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A complex adaptive agent modeling to predict the stock market prices

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ABSTRACT

Understanding the behaviors of financial markets and their participants remains a challenging problem to resolve. Adaptive agents, which switch from fundamentalist to chartist behavior, are examined in some recent work. In this paper, we propose an adaptive agent-based model that combines three forecasting behaviors of financial agents: fundamentalist, chartist, and mimetic. The weighting of each type of behavior in the final forecasting changes according to the market cycle. Our model adapts to the different cycles of the market.

We assess the ability of the proposed model to predict and explain the dynamics of stock market price formation. First, on the microscopic level, we consider four agent-based models: fundamentalist, chartist, mimetic and adaptive. We compare the prices generated by the different prediction models to the real prices generated by the US market (S&P 500 index) over the period (1990–2021). Second, at a macroscopic level, we set up a multi-agent system to simulate an artificial stock market composed of the four types of agents with different market fractions. We compare the prices generated by the artificial market with the real data generated by the US market.

The series of statistical analyses that we have carried out allows us to conclude that: the proposed adaptive agent exists in the stock market, he offers a better accuracy of price predictions compared to fundamentalist, chartist and mimetic models and that he can explain the dynamics of the stock market prices formation when he dominates.

1. Introduction

Understanding the behavior of financial markets and their participants has been a challenging problem to solve. Many researchers attempt to determine and interpret the origins of their statistical properties, otherwise known as stylized facts.

The Efficient Market Hypothesis (EMH) (Fama, 1970; Fama, 1990) assumes that the market price follows a random walk, i.e., future changes in the market's price cannot be predicted using existing information. In fact, the market price automatically readjusts to its fundamental value after a shock of information that is perfectly available to all investors. The EHM also assumes that investors are completely rational and none of them can "beat the market" by obtaining abnormally high returns following their own strategy, since information is transmitted equally and uniformly and only the most recent information is relevant for setting prices. Over time, these Hypotheses are challenged. Several financial anomalies are observed in the market such as the overreaction of financial markets (De Bondt & Thaler, 1985, 1990) and their underreaction, the existence of short-term momentum (Jegadeesh & Titman, 2001), and long-term reversal. The behavioral finance literature has submerged (Barberis & Thaler, 2003; Campbell & Cochrane, 1999; Campbell & Shiller, 1988; De Bondt & Thaler, 1985; Hirshleifer, 2001) and relaxed the assumption of investor rationality and emphasizing the relevance of sentiment, including emotions and beliefs, in decision making (Shleifer & Summers, 1990; Shleifer & Vishny, 1997). They find that traders with flawed expectations cannot always be driven from the market and when rational and irrational traders interact, irrationality can have a substantial and long-lived impact on prices (Barberis & Thaler, 2003). The impact of sentiment on price formation and returns on the stock market has interested many researchers (Kim et al., 2014; Zhong-Xin et al., 2015; Xie & Wang, 2017). Indeed, practitioners want to understand investor sentiment for two main reasons: Firstly, sentiment indicates the general attitude or feeling of investors toward a particular security or the market as a whole (Bouteska, 2020; Edelen et al., 2010). Secondly, investor sentiment can spread quickly through the market and impacts the risk aversion of investors and portfolio selection

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independently from measures of fundamental value (Ding et al., 2019).

To model the heterogeneous behaviors and the impact of agents' interactivities, researchers have developed Agent-Based Models (ABM) (Macal & North, 2010) to simulate complex systems as well as the collective effects of interactive behaviors. ABM models focus on the agents that compose a system with a minimal individual decision-making (Axelrod, 1998; Janssen & Ostrom, 2006). In Computational finance, Agent-based Computational Finance (ACF) (LeBaron, 2006) has emerged to examine the importance of investor heterogeneity on the dynamics of financial markets. ACF models explain some empirical regularity observed from financial data. (Arifovic & Gencay, 2000; LeBaron et al., 1999; Lux, 1995; Lux, 1997; Lux, 1998). They are classified by their density in terms of heterogeneity, learning, and interactions. Regarding heterogeneity, we can distinguish simple heterogeneity models from complex heterogeneity ones (LeBaron, 2000). For Example, the models of fundamentalists and chartists, where there are only two different types of agents are simple. The Santa Fe artificial stock markets (Arthur et al., 1997), where there are potentially infinite types of agents, were complex. In terms of learning, there is also a spectrum from simple learning to complex learning (or algorithms). Likewise, as for interactions, we can start from simple interactions, which either involve no network topologies or only simple networks, or progress to sophisticated interactions, which require complex network topologies.

The design of artificial financial agents is highly motivated by observing how real financial agents behave. Empirical evidence (Allen & Taylor, 1990; Frankel & Froot, 1990a) has shed new light on the forecasting behavior of financial agents. Their general findings are twofold. First, the data indicate that there are two kinds of expectations existing in the market. The expectation characterized as a stabilizing force of the market is associated with a type of financial agent, called the fundamentalist. The expectation characterized as a destabilizing force is associated with another type of financial agent, called the chartist, technical analyst, noisy trader, or trend extrapolator. The noise trader is a term that is used to describe a market participant who makes investment decisions without the use of fundamental principles, shows poor market timing, follows trends, and tends to exaggeratedly or inadequately react to good and bad news (Kyle, 1985; Black,1986; Lee & Ready,1991). Second, the proportion of fundamentalists and chartists, also called the market fraction, is changing over time, which indicates the adaptive aspects of financial agents. In the first works (Frankel & Froot, 1990b), learning does not exist in the fundamentalist-chartist model. Fundamentalist agents will continue to be fundamentalists and will never change this role, and likewise for chartists. As a result, the proportion of fundamentalists and chartists remains fixed. However, this simplification underestimates the uncertainty faced by each trader. This uncertainty causes the alerted traders to review and revise their beliefs constantly. In other words, traders are adaptive. Therefore, further development of financial agent engineering is to consider an evolving micro-structure of market participants. In this extension, the idea of adaptive agents or learning agents is introduced into the models. Consequently, an agent who was a fundamentalist (chartist) may now switch to being a chartist (fundamentalist) if he considers this switching to be more promising (Benhammada et al., 2017; Hessary & Hadzikadic, 2017a).

While this literature has advanced in modeling the forecasting behavior of financial agents to explain and predict stock market prices, the adaptive behavior of investors needs to be further developed. Indeed, this adaptive behavior is more complex, and it involves more than two forecasting behaviors (fundamentalist and chartist). The switch between forecasting behaviors (Benhammada et al., 2017; Hommes & in 't Veld, 2017) is not systematic but can be gradual, so it progressively adapt to market evolutions.

The proposal of an advanced robust model is relevant to explaining the formation and the prediction of financial asset prices. In fact, an investor can combine both forecasting behaviors (fundamentalist, chartist) in a single decision making and can also partially or fully adopt the herding behavior in times of acute crisis (Hessary & Hadzikadic, 2017b; Kanzari & Ben Said, 2019).

Machine learning techniques are also applied for stock market forecasting (Jiang, 2021; Lahmiri & Bekiros, 2019; Lahmiri & Bekiros, 2020; Maeda et al., 2020). Studies based on technical, fundamental, and historical price data are still common (Kumbure et al., 2022). However, even though these techniques can handle the nonlinear, chaotic, noisy, and complex stock market data leading to more efficient predictions (Chen & Hao, 2017), they are unable to model the investor's prediction behavior and its impact on the market. In addition, there is a risk of overfitting and prediction performance decreases when the model is overtrained. (Ying, 2019).

In our work, we propose an agent-based model which combines three behaviors: fundamentalist, chartist and mimetic to adapt to the different cycles on the market. Our proposed agent, called adaptive agent (Ad-agent), is originally fundamentalist but aware of the presence and the influence of the other types of agents in the stock market (Hommes, 2006). Such Trader does not switch between different forecasting behavior, but he combines different agents' expectations (fundamentalist, chartist (optimist or pessimist) and mimetic) to adapt to different market's cycles. In fact, our artificial stock market is composed of four kinds of agents: The adaptive, the fundamentalist, the chartist, and the mimetic. The main objective of this work is to provide a decision support tool, in the form of a prediction model, for investors in the stock market.

We set two hypotheses: the presence of adaptive agent can explain the formation of the stock market prices (H1), the adaptive agent-based model offers better accuracy in price predictions (H2),

To test our hypotheses, our work is divided into two stages. In the first step, we compare the prices generated by the adaptive agent's prediction model to the real prices generated by the US market (S&P 500 index). In a second step, we use multi-agents system simulation (MAS) on an artificial market made up of the 4 types of agents with various combinations. We compare the prices generated by the artificial market with the real data generated by the US market.

To examine how an agent's price prediction changes depending on major crises, political events, and economic conditions, we examine the sample period ranging from July 1990 to February 2021 as well as four sub-periods which are defined by different trends in the market index.

Our contribution is both theoretical and practical. On the theoretical level, we propose an innovative type of adaptive investor more complex and relevant than those proposed by the literature. The forecasting behavior model of our investor is also developed and validated. On a practical level, we propose a stock market prediction model with very good accuracy.

This paper is organized as follows. Section 2 presents the related works. We develop our proposed agent-based models in section 3. We perform a series of experiments, and we discuss the results in section 4. Finally, we conclude and outline open research directions.

2. Related works and hypothesis development

The recent literature review on stock market price dynamics remains abundant (Bouteska, 2020; Kouwenberg & Zwinkels, 2015; Rekik et al., 2014; Stefan & Atman, 2017). Some studies use models of multi-agent systems in an artificial financial market to reflect the complexity of the financial market system (Maeda et al., 2020) as well as the interactions between the agents themselves and between the agents and their environment. Related research limits heterogeneity through only a few elements of two general agent types, fundamentalists, and chartists. They also capture learning and interaction through the switching ~~the~~ mechanism, in that the overall population of fundamentalists and chartists is set due to the realized profit associated with their forecasting rules.

Several studies have emerged to remedy these limitations. Kouwenberg & Zwinkels (2015) studied a mimetic behavior among two types of traders: fundamentalists and noise traders to explain the excess volatility in the stock market. Rekik et al. (2014) built a multi-agent model in an artificial stock market composed of fundamentalists, non-fundamentalists, and loss aversion investors. Benhammada et al. (2017) considered four types of investors: fundamentalists; hybrids who are initially fundamentalists but switch to a speculative strategy when they detect an uptrend in prices; noise traders, and finally mimetic traders who imitate the decisions of their mentors on the interactions network.

Hessary and Hadzikadic (2017a) investigate the effects of rational and irrational decision-making process and social interactions on overall market dynamics and the emergence of certain key stylized facts. They develop a simple yet rich and flexible agent-based model of the stock market. Although, they adopt the two types of design framework: fundamentalist and chartist agents. Their proposed model differs from the other related works by modeling heterogeneity, interaction and learning behavior of the agents. Hessary and Hadzikadic (2017b) suggest that herding has a significant causal relationship with volatility in the market.

Hommes and in 't Veld (2017) estimate a behavioral heterogeneous agent's model with boundedly rational traders who know the fundamental stock price but disagree about the persistence of deviations from the fundamental. They consider two types of agents: fundamentalist and chartist. Agents gradually switch between the two rules, based upon their relative performance. Their main result is that behavioral regime-switching strongly amplifies booms and busts the dot-com bubble and the financial crisis in 2008. Said et al., (2018) propose a new conceptual model of financial decision-making representing the stock market dynamics during the crisis period. They focus on three main biases: overconfidence, loss aversion and mimetic behavior. Their main conclusions are that overconfidence and loss aversion are relevant to explain the formation and bursting of bubbles and that the mimetic behavior has an amplifying role in stock market disturbances.

Kanzari & Ben Said (2019) propose and simulate a new approach of traders' models that adapt their behaviors to the market conditions (stability V.S instability) variation, to explain the dynamic of the price security formation in the financial market. They consider three types of traders: The Rational-adaptive investors who are more fundamentalists during stable regimes but dynamically mutate to behavioral and mimetic during crisis regimes. The noise traders switch between overconfident and loss adverse behaviors; Mimetic traders who adopt a mimetic behavior and follow the most dominant decision in the market. Their experimental results show that the dynamic behavior of the rational-adaptive investors, that become irrational in instability periods, is a relevant determinant of the crisis periods.

As sentiment plays an important role in the decision-making of investors and stock prices movements, many researchers have studied the mechanism by which sentiment affects the price formation process.

The sentiment is defined in stock valuations by the difference between noise traders and arbitrageurs. Because investor sentiment is overly optimistic or pessimistic, it can have an increasing effect on stock prices, whose fees and arbitrage risks are becoming higher and higher (Bessière & Kaestner, 2008). Previous work points out those sentiment-driven investors are primarily noise traders and are irrational (Ding et al., 2019; Lee & Ready, 1991). They prove that these investors can make appropriate decisions based on sentiment measures.

Bouteska (2020) examined how investor sentiment affects the way with which prices reflect information and if it appears in the trading behavior of investors in the U.S. stock market. They observed that investor sentiment is indeed important and that there is a group of sentiment-driven investors who play an important role in driving stock prices.

Tetlock (2007) measures the nature of the media's interactions with the stock market using daily content from a popular Wall Street Journal column. He finds three main results. First, high media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals. Second, unusually high or low pessimism predicts high market trading volume. Third, low market returns lead to high media pessimism. In recent years, the impact of public opinion on stock market returns has attracted increasing attention. Studies provide strong evidence that information from social media has a significant influence on stock market dynamics, especially during periods of economic or political uncertainty (Cepoi, 2020; Ke et al., 2020; Teti et al., 2019).

Some recent papers examine the predictive power of sentiment on stock market volatility (Manela & Alan, 2017; Gong et al., 2022). Alomari et al., (2021) demonstrate that news sentiments have more pronounced effects on stock market volatility while social media show stronger impacts on the dynamic return correlation. Lehrer et al., (2021) suggest that including social media sentiment can significantly improve the forecasting accuracy of a popular volatility index, particularly in short time horizons.

Most existing approaches of affective computing and sentiment analysis are based on textual analysis and machine learning algorithms. For instance, Zad et al., (2021) review recent text-based semantic analysis techniques, including preprocessing, relevant feature extraction, and sentiment (positive, neutral, or negative) classification based on machine learning methods. The authors present applications of semantic analysis in the context of social media, marketing, and product evaluations. Susanto et al., (2022) exploit computer and social sciences to analyze, interpret and process opinions and feelings from web sentences. Dragoni et al., (2022) present a conceptual model OntoSenticNet based on ontology to structure emotions from multimodal resources, analyze sentiment and enhance reasoning. These approaches are limited to detecting sentiment (positive or negative) from text. However, the latter can be the object of an attempt to manipulate the market and tend to disrupt it by mispricing and inappropriate investment decisions.

Prediction of financial market data with machine learning models has achieved some level of recent success (Jiang, 2021; Lahmiri & Bekiros, 2019; Lahmiri & Bekiros, 2020; Maeda et al., 2020). However, the accuracy of stock market forecasts remains an elusive goal, not only because the stock market is affected by, among other things, politics, the market environment, and market sentiment, but also because stock price data are inherently noisy, complex, and nonlinear (Ji et al., 2022). In addition, historical financial data suffer from unknowable state space, limited observations, and the inability to model the impact of an investor's actions on the market.

One way to overcome these limitations is to explain real market data with agent-based artificial market simulation. Artificial market simulations designed to reproduce realistic market features may be used to create unobserved market states, to model the impact of an investor's investment actions on the market itself, and to train models with as much data as necessary.

Our proposed model is composed of the most relevant forecasting behavior raised by the literature: fundamentalist, chartist and herding or mimetic. We introduce the sentiment parameter in the chartist expectations. The proposed adaptive agent does not switch between strategies but combines different strategies to adapt to changes in the market. We test the following hypotheses:

H1: the presence of an adaptive agent can explain the formation of the stock market prices.

H2: the adaptive agent-based model offers better accuracy in price predictions.

3. The Agent-based models approach

The market in our model is populated by four types of agents: adaptive, fundamentalist, chartist, and mimetic traders. All investors are only interested in short term capital earnings and are not motivated by long term rent income (Kouwenberg & Zwinkels, 2015). For determining the expected returnP_{t+1}, each type of investor has its own rule.

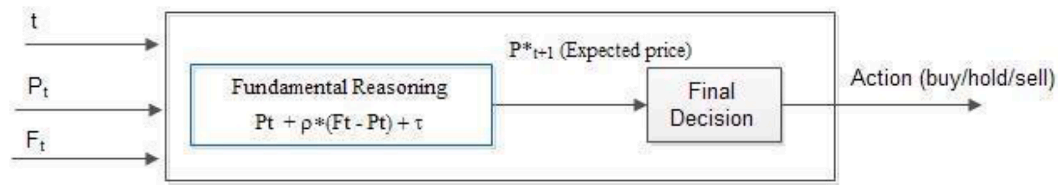

Fig. 1. Fundamentalist model.

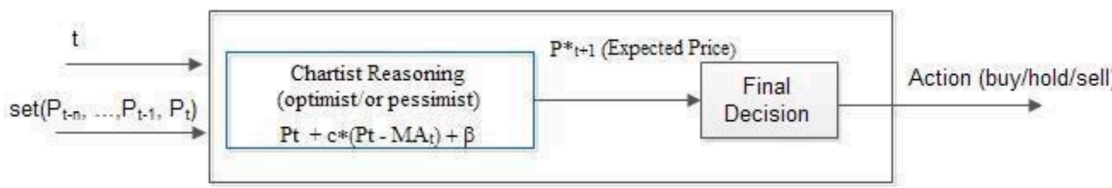

Fig. 2. The chartist model.

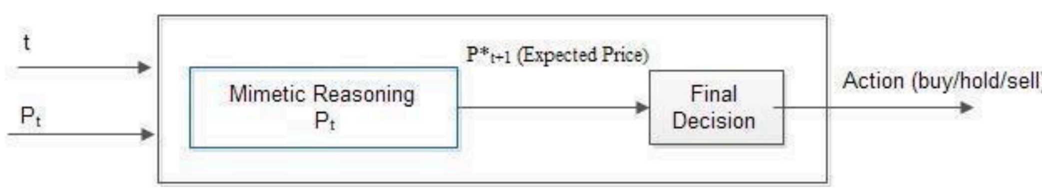

Fig. 3. The mimetic behavior.

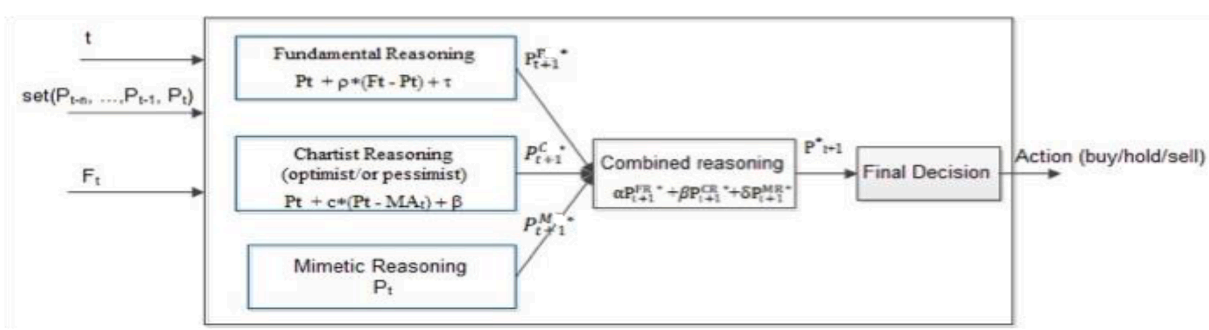

Fig. 4. Ad-agent model.

3.1. The agent's models

3.1.1. Fundamentalist agent model

Fundamentalist traders suggest that market price will revert to its fundamental value. They place orders on the mispricing securities in the stock market to create a stabilizing mean reversion effect. Accordingly, fundamental action is a buying or selling order when the price is below or above its fundamental value.

Fig. 1 presents the Fundamentalist agent model, where given the input time t, the last price P_t and the fundamental stock market value F_t, the agent makes an action of buying, holding, or selling an order. Its decision is based on fundamental reasoning.

The fundamentalist rule shown in equation (1) is based on the expectation of the mean reversion of the market price towards the long-term fundamental value (Chen et al., 2012).

$$P^*_{t+1} = P_t + \rho(F_t - P_t) + \tau \tag{1}$$

Where:

- F_t: The log real fundamental price of the security at time t.
- P_t: The log security price at time t
- $0 < \rho < 0.1$ (Gaussian distribution): the speed of the price return to its fundamental value.
- τ: A random variable (a normal, IID noise process with zero mean and constant standard deviation ∂_τ) to control the outliers.

3.1.2. Chartist agent model

The chartists tend to believe that trend in the short run ~~it~~ will continue. They make decisions based on the trends and patterns they observe in the past prices. They buy when the price rises and sell when it falls.

They extrapolate and predict the price change rate to be proportional to the latest observed change. To extend chartists to a more heterogeneous and factual setting, a memory parameter is introduced. They have the option to look further into the past to choose their next move. Each chartist can be made unique by having different memory lengths drawn randomly from a uniform distribution. Therefore, the memory parameter is considered by each chartist calculating an Exponentially Weighted Moving Average (EWMA) of the past prices (Bustos & Pomares-Quimbaya, 2020; Hessary & Hadzikadic, 2017a; Kumbure et al., 2022), shown in equation (2):

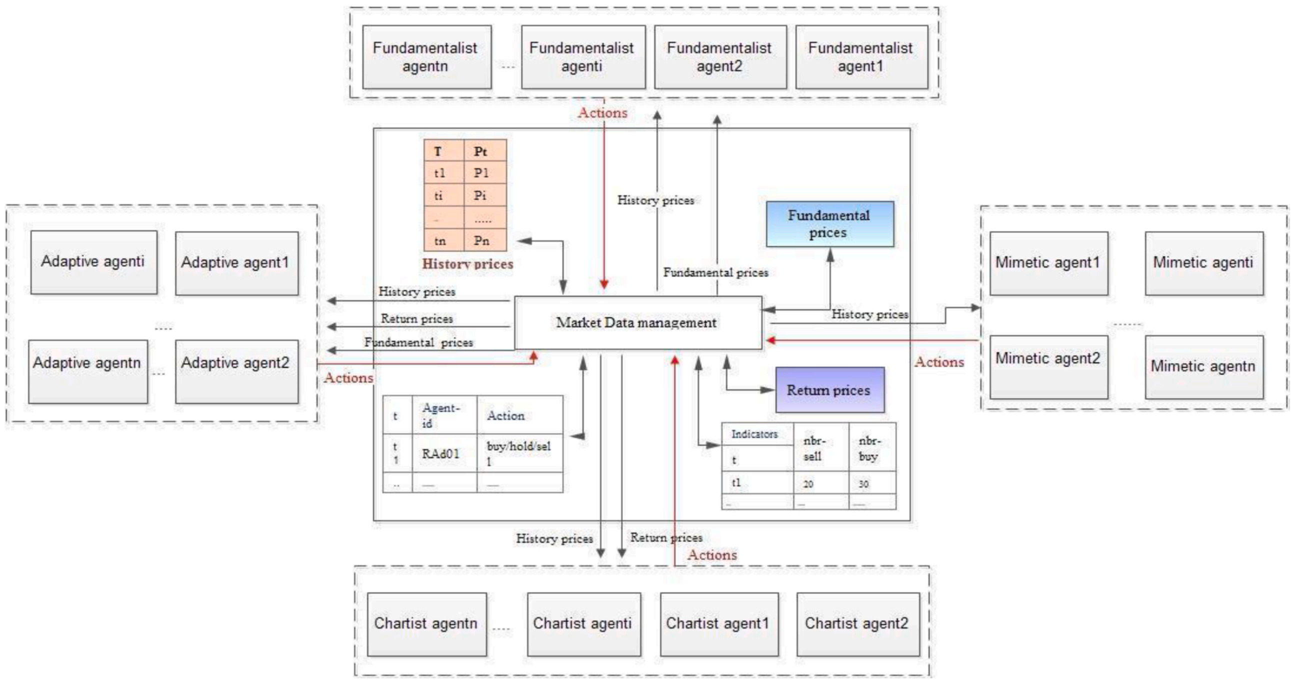

Fig. 5. Artificial financial market architecture.

Table 1
Error metrics for price prediction model evaluation.

Indicator	Definition	Formula
MAE	Mean absolute error	$\frac{\sum\lvert y_i - y_p\rvert}{n}$
MSE	Mean Squared Error	$\frac{\sum\left(y_i - y_p\right)^2}{n}$
RMSE	Root mean squared error	$\sqrt{\frac{\sum\left(y_i - y_p\right)^2}{n}}$

$$MA_t = \varnothing\sum_{i=1}^{T}(1-\varnothing)^{i-1}p_{i-1} \tag{2}$$

Where,

- $0 < \varnothing < 1$: a smoothing parameter, as $\varnothing$ increases, the weight given to the recent prices further increases.
- T: the memory length of the agent

At the beginning of the simulation, each chartist is assigned a unique extrapolating coefficient ($0 < c < 0.1$) drawn from a Gaussian distribution (Hessary & Hadzikadic, 2017a). This factor measures the sensitivity of chartists to price variation which is different for every agent and introduces further heterogeneity for this group. The chartist can be optimistic ($c \cong 0.1$) or pessimistic ($c \cong 0$).The chartist's expectation of the next period price can be written as presented in equation (3):

$$P^*_{t+1} = p_t + c^*(p_t - MA_t) + \beta \tag{3}$$

Where:

- $0 < c < 0.1$: fits the Gaussian distribution $N(\mu_c, \sigma_c)$, it indicates the agent's character optimistic or pessimistic:
- if $c \cong 0$ then the chartist agent is pessimistic
- else if $c \cong 0.1$ then the chartist agent is optimistic
- $(p_t - MA_t)$ indicates the trend. The random term β is a noise process (a normal, IID noise process with zero mean and constant standard deviation∂_β) that captures the diversity and uncontrollable elements in technical analysis.

It should be noted that, the weight $\varnothing^*(1-\varnothing)^{i-1}$in (2) controls the $MA_t$and normalizes the average value. The weight of past prices fades by $(1-\varnothing)$ at each time step, making the total area of the weight sequence upper bounded by 1. Meanwhile, the parameter $\varnothing$is chosen with respect to T to make the area below the weights close to 1. The approximation error is projected in β parameter in (3), which is restricted to a sufficiently small range with respect to p. Hence, the sign of trend value $(p_t - MA_t)$ is merely based on the current and previous values of p and the weights chartists put on past prices.

Fig. 2 resumes the chartist's behavior in the financial market. He ~~the latter~~ takes the last prices during a given period, determines the estimated following stock market price and then takes his suitable action of buying selling or holding an order.

3.1.3. Mimetic agent model

Mimetic traders consider their own information to be incomplete in deciding and make their decision by imitating others. Their final decision is based on observing the actions of other investors, determining the most dominant and then imitating the dominant behavior. As a proxy, we assume that the mimetic adopts the last price P_t as the predicted price for the next time P^*_{t+1}. The model of the mimetic agent is presented by equation (4):

$$P^*_{t+1} = P_t \tag{4}$$

Fig. 3 summarizes the mimetic behavior: so given the last price, the mimetic agent predicts the same next price and makes his adequate action (buy, hold or sell).

3.1.4. Adaptive agent model

We propose an autonomous adaptive agent (Ad-agent), described in Fig. 4, that adapts his decision according to market prices history and the related fundamental values.

The Ad-agent combines the output of the fundamental reasoning with that of the chartist and mimetic reasoning to take the appropriate decision about buying, holding, or selling action during stable and crisis

Table 2
A sample of stock prices agents' predictions.

Fundamentalist agent	t	F_t	P_t	P^*_t
	01/07/90	514.04	356.15	361.9064
	01/08/90	514.04	322.56	329.5344
Parameters	….	….	….	…
$\rho = N(0,0.1)\tau = N(0.04,0.01)$	01/02/21	1289.52	3818.325	3727.52

Chartist agent	t	P_t	P^*_t
	01/07/90	356.15	358.2499
	01/08/90	322.56	374.3148
Parameters	….	….	….
$c = N(0.05, 0.04)\beta = U(0, 0.05)\varnothing = U(0.3, 0.9)$	01/02/21	3818.325	3636.027
$T=6$			

Mimetic agent	t	P_t	P^*_t
	01/07/90	356.15	358.02
	01/08/90	322.56	356.15
	….	….	….
		3818.325	3739.425
___	01/02/21		

Ad-agent	d	α	β	γ	t	F_t	P_t	P^*_t
Parameters	0.44	$N(0.69, 0.1)$	$N(0.44, 0.06)$	$N(0.44, 0.04)$	01/07/90	514.04	356.15	360.1799
$d = \left\lvert \frac{P_t - F_t}{P_t} \right\rvert$								
α= N($\frac{1}{1+d}$, , 0.1)	0.59	$N(0.62, 0.1)$	$N(0,59,0.06)$	$N(0,59,0.04)$	01/08/90	514.04	322.56	322.5047
β= N(d, 0.06)	…	…	…	…	….	…	….	….
γ= N(d, 0.04)	0.66	$N(0.6, 0.1)$	$N(0,66,0.06)$	$N(0,66,0.04)$	01/02/21	1289.52	3818.325	3756.282

Parameters: given for each forecasting behavior model respectively eq.1, eq.3, eq.4, and eq.5), T: time of prediction, F_t: fundamental value of S&P 500, P_t: real price of S&P 500, P^*_t: predicted price of S&P 500.

periods. The different reasoning's components are based on the equations (1), (3) and (4). As presented by equation (5), the adaptive price prediction $P^{Ad*}_{t+1}$is based on the weighted average of fundamentalist ($P^{F}_{t+1}{}^{*}$) chartist($P^{C}_{t+1}{}^{*}$), and mimetic ($P^{M}_{t+1}{}^{*}$) expectations:

$$P^{Ad*}_{t+1} = \frac{1}{\alpha+\beta+\gamma}\left(\alpha P^{F}_{t+1}{}^{*} + \beta P^{C}_{t+1}{}^{*} + \gamma P^{M}_{t+1}{}^{*}\right) \tag{5}$$

Where:

- $\alpha, \beta and \gamma$:the factors of fundamentalist, chartist and mimetic forecasting behaviors that influence the decision making of an adaptive agent:
- $0< \alpha < 1$: a fundamentalist factor that fits the Gaussian distribution N (μ_{α},σ_{α}), $\mu_{\alpha,} = \frac{1}{1+d}$
- $0<\beta < 1$: a chartist factor that fits the Gaussian distribution N($\mu_{\beta,}\sigma_{\beta}$), $\mu_{\beta_,} = d$
- $0<\gamma < 1$: a mimetic factor that fits the Gaussian distribution N($\mu_{\gamma,}\sigma_{\gamma}$), $\mu_{\gamma,} = d$
- $d = \left\lvert\frac{P_t - F_t}{P_t}\right\rvert$: The weighted distance between the price and its fundamental value.

We adopt the following reasoning: in a stable period, d the distance between price and fundamental value is reduced, the decision of our agent is mainly fundamentalist ($\alpha\gg$); the further p moves away from F, the more unstable the market is, the more our agent adapts to changes and borrows mainly chartist ($\beta\gg$) then mimetic ($\gamma\gg$) decisions in times of crisis.

3.2. Artificial financial market architecture

Fig. 5 presents our proposed financial market architecture based on interactive MAS. The agents are continuously observing the market data mainly fundamentals, and historical prices and they make the appropriate sell, or buy or hold action. They make actions in the marketplace, based on their forecasting reasoning of the asset prices variations.

The proposed MAS has four main types of agents: (i) A Fundamentalist which makes a decision based on fundamental value (equation (1)); (ii) A Chartist which decision is based on past market trend to make a decision (equation (3)); (iii) A Mimetic which adopts a herding behavior (equation (4)); and (iv) An Adaptive which combines the three-forecasting behavior to adapt its decision to the market changes.

The market is managed by a Data Market Management which allows buyers and sellers to exchange assets and updates the financial market values such as prices, fundamental values, and market's trends indicators.

We aim to model the traders 'behaviors during stable and unstable periods, study their impact on the market's stability and examine which models can accurately predict the market price variation. To achieve our goal, we conceive and develop a multi-agent system that can:

- Collect and process data from financial market
- Reason according to an adaptive, fundamentalist, chartist, or mimetic models to predict the future market price
- Take the appropriate action (buy, hold, or sell) on a given period.

The choice of the multi-agent system is due to its relevance to explain and analyze complex real-world situations that theoretical foundations are unable to explain, such as financial market simulation (Casti, 1997; Liang et al., 2022). In this context, Friedman (1993) points out that agent-based market simulation provides a powerful tool for analyzing the behavior of individual participants as well as the overall market outcomes that emerge from the interaction of individual agents. He also notes that "a trader's strategies must be specified exogenously".

First, we will examine the expected price of each type of agent and compare it to the real market price. Then we will study the prediction of the stock market prices variation based on agents' actions and compare it with the real market price. After a set of buying and selling actions, the market price is recalculated according to the observed excess demand D and Supply S. The price impact function is given by the equation (6)

Table 3
Experimentation of different market compositions.

t	P_t	P_t^*
Exp. 1: nbr_{Ad} (70%) > nbr_f (10%) = nbr_c (10%) = nbr_m (10%)		
01/07/1990	356.15	358.00
01/08/1990	322.56	356.42
…	….	…..
01/02/2021	3818.325	3735.67
Exp. 2: nbr_f(70%)> nbr_{Ad} (10%)=nbr_c (10%)= nbr_m(10%)		
t	P_t	P_t^*
01/07/1990	356.15	358.03
01/08/1990	322.56	356.30
…	….	…
01/02/2021	3818.32	3694.56
Exp. 3: nbr_c(70%)> nbr_{Ad}(10%)= nbr_f (10%)= nbr_m(10%)		
t	P_t	P_t^*
01/07/1990	356.15	358.03
01/08/1990	322.56	356.80
…	….	….
01/02/2021	3818.32	3744.67
Exp. 4: nbr_m(70%)> nbr_{Ad} (10%)=nbr_f (10%)= nbr_c(10%)		
t	P_t	P_t^*
01/07/1990	356.15	357.99
01/08/1990	322.56	356.19
…	….	….
01/02/2021	3818.32	3737.15
Exp. 5: nbr_{Ad}(25%)= nbr_f (25%)= nbr_c (25%)= nbr_m(25%)		
t	P_t	P_t^*
01/07/1990	356.15	358.00
01/08/1990	322.56	356.27
…	….	…
01/02/2021	3818.32	3730.43

Ad: adaptive agent/f: fundamentalist/c: chartist/m: mimetic; nbr_{Ad}, nbr_f, nbr_c and nbr_m:The percentage of each type of agent; *T: time of prediction, F_t: fundamental value of S&P 500, P_t: real price of S&P 500, P^*_t: predicted price of S&P 500.*

Table 4
Agents' predictions for total period (07/1990–02/2021).

	P_t	P^{Ad*}	P^{F*}	P^{C*}	P^{M*}
Average	1362,922	1349,183	1339,797	1422,599	1353,519
Median	1231,705	1223,118	1211,618	1282,829	1229,02
Standard deviation	762,7148	750,7708	743,9286	793,0236	753,6372
Variance	581733,8	563656,8	553429,7	628886,5	567,969
Kurtosis	0,467615	0,441498	0,459132	0,352638	0,381188
Skewness coefficient	0,95105	0,946859	0,954889	0,91119	0,922223
Minimum	304	309,3683	311,6474	313,6335	304
Maximum	3818,325	3756,282	3727,52	3908,858	3739,425
Sum	501555,4	496499,4	493045,3	523516,6	498095,1
Number of samples	368	368	368	368	368
Confidence level (95.0%)	78,18455	76,96019	76,25881	81,29146	77,25402

P_t: S&P real price at t/P^{Ad*}: S&P predicted price by adaptive agent for t/ P^{F*}: S&P predicted price by fundamentalist for t/.
P^{C*}: S&P predicted price by chartist for t/ P^{M*}: S&P predicted price by mimetic agent for t.

(Day & Huang, 1990):

$$P_{t+1} = P_t + (1 + a((D_t) - (S_t)) + \delta \tag{6}$$

Where,

- a greater than 0: the speed of price adjustment
- D_t: the number of buying actions at date t
- S_t: the number of selling actions at date t
- δ :a normal, IID noise process with zero mean and constant standard deviation ∂_δ.

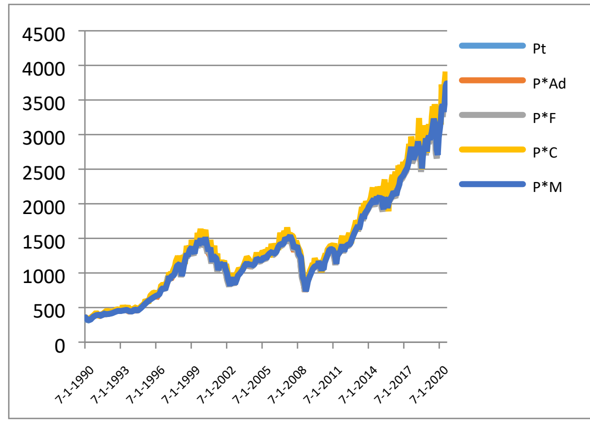

Fig. 6. Agents' predictions for total period (07/1990–02/2021).

This equation captures the basic intuition that excess demand raises the price, while excess supply lowers the price. This pricing mechanism is computationally very fast, while the price changes are very sensitive to the choice of the liquidity parameter$a$.

4. Experiments, Results, and discussions

We developed a multi-agent system composed of adaptive, fundamentalist, chartist, and mimetic agents to simulate a real stock market. We aim to evaluate the proposed adaptive model by comparing its performance with fundamentalist, chartist, and mimetic models, to prove its existence in the real stock market and to explain the behavior of the market in times of stability and crisis. For this purpose, we consider ~~six~~ four sub-periods: Period 1 (from July 1990 to December 2000), period 2 (from January 2001 to December 2006), period 3 (from January 2007 to December 2009), and period 4 (from January 2010 to February 2021). The four sub-periods coincide with the Asian financial crisis, the period before the world financial crisis (2007–2008), during the world financial crisis, and after the world financial crisis. In addition, they cover the Dotcom and European Sovereign Debt crises, and the COVID-19 crisis. We also link individual traders' forecasting behaviors to price formation in the S&P 500 stock market.

4.1. Experiments

To simulate the behavior of the adaptive, fundamentalist, chartist, and mimetic agents and to evaluate their stock price predictions, we used the monthly S&P 500 prices and S&P 500 dividend per year between January 1990 and February 2021 extracted from DataStream (Hommes & in 't Veld, 2017; Kumbure et al., 2022).

We carry out two types of experiments:

- Microscopic experiments that simulate the individual behaviors of different types of traders based on their stock price forecasting behavior. In fact, we run the adaptive, fundamentalist, chartist, and mimetic models on monthly S&P 500 data to generate the predictions of each agent.
- The macroscopic experiments that set up a multi-agent system composed of the already created agents to study the impact of their behaviors on the formation of market prices.

We use statistical properties (mean, median, minimum, maximum, kurtosis and skewness) and standard error metrics: MAE, MSE and RMSE

Table 5
Agents' predictions for the period 1990–2000.

	P_t	P^{Ad*}	P^{F*}	P^{c*}	P^{M*}
Average	743,837143	739,094409	735,887096	774,179901	736,200159
Standard error	33,7312143	33,0818762	32,5750881	35,6351474	33,5511816
Median	582,955	579,567718	580,375327	595,02305	571,78
Standard deviation	378,631942	371,343139	365,654457	400,003537	376,61108
Variance	143362,147	137895,727	133703,182	160002,83	141835,905
Kurstosis	−0,99770297	−0,99810172	−1,00248001	−0,94687091	−0,92934578
Skewness coefficient	0,71502049	0,71635069	0,71298441	0,74025365	0,75052767
Range	1213,68	1168,94972	1170,32544	1324,12344	1213,68
Minimum	304	309,368254	311,647399	313,63354	304
Maximum	1517,68	1478,31798	1481,97284	1637,75698	1517,68
Sum	93723,48	93125,8955	92721,7741	97546,6675	92761,22
Number of samples	126	126	126	126	126
Confidence level (95.0%)	66,7582595	65,4731387	64,4701423	70,5263793	66,4019524

P_t: S&P real price at t/P^{Ad*}: S&P predicted price by adaptive agent for t/ P^{F*}: S&P predicted price by fundamentalist for t/.
P^{C*}: S&P predicted price by chartist for t/ P^{M*}: S&P predicted price by mimetic agent for t.

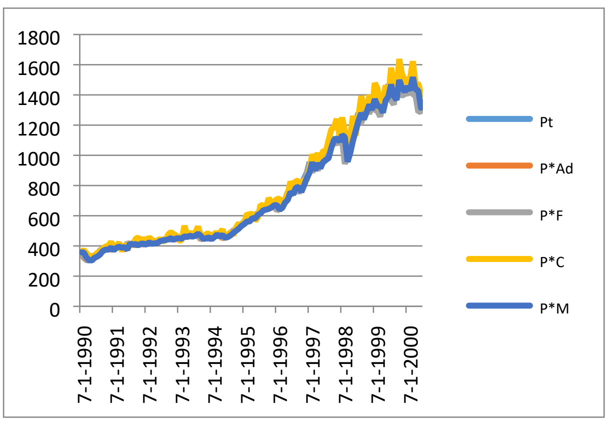

Fig. 7. Agents' predictions for the period (07/1990–12/2000).

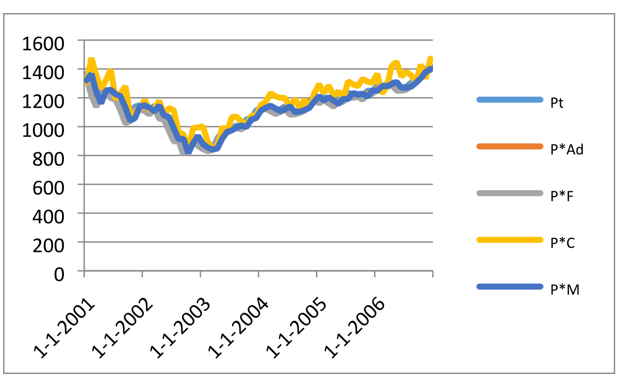

Fig. 8. Agents' predictions for the period (01/2001–12/2006).

(Table 1), to ~~prove~~ evaluate the accuracy of the proposed model and to check if the dynamics of the generated prices are realistic by comparing them with those of real price series.

y_i: Real price (observed), y_p: Predicted price, n: Number of observations.

4.2. The individual agents' predictions

As explained in section 3, the two basic data used to predict the stock price at t + 1 (P^*_{t+1}) are the fundamental value of stocks (F_t) and their past prices (P_{t-n}). To calculate F_t, we specify this value and the price dividend (PD) ratios D_t using the standard model based on Gordon (1962). The textbook Gordon solution for the fundamental price dividend (P/D) ratio under discrete time is constant and equal to δ^* (Hommes & in 't Veld, 2017), described in equation (7):

$$\delta^* = (1+g)/(r-g) \tag{7}$$

Where:

- g: is the expected growth rate of dividends, calculated by using yearly data from 1871 to 2020.
- r = (i + RP): is the sum of the expected risk-free rate i and the risk premium (RP) on stocks (S&P), both assumed to be constant.
- i: is the average real return on T-notes with a 10-year maturity; RP =(r – i): is the risk premium supposedly equal to 2.87% (estimated value per Hommes & in 't Veld, 2017).

The F_t value is defined in equation (8) by:

$$F_t = D_t{}^*\delta^*{}_t \tag{8}$$

- D_t :is the S&P 500 dividend per year.
- We perform 4 micro-experiments describing the behavior of the individual agent-based trader who can buy, sell, or do nothing according to the internal forecasting behavior:
- Micro-Experiment 1: The adaptive agent performs an adaptive behavior that changes according to the deviation of asset prices from the fundamental value. He decides to buy, sell, or do nothing according to its forecasting behavior (equation (5).
- Micro-Experiment 2: The fundamentalist agent performs a rational forecasting behavior. He makes buy, sell, or do-nothing decisions according to equation (1).
- Micro-Experiment 3: The chartist agent has an emotional forecasting behavior. He is influenced by stock market trends. He can be pessimistic or optimistic and makes his decision according to equation (3).
- Micro-Experiment 4: The mimetic agent has herding forecasting behavior. He represents an inexperienced trader who observes other investors' trades in the market. He bases his decision on equation (4).

Table 2 shows the values assigned to the parameters used in the four experiments. The Adaptive agent estimates the stock price based on equation (5). As described in table 2, d depends on the deviation of the real price from its fundamental value, α fits the Gaussian distribution$N(\mu_\alpha : \frac{1}{1+d}, \sigma_\alpha : 0.1)$,$\beta$ fits$N(\mu_\beta : d, \sigma_\beta : 0.06)$, and γ fits $N(\mu_\gamma : d, \sigma_\gamma : 0.04)$.

We emphasize that the predictive behavior of the proposed adaptive model can dynamically change into fundamentalist, chartist, mimetic or a combination of these three, depending on the stability of the market

Table 6
Agents' predictions (2001–2006).

	P_t	P^{Ad*}	P^{F*}	P^{c*}	P^{M*}
Average	1133,76	1122,40732	1113,67565	1187,78626	1132,39861
Standard error	16,8658309	16,5261839	16,4639994	18,0187859	16,5951141
Median	1142,89	1130,11835	1122,36158	1198,11727	1142,89
Standard deviation	143,111321	140,229321	139,701668	152,894468	140,814213
Variance	20480,8502	19664,2624	19516,5559	23376,7183	19828,6425
Kurstosis	−0,37758283	−0,41178329	−0,39767626	−0,39547587	−0,42074777
Skewness coefficient	−0,37324675	−0,38437072	−0,35677963	−0,30829701	−0,44783866
range	603,02	576,101984	588,267284	633,216947	585,35
Minimum	815,28	827,869209	804,076022	843,523237	815,28
Maximum	1418,3	1403,97119	1392,34331	1476,74018	1400,63
Sum	81630,72	80813,3268	80184,6468	85520,6108	81532,7
Number of samples	72	72	72	72	72
Confidence level (95.0%)	33,6295117	32,9522749	32,8282825	35,9284385	33,0897178

P_t: S&P real price at t/P^{Ad*}: S&P predicted price by adaptive agent for t/ P^{F*}: S&P predicted price by fundamentalist for t/.
P^{C*}: S&P predicted price by chartist for t/ P^{M*}: S&P predicted price by mimetic agent for t.

Table 7
Agents' predictions (2007–2009).

	P_t	P^{Ad*}	P^{F*}	P^{c*}	P^{M*}
Average	1220,99583	1211,20619	1202,2523	1302,75114	1229,41806
Standard error	41,8355068	41,3783445	40,6842323	45,8303669	42,0734951
Median	1301,35	1296,78634	1282,04803	1396,33415	1333,1925
Standard deviation	251,013041	248,270067	244,105394	274,982202	252,44097
Variance	63007,5467	61638,0261	59587,4432	75615,2112	63726,4435
Kurstosis	−1,30867021	−1,29842073	−1,31410843	−1,20532134	−1,27604309
Skewness coefficient	−0,40587079	−0,41838593	−0,40755679	−0,49060154	−0,4883627
range	803,245	792,918557	779,953057	885,743995	803,245
Minimum	735,09	729,06921	729,871018	772,962607	735,09
Maximum	1538,335	1521,98777	1509,82408	1658,7066	1538,335
Sum	43955,85	43603,4228	43281,0827	46899,041	44259,05
Number of samples	36	36	36	36	36
Confidence level (95.0%)	84,9305941	84,0025052	82,5933825	93,0405912	85,4137359

P_t: S&P real price at t/P^{Ad*}: S&P predicted price by adaptive agent for t/ P^{F*}: S&P predicted price by fundamentalist for t/.
P^{C*}: S&P predicted price by chartist for t/ P^{M*}: S&P predicted price by mimetic agent for t.

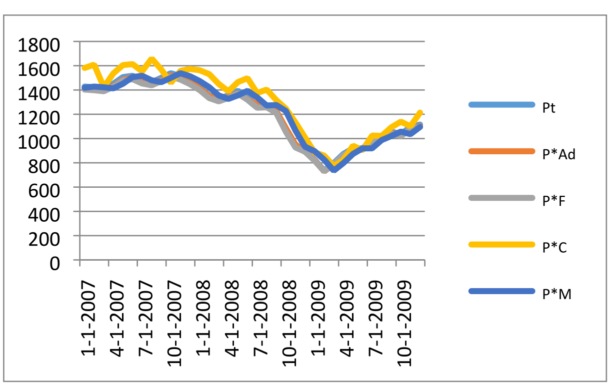

Fig. 9. Agents' predictions for the period (01/2007–12/2009).

and the deviation of the market price from its fundamental value.

4.2.1. Price market prediction

We built an agent-based prototype of the S&P 500 index to simulate interactivity between different types of investors having different behaviors and analyze the consequent impact on the stock market price evolution. The goal is to demonstrate the feasibility of the proposed agent models, prove their existence in real stock markets and explain the dynamics of asset prices.

The stock market is initially composed of 1000 agents distributed in adaptive (Ad) fundamentalist (f), chartist (c) and mimetic (m).

We perform 5 experiments, each representing the dominance of one type of agent in the market. Table 3 presents the 5 experiments defined as follows:

- Exp. 1: adaptive agents (Ad) are dominant
- Exp. 2: fundamentalist agents (f) are dominant
- Exp. 3: chartist agents (c) are dominant
- Exp. 4: mimetic agents (m) are dominant
- Exp. 5: the number of agents of each type are equal

In each experiment, we analyze the statistical properties (mean, median, minimum, maximum, kurtosis and skewness) and compare them with those of the real price series. Second, we use three standard error metrics MAE, MSE, and RMSE. The lower the number of the above metrics, the more reliable and accurate the predictions will be.

4.3. Results and discuss

We examine the sample period ranging from July 1990 to February 2021 as well as four sub-periods which are defined by different trends in the market index. To examine how agent's price prediction changes depending on major crises, we consider four sub-periods: Period 1 (from July 1990 to December 2000), period 2 (from January 2001 to December 2006), period 3 (from January 2007 to December 2009) and period 4 (from January 2010 to February 2021). We discuss two types of results: the agents' predictions and the price market prediction.

4.3.1. The agents' predictions

Table 4 presents the descriptive statistics 'values of the different agents 'predictions and those of the series of real price S&P 500 stock market index 's values over the total period (1990–2021). We note that the statistical characteristics of the different time series are very close

Table 8
Agents' predictions (2010 – February 2021).

	P_t	P^{Ad*}	P^{F*}	P^{c*}	P^{M*}
Average	2106,30847	2081,76698	2066,10287	2190,67373	2086,13515
Standard error	60,4231412	59,3942359	58,9442828	62,662468	59,4858353
Median	2064,205	2037,16782	2026,72641	2147,57855	2061,425
Standard deviation	699,448427	687,537987	682,329404	725,370509	688,598327
Variance	489228,103	472708,484	465573,415	526162,375	474167,656
Kurstosis	−0,78033844	−0,80801315	−0,793415	−0,89570238	−0,86729436
Skewness coefficient	0,34496082	0,33128994	0,33561622	0,29718229	0,31070413
range	2787,615	2722,74591	2712,75698	2897,42571	2708,715
Minimum	1030,71	1033,53658	1014,76335	1011,43214	1030,71
Maximum	3818,325	3756,28248	3727,52033	3908,85785	3739,425
Sum	282245,335	278956,775	276857,785	293550,28	279542,11
Number of samples	134	134	134	134	134
Confidence level (95.0%)	119,514633	117,479498	116,589508	123,943934	117,660678

P_t: S&P real price at t/P^{Ad*}: S&P predicted price by adaptive agent for t/ P^{F*}: S&P predicted price by fundamentalist for t/.
P^{C*}: S&P predicted price by chartist for t/ P^{M*}: S&P predicted price by mimetic agent for t.

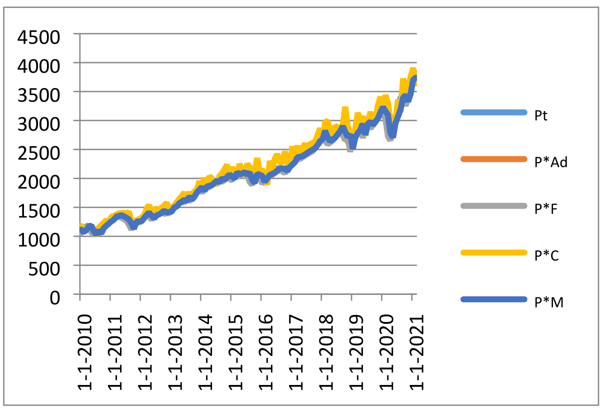

Fig. 10. Agents' predictions for the period (01/2010–02/2021).

with kurtosis less than zero and skewness coefficients<1. But we notice that the Ad-agent offers the most accurate predictions of index prices in terms of mean and standard deviation, with the mimetic agent, and in terms of kurtosis and skewness, with the fundamentalist agent. Fig. 6 confirms these results; the prediction series of the Ad agent was the closest to the real value series, followed by those of the fundamentalist, the mimetic and finally the chartist whose predictions are worse than those of the other agents.

By dividing our sample into four sub-periods, the results do not change; the Ad-agent provides the best price prediction of the index. k descriptive statistics closest to the real price series in terms of mean, standard deviation, kurtosis, and skewness (Table 5 and Fig. 8). For the 2001–2006 calm sub-period, the Ad-agent's predictions remain the most precise for all the characteristics: mean, standard deviation, kurtosis, and skewness. Even if the series of predictions of the mimetic gives better values in terms of mean and standard deviation, this can be explained by the fact that the predictive model of the mimetic is essentially based on the previous price. In terms of kurtosis, it is the fundamentalist agent and the chartist who give the best values (Table 6). Fig. 8 confirms these results.

During the period of the subprime crisis (2007–2009), the Ad-agent performs in terms of prediction and exceeded the fundamentalist and the mimetic in terms of precision (Table 7 and Fig. 9). The skewness

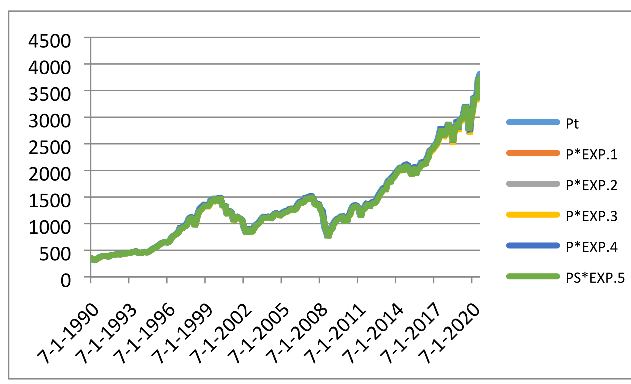

Fig. 11. Price market predictions for total period (07/1990–02/2021).

Table 9
Price market predictions for total period (1990–2021).

	P_t	P_t^*(Exp.1)	P_t^*(Exp.2)	P_t^*(Exp.3)	P_t^*(Exp.4)	P_t^*(Exp.5)
Average	1362,922	1343,087	1336,601	1355,376	1341,855	1345,895
Standard error	39,75926	39,12757	38,69014	39,37821	39,07417	39,1165
Median	1231,705	1223,229	1214,101	1230,477	1221,979	1225,27
Standard deviation	762,7148	750,5969	742,2056	755,405	749,5725	750,3846
Variance	581733,8	563395,7	550869,1	570636,7	561,859	563077,1
Kurstosis	0,467615	0,426945	0,403152	0,394366	0,422993	0,407601
Skewness coefficient	0,95105	0,94841	0,935419	0,931101	0,948099	0,938113
range	3514,325	3431,26	3390,005	3439,262	3432,877	3425,903
Minimum	304	304,4109	304,5614	305,4085	304,278	304,5275
Maximum	3818,325	3735,671	3694,566	3744,67	3737,155	3730,431
Sum	501555,4	494,256	491869,1	498778,5	493802,5	495289,5
Number of samples	368	368	368	368	368	368
Confidence level (95.0%)	78,18455	76,94236	76,08219	77,43523	76,83736	76,9206

P_t: S&P real price at t / P_t^*: S&P predicted price for t/Exp. 1: Ad-agents are dominant / Exp. 2: fundamentalist agents (f) are dominant /.
Exp. 3: chartist agents are (c) dominant /Exp. 4: mimetic agents (m) are dominant /Exp. 5: the number of agents of each type are equal.

Table 10
Price market predictions for the period 1900–2000.

1990–2000	P_t	P_t^*(Exp.1)	P_t^*(Exp.2)	P_t^*(Exp.3)	P_t^*(Exp.4)	P_t^*(Exp.5)
Average	743,837143	733,68336	731,012948	738,686398	732,956142	734,501869
Standard error	33,7312143	33,2610742	32,8728161	33,573125	33,1620406	33,2952307
Median	582,955	572,678194	572,821432	575,07998	572,385849	572,673175
Standard deviation	378,631942	373,354632	368,996445	376,857394	372,242983	373,738038
Variance	143362,147	139393,681	136158,377	142021,495	138564,838	139680,121
Kurstosis	−0,99770297	−0,90559638	−0,91972697	−0,92505799	−0,90816559	−0,91644124
Skewness coefficient	0,71502049	0,76010341	0,7494362	0,75126415	0,75790476	0,75466623
range	1213,68	1194,7387	1192,18882	1212,88867	1193,64616	1201,59843
Minimum	304	304,41089	304,561372	305,408542	304,277975	304,527471
Maximum	1517,68	1499,14959	1496,75019	1518,29721	1497,92413	1506,1259
Sum	93723,48	92444,1033	92107,6314	93074,4861	92352,4739	92547,2354
Number of samples	126	126	126	126	126	126
Confidence level (95.0%)	66,7582595	65,8277938	65,0593828	66,4453812	65,6317942	65,8953938

P_t: S&P real price at t / P_t^*: S&P predicted price for t/Exp. 1: Ad-agents are dominant / Exp. 2: fundamentalist agents (f) are dominant /.
Exp. 3: chartist agents are (c) dominant /Exp. 4: mimetic agents (m) are dominant /Exp. 5: the number of agents of each type are equal.

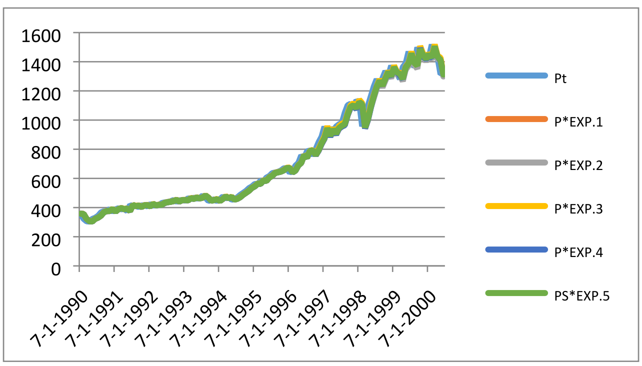

Fig. 12. Price market predictions for total period (07/1990–12/2000).

coefficient of the mimetic prediction series is negative, so the distribution spreads out to the left, inversely to the distribution of real values. The standard deviation of the distribution of the chartist's predictions is very high compared to that of the distribution of actual values; the chartist's predictions in times of crisis are very scattered.

The results of the 2010–2021 sub-period confirm one more the capacity of the Ad-model to predict market prices compared to other agent models (Table 8 and Fig. 10). Unlike the distribution of real prices, the distribution of the fundamentalist's predictions is flattened (kurtosis < 0). The sub-period studied includes the European Sovereign Debt and the COVID-19 health crisis. We can conclude that the Ad-agent's forecasts adapt to different market cycles and the adaptive agent-based model offers better accuracy in price predictions. H2 is confirmed.

4.3.2. Price market prediction

From the five experiments, shown in section 4.1, we aim to test if one type of investor is responsible for the price dynamic of market assets. For the experiments (1, 2, 3 and 4), only one type of agents dominates the market. For the 5th experiment, we consider a balanced market where each type of agent has the same proportion. The multi-agent simulation is made on real market data. Then, the series of SMA's generated prices (P_t^*)for each of experiments (Exp.1 Exp.2, Exp.3, Exp.4.and Exp.5), are compared with the series of real prices (P_t).

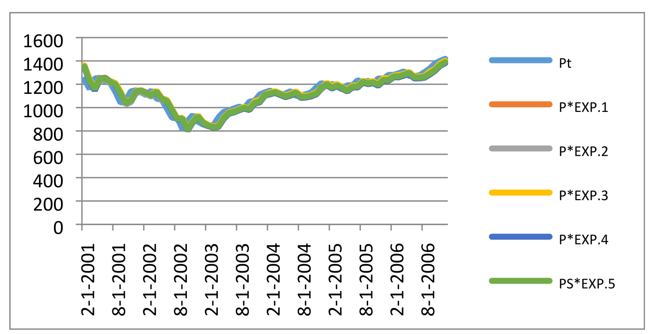

Fig. 13. Price market predictions for total period (01/2001–12/2006).

Table 11
Price market predictions for the period 2001–2006.

2001–2006	P_t	P_t^*(Exp.1)	P_t^*(Exp.2)	P_t^*(Exp.3)	P_t^*(Exp.4)	P_t^*(Exp.5)
Average	1130,48887	1115,9734	1113,08649	1128,93854	1115,25245	1120,30942
Standard error	16,7802736	16,4540516	16,3775614	16,6342099	16,4283815	16,4859996
Median	1140,84	1127,29321	1125,1071	1140,59937	1127,2819	1133,0129
Standard deviation	141,393099	138,644304	137,999785	140,162344	138,428003	138,913502
Variance	19992,0083	19222,2429	19043,9408	19645,4827	19162,312	19296,9611
Kurstosis	−0,35305882	−0,37796909	−0,39629812	−0,39634773	−0,38356123	−0,3842256
Skewness coefficient	−0,38642414	−0,48132422	−0,44890726	−0,45539571	−0,47900247	−0,46481981
range	603,02	582,544368	577,97038	583,581482	578,459548	582,786928
Minimum	815,28	802,383866	803,064972	817,899038	802,535607	806,618303
Maximum	1418,3	1384,92823	1381,03535	1401,48052	1380,99515	1389,40523
Sum	80264,71	79234,1114	79029,1411	80154,636	79182,9237	79541,9688
Number of samples	71	71	71	71	71	71
Confidence level (95.0%)	33,4672004	32,8165712	32,6640163	33,1758855	32,7653737	32,8802895

P_t: S&P real price at t / P_t^*: S&P predicted price for t/Exp. 1: Ad-agents are dominant / Exp. 2: fundamentalist agents (f) are dominant /.
Exp. 3: chartist agents are (c) dominant /Exp. 4: mimetic agents (m) are dominant /Exp. 5: the number of agents of each type are equal.

Fig. 14. Price market predictions for total period (01/2007–12/2009).

We note that the five experiments provide price series which globally reproduce the statistical characteristics of real prices (Table 9). Indeed, for a kurtosis of 0.467 of the series of real prices, the other series have a kurtosis of between 0.39 and 0.426. The market dominated by Ad-agents offers the closest value, 0.426. For skewness, it is of the order of 0.951 for the series of real prices, it oscillates between 0.931 and 0.948. The best value is provided by the market dominated by Ad-agents, followed by the market dominated by mimetic.

Our proposed Ad-agent is able not only to explain the formation of stock prices but also when dominating the market; he provides the best approximation to the real market (Fig. 11). We confirm that the presence of an adaptive agent can explain the formation of the stock market prices (H1). Our different experiments highlight the presence of four types of agents in the stock market that are the adaptive, fundamentalists, chartists, and mimetic agents. The market composition is not balanced, and according to our results, the proportion of adaptive and mimetic agents is the most significant.

For the 1990–2000 sub-periods (Table 10 and Fig. 12), experiments 1, 3, 4 and 5 generate series of prices that reproduce statistical characteristics close to the series of real prices (kurtosis between 0.905 and 0.997 and skewness between 0.715 and 0.760). Means and standard deviations are not very accurate even though they are quite close to the values of the real price series. Experiment 2 (the fundamentalists dominate) generates a series of prices with negative kurtosis (-0.919) reflecting a more flattened distribution than the series of real prices. Fundamentalist agents cannot be dominant in the real market.

For the period 2001–2006 (Table 11 and Fig. 13), our results are confirmed. Even though the markets dominated by chartists and mimetic provide averages and standard deviations close to the real market, the market dominated by adaptive ones provides characteristics closest to the real market in terms of kurtosis and skewness. A market dominated by fundamentalists once again fails to replicate the real market (negative kurtosis and skewness).

The results of the subprime crisis period (2007–2009) are very relevant (Fig. 14) and confirm our H1 hypothesis on the presence of Ad-agents in the equity market. Indeed, for this sub-period (Table 12), only the market dominated by Ad-agents (exp. 1) reproduces the characteristics of the real market with a positive kurtosis greater than 1 (1.296 *vs.* 1.308) and a positive skewness too (0.472 *vs.* 0.405), Sharp distributions

Table 12
Price market predictions for the period 2007–2009.

2007–2009	P_t	P_t^*(Exp.1)	P_t^*(Exp.2)	P_t^*(Exp.3)	P_t^*(Exp.4)	P_t^*(Exp.5)
Average	1220,99583	1214,84369	1213,72987	1230,01672	1213,74927	1219,7121
Standard error	41,8355068	41,0942256	40,9120088	41,9274168	40,9299508	41,3222997
Median	1301,35	1311,71405	1313,07745	1333,35648	1312,23601	1319,84085
Standard deviation	251,013041	246,565353	245,472053	251,564501	245,579705	247,933798
Variance	63007,5467	60794,4735	60256,5287	63284,698	60309,3915	61471,1683
Kurstosis	−1,30867021	−1,29608934	−1,29350466	−1,28793885	−1,29515449	−1,2892143
Skewness coefficient	−0,40587079	−0,47251696	−0,48158786	−0,47690928	−0,47927398	−0,48090705
range	803,245	784,839504	778,993831	798,807198	780,532166	789,321122
Minimum	735,09	736,251434	736,280316	738,92261	736,240119	736,687469
Maximum	1538,335	1521,09094	1515,27415	1537,72981	1516,77228	1526,00859
Sum	43955,85	43734,373	43694,2752	44280,602	43694,9735	43909,6355
Number of samples	36	36	36	36	36	36
Confidence level (95.0%)	84,9305941	83,4257131	83,0557934	85,1171812	83,0922177	83,8887282

P_t: S&P real price at t / P_t^*: S&P predicted price for t/Exp. 1: Ad-agents are dominant / Exp. 2: fundamentalist agents (f) are dominant /.
Exp. 3: chartist agents are (c) dominant /Exp. 4: mimetic agents (m) are dominant /Exp. 5: the number of agents of each type are equal.

Table 13
Price market predictions for the period 2010–2021.

2010–2021	P_t	P_t^*(Exp.1)	P_t^*(Exp.2)	P_t^*(Exp.3)	P_t^*(Exp.4)	P_t^*(Exp.5)
Average	2114,07117	2078,39548	2064,94123	2096,46997	2076,36148	2081,72822
Standard error	60,3746722	59,8331271	58,8468838	59,8330944	59,7442097	59,5844542
Median	2065,3	2038,92483	2034,24063	2060,96904	2032,96257	2044,46797
Standard deviation	696,274686	690,029284	678,655371	690,028906	689,003838	687,161448
Variance	484798,439	476140,413	460573,113	476139,892	474726,289	472190,856
Kurstosis	−0,77529619	−0,87181499	−0,8633607	−0,86992573	−0,87972068	−0,8704105
Skewness coefficient	0,3435061	0,31265369	0,30767408	0,30649053	0,31031351	0,30887024
range	2787,615	2721,67308	2679,50869	2710,23964	2722,13814	2710,87205
Minimum	1030,71	1013,99779	1015,05738	1034,4307	1015,01718	1019,5586
Maximum	3818,325	3735,67086	3694,56607	3744,67034	3737,15532	3730,43065
Sum	281171,465	276426,598	274637,184	278830,506	276156,077	276869,853
Number of samples	133	133	133	133	133	133
Confidence level (95.0%)	119,427069	118,35584	116,404953	118,355775	118,179952	117,86394

P_t: S&P real price at t / P_t^*: S&P predicted price for t/Exp. 1: Ad-agents are dominant / Exp. 2: fundamentalist agents (f) are dominant.
/Exp. 3: chartist agents are (c) dominant /Exp. 4: mimetic agents (m) are dominant /Exp. 5: the number of agents of each type are equal.

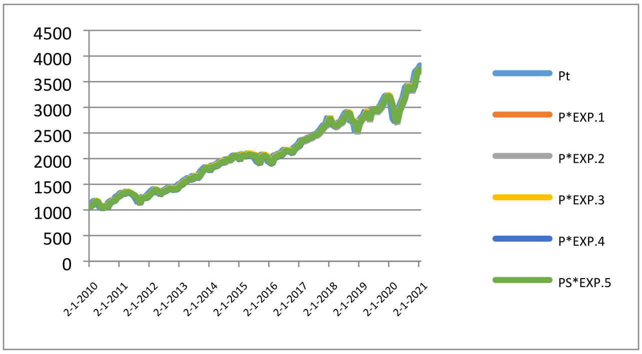

Fig. 15. Price market predictions for total period (01/2010–02/2021).

that sprawl out to the right. The other experiments (exp. 2, 3, 4, 5) provide negative kurtosis and skewness values, hence rather flattened distributions that spread out to the left.

We can conclude that in times of crisis, Ad-agents dominate the market. They can also be fundamentalist agents who have adapted to new market conditions by combining different decision rules. During a crisis, the chartists and mimetic do not dominate the market and their behavior affects that of Ad-agents and fundamentalists.

For the 2010–2021 sub-period (Table 13 and Fig. 15), a period which includes the European Sovereign Debt and the COVID-19 health crises. Means and standard deviations are not very accurate even though they are quite close to the values of the actual price series. Experiments 2 and 5 generate price series with negative kurtosis (-0.863 and −0.870) reflecting a more flattened distribution than the real price series. We can see that fundamentalist agents cannot be dominant in the real market and that the market is not balanced.

The previous statistical analysis demonstrates that Ad-agents have variable and adaptive prediction behaviors depending on the evolution of market metrics, the best stock price prediction compared to other agents (fundamentalist / chartist / and mimetic) and dominate the stock market.

4.3.3. MAE, MSE and RMSE tests

The performance of the proposed model is evaluated lby considering the MAE, MSE, and RMSE values (Table 14). The performance of the adaptive agent-based model is compared to the other three agent-based models. The adaptive agent-based model has the best value of the three error measures. When the performance of the adaptive agent-based model is compared to the fundamentalist, chartist, and mimetic models, there is a 16, 42%; 77, 20% and 60, 84% improvement in RMSE values, respectively. For the five experiments carried out over the total period (1990–2021), experiment 3 (chartists dominate the market) has the best values of the error metric (RMSE: 0, 04123; MSE: 0, 00170; MAE: 0, 03188). Then, experiment 1 (Ad- agents dominate) comes second (RMSE: 0, 04178; MSE: 0, 00174; MAE: 0, 03282). These results can confirm hypotheses H1 and H2.

5. Conclusion

In this paper we propose a new agent-based model called the Adaptive-agent model. The adaptive agent combines three behaviors: fundamentalist, chartist, and mimetic to adapt its decision to the different cycles on the market. The market is populated by four different types of traders: (1) fundamentalists who make their decisions based on the estimated fundamental value, (2) chartists who tend to believe that in the short run it will continue, (3) mimetic who take decisions by imitating the dominant behavior, (4) Ad-agent which the investment decision is a weighted average of the three other decisions. The importance of the weighting of each decision depends on the market cycle and the distance between the price and the fundamental value.

To test the model, we first generate the predicted prices of different models and compared statistical properties of the generated prices series with those observed in the real market. Secondly, we use multi-agent's system simulation (MAS) on an artificial market made up of the 4 types of agents with various combinations. We conduct a series of experiments, and we compare statistical properties of the market prices generated by the artificial market with those observed in the real market. As a robustness test, we use error metrics to evaluate the forecasting accuracy of the adaptive agent model.

We examine the sample period ranging from July 1990 to February 2021 as well as four sub-periods which are defined by different trends in the market index. The four sub-periods coincide with the Asian financial crisis (from 1990 to December 2000), the period before the world financial crisis (from January 2001 to December 2006), during the world financial crisis (from January 2007 to December 2009), and after the world financial crisis ((from January 2010 to February 2021). The last period covers European Sovereign Debt crises, and the COVID-19 crisis. We also link individual traders' forecasting behaviors to price formation in the S&P 500 stock market.

The predicted price series generated by our model have statistical properties that are close to the real series. We demonstrated that the adaptive agent model offers better accuracy of price predictions compared to fundamentalist, chartist, and mimetic agents-based models in both calm and crisis periods (H2 confirmed). An artificial market dominated by adaptive agents performs to replicate the statistical properties of the real one. We conclude that the adaptive agents exist in the stock market and they can explain the dynamic of the stock market's price formation (H1 confirmed).

As perspectives, we aim to deepen our study on the chartist decision by adding fuzzy logic to express the agent's emotions and examine their impact on the adaptive agent's final decision. We also plan to introduce machine learning to acquire knowledge from past experiences.

Table 14
Error metrics of agent's prediction and Price market predictions for the period 1990–2021.

Agents' prediction				Price Market prediction			
Agent/metrics	RMSE	MSE	MAE	Exp//metrics	RMSE	MSE	MAE
Ad-agent	0.01620	0.00026	0.01413	Exp.1	0.04178	0.00174	0.03282
Fundamentalist	0.01939	0.00037	0.01823	Exp.2	0.04179	0.00174	0.03281
Chartist	0.07108	0.00505	0.05667	Exp. 3	0.04123	0.00170	0.03188
Mimetic	0.04137	0.00171	0.032174	Exp.4	0.04181	0.00174	0.03284
				Exp. 5	0.15356	0.02358	0.1417993

Exp. 1: Ad-agents are dominant / Exp. 2: fundamentalist agents (f) are dominant /Exp. 3: chartist agents are (c) dominant /Exp. 4: mimetic agents (m) are dominant /Exp. 5: the number of agents of each type are equal

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Appendix

Appendix 1:. agents' predictions

Fig. 6, Fig. 7, Fig. 8, Fig. 9, and Fig. 10 show the real stock market price (P_t) compared to the four different market prices forecast of adaptive agent (PAd*), fundamentalist agent (P*F), chartist agent (P*C), and mimetic agent (P*M), respectively for total period (07/1990–02/2021), the period (07/1990–12/2000), the period (01/2001–12/2006), the period (01/2007–12/2009), and the period (01/2010–02/2021).

Appendix 2:. Price market predictions

We perform 5 experiments, each representing the dominance of one type of agent in the market:

Exp. 1: adaptive agents (Ad) are dominant.
Exp. 2: fundamentalist agents (f) are dominant.
Exp. 3: chartist agents (c) are dominant.
Exp. 4: mimetic agents (m) are dominant.
Exp. 5: the number of agents of each type are equal.

In each experiment we run 1000 agents splitted into adaptive, fundamentalist, chartist and mimetic agents.

Fig. 11, Fig. 12, Fig. 13, Fig. 14, and Fig. 15 show the real stock market price (Pt) compared to the different market prices forecast generated from Exp. 1 (P*EXP.1), Exp. 2 (P*EXP.2), Exp. 3 (P*EXP.3), Exp. 4 (P*EXP.4), and Exp. 5 (P*EXP.5), respectively for total period (07/1990–02/2021), the period (07/1990–12/2000), the period (01/2001–12/2006), the period (01/2007–12/2009), and the period (01/2010–02/2021).

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