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Full Length Article

An agent-based model of financial market efficiency dynamics

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Abstract

We build a parsimonious agent-based model under the adaptive market hypothesis (AMH), which can explain the formation of equilibrium prices and market efficiency dynamics. Our model combines heterogeneous interacting agents, switching behavior, and investor feedback on past realized returns, with realistic assumptions on the market microstructure. Numerical simulations show that our model is empirically robust to the facts observed in returns of developed and emerging financial markets (leptokurtic distribution, excess volatility, time-varying linear and nonlinear autocorrelations in returns, and time-varying degree of market efficiency). These results reveal that the elements in the model are necessary for generating these empirical facts. They also confirm the AMH. The model can be used as an artificial laboratory to assess the effectiveness of regulatory policies and the profitability of trading strategies.

JEL classification: C58; G14; G15; G17; G41

Keywords: Adaptive market hypothesis (AMH); Price dynamics; Stylized facts; Time-varying degree of efficiency

1. Introduction

Academic researchers have widely discussed equilibrium prices in financial markets. Several models have been developed to explain the underlying price dynamics and market efficiency. The first models were constructed based on the efficient market hypothesis (EMH), which was established based on complete investor rationality. However, price dynamics, which result from the models based on the assumption of the EMH, do not match the characteristics of the actual return series. Consequently, since 1980, behavioral finance has rejected the EMH and shows that many psychological biases might influence the judgment of investors and ultimately lead to market inefficiency. Subsequently, certain behavioral models based on human psychology have emerged to account for market anomalies (Barberis et al., 1998; Daniel et al., 1998). The price dynamics obtained with these models reproduce the short-run momentum and long-run reversal.

Nevertheless, neither the EMH nor the behavioral finance can satisfactorily explain market behavior. Thus, an alternative framework, called the adaptive market hypothesis (AMH) (Lo, 2004, 2005), attempts to reconcile these two paradigms based on an evolutionary approch to market and investor behavior, implying that a rational agent can become irrational under certain market conditions and vice versa (switching behavior). Accordingly, the degree of market efficiency is time-varying, depending on market conditions.

The two approaches to financial market modeling can be divided into an up-down approach and a bottom-up approach. The second approch (an agent-based model) starts with a description of the behavior of agents and the way in which transactions are executed in the market before moving on to equilibrium prices (Cross et al., 2005). The prices obtained are then compared with real empirical data from financial markets to confirm whether the model is likely to reproduce the stylized

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facts and solve certain puzzles (LeBaron, 2006). The stylized facts are seen as statistical properties of the return series that are common in a wide variety of markets and instruments, namely, excess volatility, a lack of linear autocorrelation, fat tails, volatility clustering, and correlation between trading volume and volatility (Cont, 2001). Several agent-based models have been developed to explain the origin of the main stylized facts (Challet et al., 2001; Farmer & Joshi, 2002; Giardina & Bouchaud, 2003; Iori, 2002). However, most agent-based models are formulated in a complex manner so it is not clear which parameters in the model are necessary for explaining empirical observations. This complexity reduces the explanatory power of such models (Ghoulmie et al., 2005). Therefore, recent research focuses on parsimoniously parameterized agent-based models by proposing minimalist models in terms of complexity to better explain the stylized facts. In addition, although some agent-based models address the issue of efficiency (Arthur et al., 1997), models dealing with efficiency within the framework of the AMH are in short supply in the literature.

The goal of this paper is to propose a parsimonious agent-based model capable of explaining price and efficiency dynamics under the AMH. Our model has two components: the market microstructure and the behavior of agents. We therefore reconcile research on the impact of the microstructure on the process of price discovery and market efficiency (Bouchaud, 2018; O'Hara, 1997) and those related to the effect of heterogeneous interacting agents on price dynamics (for a detailed literature review, see Dieci & He, 2018).

We make three contributions to the existing literature. First, we propose a model that combines realism and parsimony. The model is realistic because it includes both market microstructure and agents' behavior. Most agent-based models consider that the stylized facts are common in a wide range of markets, suggesting that their origin is largely independent of market microstructure, and thus they are based only on a stylized description of the behavior of agents. However, our model shows that agents' behavior and the market microstructure simultaneously influence actual price dynamics in line with some previous models (Chiarella & Iori, 2002; Staccioli & Napoletano, 2020). The model is also parsimonious as it introduces only the main elements that have an impact on market dynamics. Second, our model is the first developed under the AMH, as it includes the arguments of this hypothesis, namely, the heterogeneity of agents (rational and irrational), investor feedback on market conditions, and switching behavior. Third, the model is designed to jointly generate well-known stylized facts, along with nonlinear autocorrelation and time-varying market efficiency, which are also common characteristics of a variety of financial markets.

Numerical simulations show that our agent-based model can reproduce the same empirical facts observed empirically, namely, fat tails, excess volatility, time-varying linear and nonlinear autocorrelation in returns, and therefore the time-varying degree of market efficiency implied by the AMH. Thus, the heterogeneity of interacting agents, investor feedback on past realized returns, and switching behavior as well as the market microstructure are responsible for generating empirical observations.

The remainder of the paper is organized as follows. Section 2 examines the main empirical facts in developed and emerging financial markets. Section 3 describes our agent-based model. Section 4 reports the results of numerical simulations under different scenarios and validates the model based on the facts observed in the markets examined. Section 5 performs relevant experiments on regulatory policies and trading behavior. Section 6 concludes.

2. Empirical facts

This section examines the common empirical facts observed in various developed and emerging financial markets, namely, the fat tails, the linear and nonlinear autocorrelations, and the degree of time-varying efficiency. Our sample consists of three developed markets (the US, Europe, and Japan) and three emerging markets (Turkey, China, and Brazil). We use daily returns over the period from January 2012 to August 2021, obtained from the website investing.com.

Descriptive statistics of the returns in the DJIA index (US), the Euro Stoxx 50 index (Euronext), the Nekkei 225 index (Japan), the BIST 100 index (Turkey), the Shanghai Composite index (China), and the Bovespa index (Brazil) are given in Table 1.

In Table 1, the kurtosis coefficient is greater in all the markets than in the normal distribution, which by construction equals 3. Moreover, the data are negatively skewed, unlike in normal distribution, in which the skewness coefficient is zero. The Jarque-Bera test rejects the null hypothesis of a normal distribution of the data at the 1 percent significance level ($p < .01$). Hence, the distribution is leptokurtic, which is a stylized fact.

To measure the linear and nonlinear autocorrelation as well as the degree of evolution in the efficiency of the markets examined, we perform a linear automatic portmanteau test (AQ) (Escanciano & Lobato, 2009) and a nonlinear McLoed-Li test (McLeod & Li, 1983) with a rolling window. In contrast to most previous studies, which measure autocorrelation in the returns based on the full sample and consider the absence of such autocorrelation a stylized fact, we consider time-varying autocorrelation as returns displaying structural breaks.

Fig. 1 illustrates the evolution over time of the automatic portmanteau test statistics for the US market (a), Euronext

Table 1
Descriptive statistics and Jarque-Bera test.

Index	Skewness	Kurtosis	JB	*N*
DJIA	−1.096	27.884	0.000	2424
Euro Stoxx 50	−0.830	13.676	0.000	2470
Nekkei 225	−0.273	4.578	0.000	2385
BIST 100	−0.775	5.317	0.000	2418
Shanghai Composite	−0.994	10.054	0.000	2343
Bovespa	−0.894	16.040	0.000	2382

*Notes:*JB is the p-value of the of Jarque-Bera test (1980); n is the number of observations; R version 3.6.1 was used to calculate the statistics.

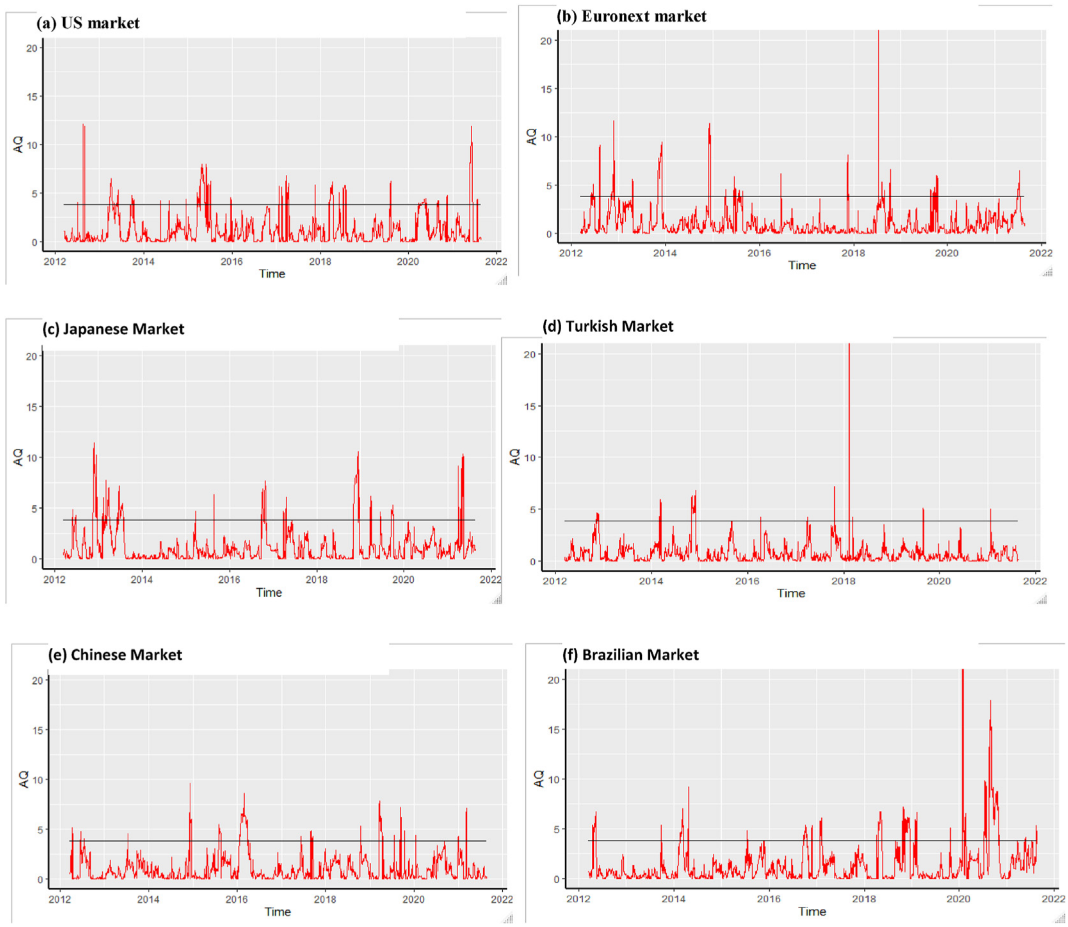

Fig. 1. Automatic portmanteau test results. *Notes*: The red line indicates the automatic portmanteau test statistic, and the black line represents the F-statistic at the 5% significance level. (a), (b), (c), (d), (e), and (f) show, respectively, the time-varying linear autocorrelation in returns in the US, Euronext, Japanese, Turkish, Chinese, and Brazilian financial markets. R version 3.6.1 was used to calculate the statistics.

market (b), Japanese market (c), Turkish market (d), Chinese market (e), and Brazilian market (f). This test indicates the time-varying linear dependence in the returns. The returns are autocorrelated when the test statistics are above the 5 percent level significance and independent when they are below this level. In all the markets examined, the autocorrelation in returns varies over time, fluctuating between periods with significant dependence and periods with significant independence.

Nevertheless, linear tests can fail to detect nonlinear dependence in returns, which is also considered a stylized fact (Lim & Brooks, 2011). To intercept that nonlinear dependence in returns, we perform the McLeod-Li test (Fig. 2). The empirical findings show that the nonlinear autocorrelation in returns has alternating periods of dependence and independence. The p-value above the 5 percent significance line indicates the absence of autocorrelation but when the p-value is below that line, autocorrelation occurs. This finding is consistent with previous studies (Almudhaf et al., 2020; Ghazani & Ebrahimi, 2019; Shahid et al., 2019). Market psychology, investor heterogeneity, and transaction costs are the major factors that cause nonlinearity in returns.

According to the weak-form version of market efficiency, stock returns are independent, and no one can forecast future returns based on past information. Empirical results from both linear and nonlinear tests (Figs. 1 and 2) suggest that the autocorrelation in returns is time-varying, which implies the evolution of market efficiency caused by changing market conditions. Thereby, the AMH is confirmed in these markets and can explain their behavior better than the EMH. Our findings are consistent with previous studies in confirming the AMH in developed (Boya, 2019; Ito et al., 2016; Lim et al., 2013) and emerging markets (Akhter & Yong, 2019; Lekhal & El Oubani, 2020; Phan Tran Trung & Pham Quang, 2019; Shahid et al., 2019; Xiong et al., 2019).

3. Description of the model

The model considers an order-driven market in which a single risky asset is traded by heterogeneous interacting participants. Thus, the model has two parts: the market microstructure and investor behavior. The former is borrowed from major developed and emerging financial markets, for which we consider two trading strategies:

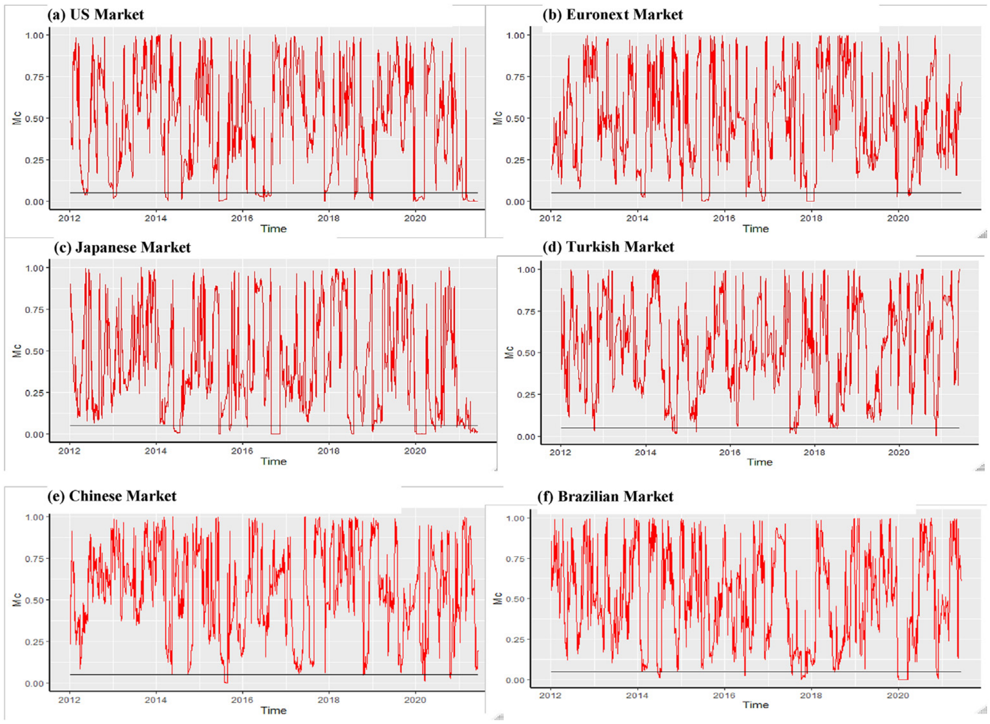

Fig. 2. The p-values of the McLeod-Li test. *Notes*: The red line indicates the p-values of the McLeod-Li test, and the black line represents the 5% significance level. (a), (b), (c), (d), (e) and (f) show, respectively, the time-varying nonlinear autocorrelation in returns in the US, Euronext, Japanese, Turkish, Chinese, and Brazilian financial markets. R version 3.6.1 was used to calculate the statistics.

fundamentalist and chartist. A fundamentalist agent trades primarily on the basis of fundamental information, whereas a chartist agent believes that the future return of an asset can be forecasted using the trend in past realized returns. Despite using such simple behavioral rules, we show that, together with the microstructure of the market, they can replicate realistic financial dynamics. We present the two parts of the model below.

3.1. Investor behavior

We consider a market in which a single asset, whose price is denoted p_t, is traded by N agents divided into two interacting groups, namely, the rational (fundamentalist) and the irrational agents (noise traders). The rational traders assess the fundamental information received by making some idiosyncratic errors, which are minimal (bounded rationality). By contrast, noise traders make large errors because of the influence of psychological biases. However, in contrast to most models, which introduce this heterogeneity by specifying an equation for each group, we implicitly introduce the heterogeneity of agents with evolving investors biases in a random manner.

Specifically, trading takes place at discrete periods of $t_i = i.s$, in which $i \geq 1 \in \mathbb{N}^*$, and s is the time between two transactions, which is measured in our model in terms of minutes. In the context of the intraday transactions, the effect of the dividend and the risk-free rate could be overlooked. The asset price moves following the arrival of external information $I_t, t \in \mathbb{T} = \{t_0, t_1, \ldots, t_n, \ldots\}$. We describe investor behavior in the following way: at time t_{n-1}, all agents receive the same public information I_{t_n}, and then each agent $k \in \mathbb{K} = \{1, ., N\}$ interprets this information in his own way to form his expectations about the future return over the time horizon h and consequently deduces a signal to sell or buy $S^k_{t_{n+h}}$. By evaluating the public information, the investor might commit an idiosyncratic error$\varepsilon^k_{t_n}$. Accordingly, we have:

$$S^k_{t_{n+h}} = I_{t_n} + \varepsilon^k_{t_n},\ \varepsilon^k_{t_n} = c_k \overline{r}^k_{t_{n-1}} B^k_{t_n} \tag{1}$$

where,$I_t \sim \mathcal{N}(0, \sigma_I^2)$; $B^k_t \sim \mathcal{N}(\mu, \sigma_B^2)$; $c_k \in \mathbb{R}_+$ is a strictly positive constant that denotes the intensity of investor reaction to past realized outcomes; $\overline{r}^k_{t_{n-1}}$ is the average past return generated over a time span of length M^k, which is defined by: $\overline{r}^k_{t_{n-1}} = \frac{1}{M^k} \sum_{j=1}^{M^k} \ln \frac{p_{t_{n-j}}}{p_{t_{n-j-1}}}$, with each trader using a potentially different value of M^k drawn uniformly in $[M_{min}, M_{max}]$. This quantifies the memory of traders and is another way to introduce heterogeneity among chartist traders. $B^k_{t_n}$ refers to the behavioral biases of investor k, which lead to an idiosyncratic error that the investor might commit when trying to interpret the information I_{t_n}. We assume that these behavioral biases follow the normal distribution $\mathcal{N}(\mu, \sigma_B^2)$ and measure the heterogeneity in our model. Because they are drawn from a continuous probability distribution, they allow for the presence of an ecology of agents in the financial market at any moment. If $B^k_{t_n} > 0$, the trader is trend chasing (momentum strategy); if $B^k_{t_n} < 0$, the trader is contrarian; otherwise, the trader is rational.

With $S^k_{t_{n+h}}$, the investor decides to buy if $S^k_{t_{n+h}} > 0$ or to sell if $S^k_{t_{n+h}} < 0$, or neither if this signal is null. Therefore, we have:

$$D^k_{t_n} = \begin{cases} 1 \; if \; S^k_{t_{n+h}} > 0 \\ -1 \; if \; S^k_{t_{n+h}} < 0 \\ 0 \; if \; S^k_{t_{n+h}} = 0 \end{cases}$$

To enable the model to generating switching behavior and stochastic price dynamics, we make the following assumptions.

Assumption 1: $\forall k \in \mathbb{K}$, the random variables $(B^k_t)_{t\in\mathbb{T}}$ and $(I_t)_{t\in\mathbb{T}}$ are mutually independent.

The meaning of this assumption is that the term $\varepsilon^k_{t_n} = c_k \overline{r}^k_{t_{n-1}} B^k_{t_n}$ (in Equation (1)) is an idiosyncratic error that emerges when traders evaluate the fundamental information I_{t_n}. Thus, $(B^k_t)_{t\in\mathbb{T}}$ and $(I_t)_{t\in\mathbb{T}}$ have to be mutually independent for any trader $k = 1,\ldots, N$ to avoid causality between these two processes.

Assumption 2: $\forall t \in \mathbb{T}$, the random variables $(B^k_t)_{k\in\mathbb{K}}$ are mutually independent. This assumption considers the absence of any "social interaction" among traders.

The switching behavior implies that a rational agent can switch to being a noise trader at a particular time in the future, and vice versa. According to the AMH, individuals make mistakes, but they learn from their experience and adapt to changing market conditions. Thus, agents are boundedly rational (Simon, 1957, 1982), but, under certain market conditions (e.g., high volatility) they can overreact and be subject to behavioral biases. Anecdotal evidence of this switching behavior is seen in *Thinking, Fast and Slow* (Kahneman, 2011).

Now, we show that our model is endowed with the switching behavior of agents. Following Konté (2011), we first show that an irrational agent cannot remain irrational when the time horizon is long. In fact, agents are noise traders if they form a positive signal $S^k_{t_{n+h}}$ whereas the value of information I_{t_n} is negative, or vice versa. This corresponds to an example in which the committed error $\varepsilon^k_{t_n}$ exceeds the value of I_{t_n} and has a different sign than I_{t_n}. We therefore have $S^k_{t_{n+h}}.I_{t_n} < 0$, which indicates that the agent is a noise trader. For each noise trader k, we have, according to Equation (1):

$$\left\{S^k_{t_{n+h}}.\, I_{t_n} < 0\right\} = \left(c_k\left|\overline{r}^k_{t_{n-1}}\right|\left|B^k_{t_n}\right| > \left|I_{t_n}\right|\right\} \cap \left\{I_{t_n}.B^k_{t_n} \le 0\right\}$$
$$\cap \left\{I_{t_n}.\overline{r}^k_{t_{n-1}} \le 0\right\}\Big) \subset \left\{I_{t_n}.B^k_{t_n} \le 0\right\} = L_{t_n}$$

According to Assumption 1, events $L_{t_n} = \{I_{t_n}.B^k_{t_n} \le 0\}$, $t_n \in \mathbb{T}$ are independent. Therefore, $P(L_{t_n}) = P(I_{t_n} \ge 0, B^k_{t_n} \le 0) + P(I_{t_n} \le 0, B^k_{t_n} \ge 0) = \frac{1}{2}$.

We know that $\{S^k_{t_{n+h}}.\, I_{t_n} < 0\} \subset L_{t_n}$ implies that $P(\{S^k_{t_{n+h}}.\, I_{t_n} < 0\}) \le P(L_{t_n})$. Thus,

$$P\left(\bigcap_{n=1}^{T}\left\{S^k_{t_{n+h}}.\, I_{t_n} < 0\right\}\right) \le P\left(\bigcap_{n=1}^{T} L_{t_n}\right)$$
$$= \prod_{n=1}^{T} P\left(L_{t_n}\right) = \frac{1}{2^T} \to 0, \; as \; T \to +\infty \tag{2}$$

Similarly, a rational agent cannot remain so over the long term; at certain moment, he might become irrational. We consider agents rational if their signal $S^k_{t_{n+h}}$ has the same sign as I_{t_n}, that is, $S^k_{t+h}.\, I_{t_n} \ge 0$. We show that a rational agent can become irrational at a certain moment when the time horizon tends toward infinity:

$$\left\{S^k_{t_{n+h}}.I_{t_n} \ge 0\right\} = \left\{c_k\left|\overline{r}^k_{t_{n-1}}\right|\left|B^k_{t_n}\right| \le \left|I_{t_n}\right|\right\} \cup \left(\left\{I_{t_n}.B^k_{t_n} > 0\right\}\right.$$
$$\left.\cap \left\{I_{t_n}.\overline{r}^k_{t_{n-1}} > 0\right\}\right) \subset \left\{c_k\left|\overline{r}^k_{t_{n-1}}\right|\left|B^k_{t_n}\right| \le \left|I_{t_n}\right|\right\} \cup \left\{I_{t_n}.B^k_{t_n} > 0\right\}$$

We set $r_{min} = min\{\left|\overline{r}^k_{t_{n-1}}\right|, \; t \in \mathbb{T}\}$, which is strictly positive with a probability of one because the event $\{r_{min} = 0\}$ is identical to $\bigcup_{t\in\mathbb{T}} \{\overline{r}^k_t = 0\}$ and thus negligible. Accordingly,

$$\left\{S^k_{t_{n+h}}.\, I_{t_n} \ge 0\right\} = \left\{c_k\left|\overline{r}^k_{t_{n-1}}\right|\left|B^k_{t_n}\right| \le \left|I_{t_n}\right|\right\} \cup \left(\left\{I_{t_n}.B^k_{t_n} > 0\right\}\right.$$
$$\left.\cap \left\{I_{t_n}.\overline{r}^k_{t_{n-1}} > 0\right\}\right) \subset \left(\left\{c_k\left|\overline{r}^k_{t_{n-1}}\right|\left|B^k_{t_n}\right| \le \left|I_{t_n}\right|\right\} \cup \left\{I_{t_n}.B^k_{t_n} > 0\right\}\right) \subseteq \Big($$
$$\times \left\{c_k r_{min}\left|B^k_{t_n}\right| \le \left|I_{t_n}\right|\right\} \cup \left\{I_{t_n}.B^k_{t_n} > 0\right\}\Big) = F_{t_n}$$

where F_{t_n}, $t_n \in \mathbb{T}$ are independent events according to Assumption 1. Because the probability $P(F_{t_n})$ is almost surely in $]\frac{1}{2}, 1[$, we have:

$$P\left(\bigcap_{n=1}^{T}\left\{S^k_{t_{n+h}}.I_{t_n} \ge 0\right\}\right) \le P\left(\bigcap_{n=1}^{T} F_{t_n}\right) = \prod_{n=1}^{T} P\left(F_{t_n}\right) \to 0, \; as \; T \to +\infty \tag{3}$$

Equations (2) and (3) show that when the time horizon is long, agent k cannot remain either rational or irrational. This switching phenomenon shows that our model is consistent with the AMH.

The next section presents the second part of the model.

3.2. Market microstructure

We design a transaction mechanism to closely replicate the real functioning of most financial markets. We therefore model an order-driven market via a limit central order book borrowed from major developed and emerging financial markets. The trading day of our model is as follows. We identify a single iteration with a time step in terms of a certain number of minutes. We assume that the trading day corresponds to twenty time steps, and we repeat our simulation over 2500 days.

At each time step, some of the traders are randomly activated by forming their expectations about the future return according to Equation (1) and submit the limit order accordingly. Specifically, after traders have formed their expectation of future returns, they deduce a signal to buy or sell or do nothing. If $S^k_{t_{n+h}}$ is positive, they send a buy order to the central order book; if it is negative, they submit a sell order; and if it is zero, they remain inactive. Then, they convert their expected future return $S^k_{t_{n+h}}$ to a price forecast $p^k_{t_{n+h}}$ using the following equation (Chiarella et al., 2009; Chiarella & Iori, 2002):

$$\widehat{p}^k_{t_{n+h}} = p_{t_n}.\exp\left(S^k_{t_{n+h}}\right) \quad (4)$$

Then, the price chosen by the buyer equals the expected price minus a certain value v^k using

$$p^k_{t_n} = \widehat{p}^k_{t_{n+h}}\left(1 - v^k\right)$$

However, the price chosen by the seller equals the expected price increased by a certain value v^k using

$$p^k_{t_n} = \widehat{p}^k_{t_{n+h}}\left(1 + v^k\right)$$

where v^k is a random value across agents but constant over time. This value is drawn uniformly in $[0, v_{max}]$.

The order book considers only orders at discrete price levels. All prices therefore are rounded to the nearest tick. A limit order O_{k,t_n} is a tuple {Price, quantity, validity}. The price equals $p^k_{t_n}$, rounded to the nearest tick. The quantity always equals 1 in the event of a buy and −1 in the event of a sell. The validity corresponds to the time at which the order expires and is automatically deleted from the central order book. We assume that all unmatched orders are canceled at the end of each day. We also assume that short selling is allowed; however, traders are prevented from borrowing an infinite amount of stocks by the unitary quantity rule. In addition, the price variation thresholds should not exceed 10 percent in order to reproduce the circuit breaker rule adopted in various financial markets. Formally, the limit order O_{k,t_n} submitted by the trader k at time t_n is as follows:

$$O_{k,t_n} = \left\{round\left(p^k_{t_n}, \ tick\right), \ sign\left(S^k_{t_{n+h}}\right), \ \tau\right\}$$

where $round(.)$ denotes the rounding function, tick is the minimum price increment/decrement, the $sign(.)$ is the sign function, which takes a value of 1 if $S^k_{t_{n+h}} > 0$, −1 if $S^k_{t_{n+h}} < 0$, or 0 if $S^k_{t_{n+h}} = 0$, and τ is the validity of the order.

If the bid price is greater than the best asking price in the order book, then the transaction takes place, the trader buys a unit at the best ask price, and then the quantities traded are removed from the central order book. However, if the bid price is lower than the best asking price, then the order is inserted on the bid side of the limit order book, respecting the rules of price and arrival time priorities. In the event of a sell order, if the price is lower than the best bid price, the transaction takes place at the best bid price; otherwise, it is placed on the ask side of the order book, according to the rules of price and arrival time priorities.

Table 2
Value parameters of the model.

Parameters	Label	Value
Number of traders	N	1000
External information	I_t	$\mathcal{N}(0, \sigma_I = 10^{-4})$
Investor biases	B^k_t	$\mathcal{N}(0.01, 1)$
Reaction intensity	c_k	1
Simulation period in terms of days	T	2500
Initial price	p_{t_n}	1000
Tick	Tick	0.01
Order validity	Order validity	20
Memory of chartist traders	$[M_{min}, M_{max}]$	$[1, 20]$

4. Numerical simulations

The agent-based models are analyzed either analytically or numerically. Given the complexity associated with the endogenous nature of the dynamics of the central order book, we cannot study the system analytically and arrive at a closed-form solution. Thus, we follow the standard practice in agent-based models of simulating the model numerically and then performing the statistical analysis on the generated return time series.

We start by fixing certain parameters of the model. The market is simulated with 1000 traders, the initial price is 1,000, the tick value is 0.01, and the sigma value of the noise generated by the public information σ_I is set at 10^{-4}. We chose this low magnitude because on the intraday scale, the values of public information and its dispersion are small. We set the parameter μ at 0.01 in order to generate a population of chartists skewed slightly toward trend following, as opposed to traders with contrarian strategies. This allows us to introduce a persistence characteristic into the dynamics of returns and evokes the reasonable belief that trend extrapolation is mainly exploited by momentum traders in order to "ride the wave." Assuming 20 transactions per day, each taking place at time t_n, the closing price of the first day corresponds to the price at time t_{20}. The specific parameters of the model are summarized in Table 2. Under the initial parameters and conditions, we iterated our model over 50,000 periods. As 20 periods correspond to a trading day, we have 2500 simulated days.

For validation, we simulate our model under two scenarios in order to emphasize the impact of each component on price dynamics. In the first scenario, we integrate the two components of the model, that is, the behavior of heterogeneous agents and the market microstructure. In the second scenario, we eliminate the heterogeneity of agents by assuming that all agents are perfectly rational and homogeneous, so that they can correctly evaluate the external information and trade accordingly. Therefore, we set $\mu = 0$ and $\sigma_B = 0$. Consequently, the model becomes $S^k_{t_{n+h}} = I_{t_n}$, in which I_{t_n} is white noise.

The goal is to disentangle the impacts implied by the heterogeneity and adaptability of agents on price dynamics from those implied by the microstructure rules. To validate our model, we compare the properties generated by the simulated series with the empirical facts observed in the markets examined earlier.

4.1. Heterogeneous interaction agents and market microstructure

Under this scenario, we assume that some heterogeneous agents make idiosyncratic errors in valuing public information and adapt to market conditions, that is, past realized returns. We study the impact of this behavior combined with that of the microstructure on the dynamics of returns and market efficiency.[1]

[1] The simulation of the model was performed using Python version 3.8.5. Our Python software is an object-oriented program made up of three classes: the class of return forecasts, the class of agents, and the class of the central order book. The main program imports these classes and allows the simulations to be carried out according to the parameters entered.

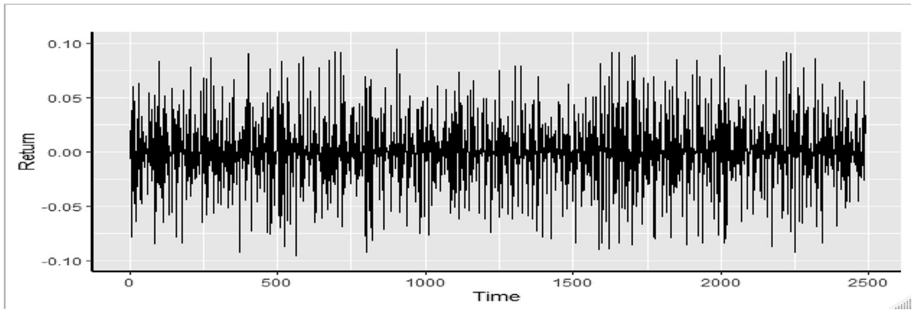

Fig. 3. Simulated return series. *Note:* R version 3.6.1 was used to plot the time series of returns.

Table 3
Descriptive statistics and Box-Pierce and Jarque-Bera tests of the simulated return series.

Standard deviation	Skewness	Kurtosis	JB	BP	N
0.0245	−0.0223	6.53	0.000	0.000	2500

Notes: JB denotes the p-value of the Jarque and Bera (1980) test; BP is the p-value of the Box and Pierce (1970) test; N is the number of observations; R version 3.6.1 was used to calculate the statistics.

Fig. 3 shows a plot of the simulated return series. The statistical properties of the simulated return series are given in Table 3. To measure the time-varying linear and nonlinear autocorrelation in returns and therefore evolution of the degree of efficiency related to the simulated return series, we perform the linear automatic portmanteau test (Escanciano & Lobato, 2009) and the nonlinear McLoed-Li test (McLeod & Li, 1983) with rolling windows. The results of these tests are shown in Fig. 4.

The validation of the model is assessed by its ability to account for the empirical facts observed in real financial markets. We therefore compare the simulated results with the results observed empirically.

4.1.1. Non-Gaussian distribution

Table 3 shows that the kurtosis coefficient corresponding to the distribution of the simulated return series (6.53) greatly exceeds the kurtosis coefficient of the normal distribution, which is 3. This implies that extreme returns are more likely to occur with this distribution than with a Gaussian distribution. The high probability of abnormal returns is triggered by the heterogeneity of traders. The asymmetry coefficient is negative (−0.022), which means that the distribution is skewed to the left because of negative changes in returns in line with conditions in real markets, in which the skewness of the returns is found to be negative, indicating that the tail due to negative returns is fatter than that due to positive returns (Lux, 2001). Thus, the model reproduces the same distribution as that of the real return series examined earlier (cf. Table 1). The Jarque-Bera test strongly rejects the null hypothesis of a normal distribution of data at the 1% significance level (p-value $< .01$). Therefore, the distribution is leptokurtic, which is a common characteristic in a wide variety of financial markets.

4.1.2. Excess volatility

Table 3 indicates that the standard deviation is higher for the returns (0.0245) than for noise I_t, which represents the arrival of new information (0.0001) ($\widehat{\sigma}_t \gg \sigma_I$). This finding implies excess volatility, which is also a stylized fact, suggesting that the variability of returns is not always explained by the fundamental economic variables. Therefore, the volatility emerges endogenously from the interaction of heterogeneous traders whose trading philosophy differs (fundamentalist or chartist) and of the parameters B_t^k and M^k, which vary across traders. The heterogeneity is strengthened by the extent to which chartists disagree about future returns and thus increases with σ_B^2 ($\sigma_B^2 = 1$ in our model) because the weights of

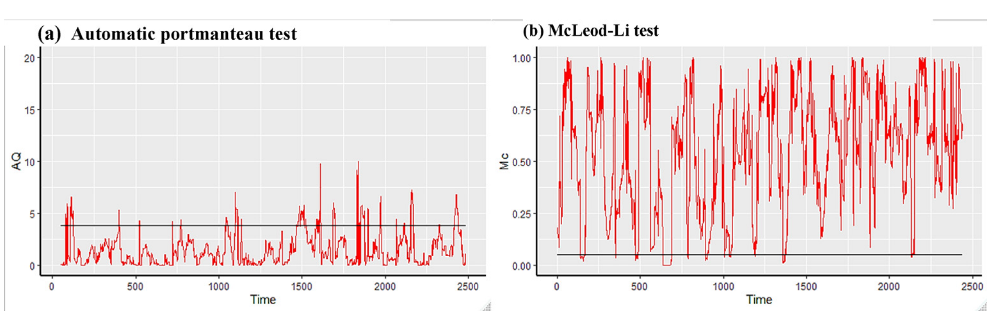

Fig. 4. Time-varying autocorrelation in returns. *Notes:* Fig. 4a illustrates the results of the automatic portmanteau test related to the simulated return series. The red line indicates the automatic portmanteau test statistic, and the black line represents the F-statistic at the 5% significance level. Fig. 4b shows the p-values of the McLeod-Li test related to the simulated return series. The red line indicates the p-values of the McLeod-Li test, and the black line represents the 5% significance level. R version 3.6.1 was used to calculate the statistics.

momentum and contrarian traders are more distant from each other.

4.1.3. Autocorrelation in returns and degree of time-varying efficiency

The simulation results of the linear test (Fig. 4a) show that the linear autocorrelation in returns is time-varying, with some periods of significant autocorrelation in returns and other periods of insignificant autocorrelation. However, the lack of autocorrelation occurs most of the time, which is consistent with the empirical results in Fig. 1. Furthermore, the nonlinear test results (Fig. 4b) also display alternating periods of significant nonlinear autocorrelation in returns and periods of insignificant autocorrelation, which is consistent with our empirical results in Fig. 2. These results suggest that the degree of market efficiency varies over time with alternating periods of efficiency and inefficiency, depending on market conditions. Our model can therefore generate returns with the same behavior as that of the returns observed in real markets. This time-varying efficiency is caused by the interaction between fundamental and chartist traders in a dynamic setting. In fact, as noise traders try to push the price away from its current value, fundamentals try to mean revert the price to its current value. Thus, when fundamentals dominate the market, returns are more likely to follow a random walk; conversely, if chartists dominate, the returns are autocorrelated.

4.2. Rational agents and market microstructure

This section assesses the impact of the market microstructure on price dynamics, assuming that the agents are rational and homogeneous. By setting $\varepsilon^k_{t_n} = 0$ in our model, we assume that all traders correctly evaluate the exogenous signal corresponding to the arrival of public information, which is by nature unforeseen and random. Accordingly, it is unlikely that the price moves far from its current value. If the microstructure effects were totally irrelevant, then the realized returns would follow a random walk. Indeed, the model becomes:

$$S^k_{t_{n+h}} = I_{t_n}$$

In Equation (4), the logarithm (ln) of the expected price is as follows: $\ln \widehat{p}^k_{t_{n+h}} = \ln p_{t_n} + I_{t_n}$, where I_{t_n} is white noise.

Accordingly, prices follow a random walk. In this case, if the microstructure has no effect on price dynamics, we find the same statistical properties in the random walk, such as normal distribution, low volatility, and independent returns. However, the simulation results corresponding to this scenario (Table 4) show that the distribution is leptokurtic (*kurtosis* = 7.18, *skewness* = 0.072), which contradicts a random walk characterized by a normal distribution (*kurtosis* = 3 *and skewness* = 0). The deviation in the simulated return series from a Gaussian distribution is confirmed by the Jarque-Bera normality test (p-value < .01). In addition, excess volatility is observed, as the standard deviation of the returns (0.0235) largely exceeds that of the fundamental information (0.0001). The effect of the microstructure is therefore well established.

To ensure that the stylized facts are not due solely to the effect of microstructure and that investor behavior contributes to it as well, we compare the results of the two simulations (Tables 3 and 4). The main finding is that, after the heterogeneous and adaptive investors' behaviors are eliminated, the returns become unpredictable. Indeed, the p-value of the Box-Pierce test ($BP = .000$) is less than 0.01 in the first simulation, which rejects the null hypothesis of independence in returns; but it becomes greater than 0.1 ($BP = .147$), which accepts the null hypothesis of independence (unpredictability of returns). In addition, the volatility is higher in the first scenario than the second scenario. In fact, the presence of chartists leads to the placement of orders far from the best bid and the best ask, which creates larger gaps between orders on both sides of the book, and subsequent orders that match existing orders cause large price changes. Thus, the presence of heterogeneous agents accentuates price fluctuations, and it is obvious that this heterogeneity is needed to obtain more realistic dynamics.

In sum, we conclude that the two components of our model are necessary for generating the stylized facts and the time-varying degree of market efficiency observed empirically, which is consistent with the AMH.

Having been validated against empirical facts observed in various markets, the model can be fruitfully used as a test for regulatory experiments aimed at improving market efficiency. With respect to traders, the model can also be used to perform simulations by creating certain specific market conditions in which they can test the profitability of some investment strategies (momentum strategy, contrarian strategy, buy and hold strategy …).

Table 4
Statistical properties of the simulated return series corresponding to scenario 2.

Standard deviation	Skewness	Kurtosis	JB	BP	N
0.0235	0.072	7.1867	0.000	0.1474	2500

Notes: JB denotes the p-value of the Jarque and Bera (1980) test; BP is the p-value of the Box and Pierce (1970) test; N is the number of observations; R version 3.6.1 was used to calculate the statistics.

5. Experiments on regulatory policies and trading behavior

The simple structure of our model enables it to be used for experiments on certain regulatory policies and trading behavior. Therefore, the model can be used to assess the effectiveness of certain regulatory measures or to choose investment strategies based on certain specific market conditions created by the model. These experiments can be performed by changing the value of the model parameters.

5.1. Tick size change

The first parameter that we change is the minimum tick size. Many empirical studies document the implication of changes in the minimum tick size on the price dynamics. They find evidence that market efficiency increases following a reduction in the minimum tick size. Indeed, the reduction in minimum tick size decreases the transaction cost (lower bid-ask spreads) and improves market liquidity, the trading volume, and the price discovery process (Chung & Chuwonganant, 2002; Harris, 1994; Zhao & Chung, 2006). It also causes prices to adjust more rapidly to information and better reflect the true value, resulting in the enhancement of price efficiency (Fleming et al., 2019). Following a reduction in the tick size on quote revisions in US. equity markets, first from 1/8 to 1/16 in 1997 and then from 1/16 to 0.01 in 2001, Chung and Chuwonganant (2002) examine the effect of these reductions and find that, as the tick size diminishes, price competition increases, and prices become more flexible and efficient. In the same vein, Albuquerque et al. (2020) investigate the Securities and Exchange Commission's tick size pilot program and report a decrease in price efficiency for stocks whose tick size increases.

However, empirical studies of the effects of this policy, which remains an interesting question, must wait several periods after its implementation before examined. Moreover, before implementing any change in the tick size, regulators should examine its effectiveness ex ante. Another problem with this question is finding an optimal value, as an even greater reduction in tick size will eventually lead to a deterioration in market liquidity. All these issues can be addressed by performing experiments using the agent-based model.

In this regard, we can use our model to assess the influence of this policy on price dynamics. To this end, we reduce the tick size from 0.01 to 0.001 and examine its impact on market efficiency. We measure market efficiency using the nonlinear McLeod-Li test with the rolling-window approach (Fig. 5). Fig. 5 illustrates that market efficiency is significantly improved over the situation in which the tick size was 0.01 (cf. Fig. 4b) as the returns become unpredictable most of the time. Therefore, our finding is consistent with that in previous work. The new tick size is less constraining and encourages more traders to submit orders in smaller price increments and thus narrows the bid-ask spread. Concentrating orders into fewer price points may also increase the likelihood of matching orders quickly. This improves pricing flexibility and decreases the realized volatility, consistent with a shrinking microstructure noise component attributable to price discreteness. As a result, the magnitude of autocorrelation in price changes decreases significantly and returns follow a random walk, implying an improvement in market efficiency.

Table 5
Statistical properties of the simulated return series corresponding to the reduction in order validity.

Standard deviation	Skewness	Kurtosis	JB	BP	N
0.03519	0.0144	3.849	0.000	0.000	2500

Notes: JB denotes the p-value of the Jarque and Bera (1980) test; BP is the p-value of the Box and Pierce (1970) test; N is the number of observations; R version 3.6.1 was used to calculate the statistics.

5.2. Change in order validity

Order validity is another microstructure parameter that could influence price dynamics. All markets set the rules about order validity. We examine the impact of change in order validity on price dynamics based on some relevant statistics. In this regard, we reduce the order validity from 20 to 10 transaction steps. Table 5 shows the statistical properties related to this situation.

Kurtosis decreases from 6.53 (Table 3) to 3.84 (Table 5). The distribution becomes right skewed because of positive changes in returns. Thus, the order validity also contributes to an explanation of kurtosis and skewness. In addition, volatility increased from 0.024 to 0.035. In fact, the shorter the order validity, the fewer orders that are stored on the book at any moment. Therefore, the relative emptiness of the limit order book causes transactions to sweep through large empty spaces in the book, leading to increased volatility (Chiarella & Iori, 2002).

5.3. Change in trading behavior

In this experiment, we create specific market conditions and see the impact on the price dynamics and profitability of certain investment strategies. In fact, we create a large imbalance between momentum traders and contrarians by setting $\mu = 1$ and

Table 6
Statistical properties of the simulated return series related to dominance by momentum traders.

Skewness	Kurtosis	JB	BP	N
0.0011	2.19	0.000	0.000	2500

Notes: JB denotes the p-value of the Jarque and Bera (1980) test; BP is the p-value of the Box and Pierce (1970) test; N is the number of observations; R version 3.6.1 was used to calculate the statistics.

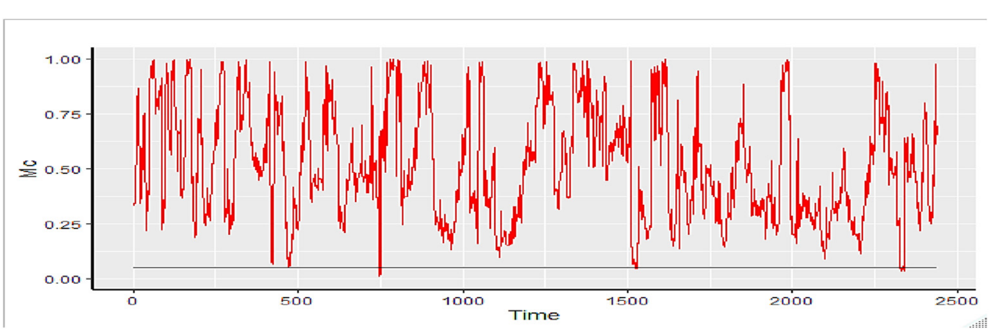

Fig. 5. The p-values of the McLeod-Li test related to the tick size reduction. *Notes*: The red line indicates the p-values of the McLeod-Li test, and the black line represents the 5% significance level. R version 3.6.1 was used to calculate the statistics.

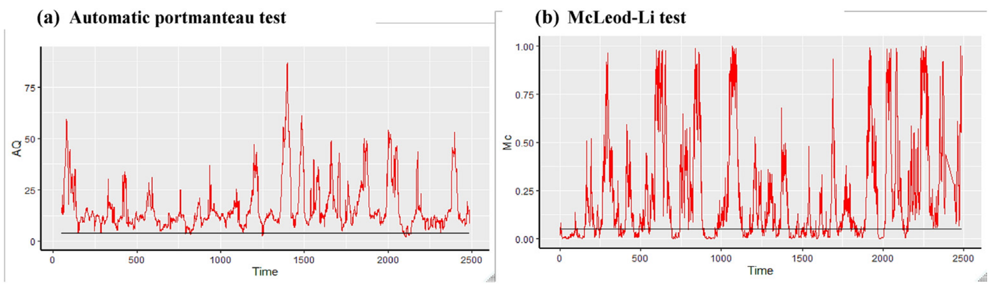

Fig. 6. Time-varying autocorrelation in returns. *Notes:* Fig. 6a shows the results of the automatic portmanteau test related to the momentum traders' dominance. The red line indicates the automatic portmanteau test statistic, and the black line represents the *F*-statistic at the 5% significance level. Fig. 6b shows the *p*-values of the McLeod-Li test related to the momentum traders' dominance. The red line indicates the *p*-values of the McLeod-Li test, and the black line represents the 5% significance level. R version 3.6.1 was used to calculate the statistics.

$\sigma_B^2 = 1, 2$. This corresponds to the situation in which momentum traders dominate the market. Table 6 shows relevant statistics related to this scenario. Using Table 3 as a benchmark, we observe that the skewness turns positive because of positive changes in the returns, which is in contrast to the normal case in a real market in which the skewness of the returns is found to be negative (cf. Table 1). Specifically, when asymmetry arises between trend followers and contrarians in favor of the former, the rate of buy orders exceeds that of sell orders, creating a gap in the book on the sell side, which generates positive skewness. Furthermore, kurtosis falls severely, to less than 3, indicating a platykurtic distribution. This implies that the extreme returns (abnormal returns) are less likely to occur.

Moreover, domination by momentum traders has the effect of adding memory to the autocorrelation function of returns, resulting in persistent autocorrelation in returns most of the time and large market inefficiency. In this setting, the heterogeneity of traders (rational vs. technical traders and momentum vs. contrarian traders) decreases considerably. This implies that the effect of momentum traders who push the price away from its current value is not countered by the effect of fundamentalists or contrarians. This pattern is clearly visible in Fig. 6. Indeed, the linear and nonlinear autocorrelation tests show that the returns are significantly autocorrelated over time, resulting in persistent market inefficiency. This condition attracts traders to exploit the autocorrelation by constructing momentum strategies. Nevertheless, even though these strategies can obtain positive returns because of the autocorrelation in returns and the positive skewness, the probability of obtaining abnormal returns is low, as kurtosis is below 3. Therefore, we conclude that when momentum traders dominate the market, a momentum strategy could offer opportunities for risk-averse traders. However, this condition may lead to large inefficiency and ultimately to bubbles that might result in crashes as the effect of rational and contrarian traders on stabilizing prices becomes less significant.

In a nutshell, our model can be used as an alternative to empirical studies using real data to examine the effectiveness of certain regulatory policies or the profitability of trading strategies.

6. Conclusion

The goal of this paper was to develop a parsimonious agent-based model capable of reproducing the main stylized facts as well as the time-varying degree of market efficiency. This model is designed with the AMH approach. Thus it includes the arguments of this approach, such as interaction between heterogeneous agents (rational and irrational traders), switching behavior (a rational agent switches to irrational and vice versa), and feedback on past realized returns, which amplifies or attenuates the effect of an agent's psychological biases, depending on the extent of these returns. In particular, we relaxed the hypothesis of full rationality by assuming that agents make idiosyncratic errors by under- or overestimating information according to market conditions. To obtain a realistic model, we added the market microstructure, borrowed from the major developed and emerging financial markets (NYSE, Euronext, Tokyo Stock Exchange, Borsa Istanbul, Shanghai Stock Exchange, and São Paulo Stock Exchange). In fact, we devised an order-driven market via a limit central order book with certain transaction rules, such as order validity, price variation thresholds, short selling, and a minimum tick size.

Numerical simulations of the model generate time series of returns that replicate the same statistical properties observed in the real series of the examined markets, namely, the leptokurtic distribution, the excess volatility, and time-varying linear and nonlinear autocorrelation in returns and therefore the time-varying degree of market efficiency in line with the AMH. Simulation results under different scenarios lead us to conclude that the heterogeneity of traders, the adaptive behavior of agents, and the market microstructure are necessary components for generating price and efficiency dynamics.

Our model can be used by both traders and policy makers. In fact, by calibrating the underlying parameters under different scenarios, the model could be useful for assessing the profitability of certain trading strategies. Moreover, the model can be fruitfully used for experiments on regulatory policies in order to assess the effectiveness of these policies. Therefore, the model can be successfully employed as an alternative to empirical studies using real data in order to examine financial market dynamics.

Our model is calibrated to generate the main empirical facts observed in the major developed and emerging markets. However, it can be tested in other markets and against other stylized facts. This point should be investigated in further research to broadly confirm our model.

Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2021.10.005.

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