the EGX 30 (3.72) lays within the lower and upper quartile (3.28 and 3.74, respectively) of the estimated tail indices. Moreover, most estimated tail indices from real financial markets always range between 2 and 5 as indicated by Lux [21]. Accordingly, the estimated Hill tail indices of our model match the Hill tail indices not only for the EGX 30 but also for other real financial markets.

Table 3. The Hill tail index estimator $\widehat{\alpha}_k$ for the left and right tails

		Left-tail exponent			Right-tail exponent		
	Mean/quantile	$\widehat{\alpha}_{2.5\%}$	$\widehat{\alpha}_{5\%}$	$\widehat{\alpha}_{10\%}$	$\widehat{\alpha}_{2.5\%}$	$\widehat{\alpha}_{5\%}$	$\widehat{\alpha}_{10\%}$
EGX 30		3.39	3.32	3.47	3.56	3.72	3.92
		(0.077)	(0.038)	(0.020)	(0.063)	(0.032)	(0.025)
The model							
	Mean	3.27	3.52	3.40	3.38	3.61	3.46
	0.05	2.68	2.97	2.96	2.68	2.97	2.96
	0.25	3.01	3.28	3.21	3.01	3.28	3.20
	0.50	3.25	3.50	3.39	3.25	3.50	3.39
	0.75	3.52	3.74	3.59	3.52	3.74	3.59
	0.95	3.90	4.13	3.90	3.90	4.13	3.90

The table reports, the Hill tail index estimators $\hat{\alpha}_k$ for $k \in \{2.5,5,10\}$ percent of the smallest (left-tail) and largest (right-tail) returns of the EGX 30 along with estimates of the mean, the 5 percent, 25 percent, 50 percent, 75 percent, and 95 percent quantiles of these statistics for the model, with asymptotic standard errors shown in brackets. Computations are based on 5000 time series, each containing 4120 observations.

To continue investigating the robustness of our results Table 4 reports the statistical properties of the EGX 30 and our model. Table 4 contains the autocorrelation function of raw returns $\mathrm{AC}_{\mathrm{r}}^{l}$ for lags $l \epsilon \{1,2,3\}$, and the autocorrelation function of absolute returns $\mathrm{AC}_{|\mathrm{r}|}^{l}$ for lags $l \epsilon \{1,20,50,100\}$ of the EGX 30 along with estimates of the mean, the 5 percent, 25 percent, 50 percent, 75 percent, and 95 percent quantiles of the same statistics.

The reported autocorrelation coefficients of simulated raw returns in Table 4 reveal that, price increments are mainly uncorrelated. Although autocorrelation coefficient for the EGX 30 shows a value of 0.18 for the first lag, the price increments do not last for the second lag. However, in most real financial markets future prices cannot be predicted [22]. Also, autocorrelation coefficients of simulated absolute returns show a median value of 0.28 for the first lag that seems to be quite close to that of the EGX 30 (0.29). However, our model has a longer memory than that of the EGX 30 as the autocorrelation of the simulated absolute returns lasts for the 20$^{\text{th}}$ lag.

To summarize our results, the illustrated figures and the performed large Monte Carlo analysis show that, our model can replicate detailed stylized facts of real financial markets. These properties include; fat-tailed distribution, absence of autocorrelation between raw returns, excess volatility, and volatility clustering.

Table 4. The autocorrelation functions of raw and absolute returns

	Mean/ quantile	AC_r^1	AC_r^2	AC_r^3	$AC_{\|r\|}^1$	$AC_{\|r\|}^{20}$	$AC_{\|r\|}^{50}$	$AC_{\|r\|}^{100}$
EGX 30		0.18	0.02	0.04	0.29	0.09	0.05	0.03
The model	Mean	0.02	0.005	0.004	0.28	0.17	0.08	0.02
	0.05	-0.02	-0.04	-0.04	0.23	0.11	0.02	-0.03
	0.25	0.004	-0.01	-0.01	0.26	0.15	0.05	-0.001
	0.50	0.02	0.01	0.004	0.28	0.17	0.08	0.02
	0.75	0.04	0.02	0.02	0.30	0.20	0.11	0.04
	0.95	0.07	0.05	0.05	0.33	0.23	0.15	0.09

The table contains, the autocorrelation function of raw returns AC_r^l for lags $l\epsilon\{1,2,3\}$, and the autocorrelation function of absolute returns $AC_{|r|}^l$ for lags $l\epsilon\{1,20,50,100\}$ for the EGX 30 along with estimates of the mean, the 5 percent, 25 percent, 50 percent, 75 percent, and 95 percent quantiles of these statistics for the model. Computations are based on 5000 time series, each containing 4120 observations.

3.2.3 Micro-Macro Dynamics

For the sake of checking the robustness of our model dynamics evolution, we perform a Monte Carlo study on the volatility (to measure volatility we follow Guillaume, et al., [23] and calculate the average absolute returns), distortion ($\text{dist} = \frac{1}{T}\sum_{t=1}^{T}|F_t - p_t|$), and the fraction of agents follow each strategy; w_t^c, w_t^f, and w_t^0. Table 5 reports estimates of the mean and the 5 percent, 25 percent, 50 percent, 75 percent, and 95 percent quantiles of these statistics.

We note from Table 5 that, the average value of volatility of 1.60 percent is considered to be slightly higher than the 1.23 percent of the EGX 30. The distortion hovers between 8.02 percent and 16.44 percent in 90 percent of the cases. These values of distortion indicate a substantial boom-bust cycles in almost all simulation runs.

Now, the most important part is analysing the fraction of traders following each strategy. Generally speaking, all estimates of the mean and quantiles reveal that agents prefer to follow the fundamental analysis the most, then no-trade strategy, and the technical analysis the least. Is the technical analysis least appealing due to the loss aversion behavioural bias? What is the effect of loss aversion on the adaptive belief system and on the pricing dynamics? To answer these questions we run the model with the chartists symmetrically perceiving losses and gains. That is, when $\lambda = 1$.

Table 5. Statistical properties and evolutionary dynamics of our agent-based model

Mean/ quantile	Volatility	Distortion	w_t^c	w_t^f	w_t^0
Mean	1.60	11.53	29	38	33
0.05	1.40	8.02	23	35	29
0.25	1.50	9.65	26	37	32
0.50	1.59	11.07	29	38	33
0.75	1.68	12.91	31	39	35
0.95	1.82	16.44	35	41	37

The table contains estimates of the mean, the 5 percent, 25 percent, 50 percent, 75 percent, and 95 percent quantiles of the volatility, distortion, and the weights of agents follow each trading strategy, in percentage values.

Table 6. Statistical properties and evolutionary dynamics of the model with chartists symmetrically perceiving gains and losses.

Mean/ quantile	Volatility	Distortion	w_t^c	w_t^f	w_t^0
Mean	1.70	12.44	34	35	30
0.05	1.51	8.80	29	33	27
0.25	1.61	10.46	32	34	29
0.50	1.70	12.02	34	36	31
0.75	1.79	13.96	36	37	32
0.95	1.92	17.80	40	38	34

The table contains estimates of the mean, the 5 percent, 25 percent, 50 percent, 75 percent, and 95 percent quantiles of the volatility, distortion, and the weights of agents follow each trading strategy, in percentage values.

Table 6 reports the results of the Monte Carlo analysis we performed where chartists symmetrically perceiving gains and losses. Table 6 contains the same statistics as Table 5 and reveals, for instance, that the average volatility of 1.70 percent is higher than that of our model. Also, the distortion hovers between 8.80 percent and 17.80 percent in 90 percent of the cases. Also, we can notice that, for example; the median of weights of the three trading strategies are ($w_t^c = 34$ percent, $w_t^f = 36$ percent, and $w_t^0 = 31$ percent). These values of weights are very close, indicating that; the three trading strategies are equally preferred by the agents. However, in our model agents prefer to follow fundamental analysis more than technical analysis due to the loss aversion behavioural bias. The distortion and volatility in the market populated with symmetrical perception of gains and losses seems to be higher than our model. Obviously, loss aversion behavioural bias decreases the market volatility and price deviation from fundamental value. This shows that loss aversion can improve the quality of the market[9].

4. Conclusions

In 1979, Kahneman and Tversky proposed their famous psychological theory; the prospect theory in order to understand the psychological motivations for traders' behaviours. The prospect theory considers loss aversion to be one of the main behavioural biases that affect traders' decisions. This implies that, traders recognize their losses more than twice their recognition of gains.

To increase our understanding of traders' behaviours and their adaptive beliefs, we develop an agent-based financial market model. Agent-based modelling provides the link between macro and micro behaviours. In our model, agents can trade following either stochastic technical trading rules or stochastic fundamental trading rules. While technical analysis builds decisions upon past price trends, fundamental analysis advises betting on mean reversion. Since traders are loss averse, any losses following technical analysis cause a rapid switching to fundamental analysis or staying in-active. Price adjusted by the market maker according to the net submitted orders without any intervention from her/him.

Our model provides a remarkable capability to replicate many detailed stylized facts of real financial markets. These facts include; random walk price dynamics, bubbles and crashes, fat-tailed returns distribution, excess volatility, and volatility clustering.

The dynamics of our model can be summarized as follows. The farther the asset prices deviate from their fundamental value, the more aggressive the chartists will become. The increase in market shares of the chartists will increase the volatility causing a bubble or a crash to emerge. However, the loss aversion behavioural bias improved the market by minimizing its volatility and distortion. As the distortion reaches its maximum value the fundamental analysis becomes more appealing for traders to follow. The increase in switching to the fundamental analysis will pull asset prices to their fundamentals and the

[9] Distortion and volatility are considered to be important determinants of market quality [24].

volatility diminishes. Due to the market dynamics, no trading strategy dominates the others. This causes substantial long memory effects in returns volatility.

To sum up, loss aversion directly affects the adaptive belief system; as recognized losses stimulate chartists to adopt fundamental trading or stay inactive. This adaptation works for the market stability and prices efficiency. The proposed agent-based model and simulation results successfully replicate the macro-behaviour of real financial markets and can help us to understand asset pricing dynamics in these markets.

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