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Noise traders in an agent-based artificial stock market

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Abstract
This paper investigates whether noise traders can survive in the long run and how they influence financial markets by proposing an agent-based artificial stock market, as one simulation model of computational economics. This market contains noise traders, informed and uninformed traders. Informed and uninformed traders can learn from information by using Genetic Programming, while noise traders cannot. The system is first calibrated to real financial markets by replicating several stylized facts. We find that noise traders cannot survive or they just transform to other kind of traders in the long run, and they increase market volatility, price distortion, noise trader risk, and trading volume in the market. However, regulation intervention, e.g., price limits, transaction tax and longer settlement cycle, can affect noise trader's surviving period and their influence on markets.

Keywords Noise traders · Agent-based modeling · Computational economics · Simulation models · Price limits · Transaction tax · The settlement cycle · Risk and volatility dynamics

1 Introduction

Black (1986) made his Presidential Address and expressed, "Noise makes financial markets possible. Noise causes markets to be somewhat inefficient, but often prevents us from taking advantage of inefficiencies." According to the Grossman–Stiglitz paradox, asset prices would perfectly reveal traders' private information, thereby undermining the incentive to collect costly information in the first place. Noise traders are often defined as the ones who use "incorrect" information during decision-making. Bloomfield et al. (2009), and Black (1986) described noise traders as the agents who may trade against recent price movements and result in their own losses without considering informational fundamentals. Choi et al. (2020) believed that noise traders result in irreplaceable risks and they have long been considered to have uninformed investment decisions with cognitive bias. They also provided pieces of evidence that noise traders could undermine the valuations of firms. Banerjee and Green

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(2015) explained that noise traders make their investment decisions based on a spurious signal that they believe to be correct and informative. Ding et al. (2019) also assume that noise traders have different misperceptions of the risky assets in their model, which create "noise trader risk".

Classical finance theory assumes that traders are forming fully rational expectations about future cash flows and investment risks. The classical theory concedes that noise traders cannot be rational and believes that noise traders' positions are offset by smart investors' actions. Nevertheless, proponents of behavioral finance challenge this view by invoking the implications of investors' cognitive biases for the price formation process. Several theoretical studies provide a framework in which noise traders' attention can lastingly affect asset pricing (Black 1986; DeLong et al. 1991). Generally, although previous studies acknowledge the existence of noise traders and influences of noise traders on financial markets, there are remaining debates on noise trader's precise role in financial markets, especially whether they can survive in the long term. We extend this line of research and attempt to investigate whether noise traders could survive in the long run, and how they influence market volatility, price distortion, noise trader risk, and trading volume in the market. Furthermore, we also contribute to examine the consequences of imposing financial regulations. We also attempt investigate how regulatory intervention affects noise trader's surviving period and their influences on markets. We find that noise traders could not survive or they just transform to other kind of traders in the long run, and they increase market volatility, price distortion, noise trader risk, and trading volume in the market. However, regulation intervention can affect noise trader's surviving period and their influence on markets. Price limit and transaction tax shorten the surviving periods of noise traders, while they can survive in longer periods with a longer settlement cycle. Nevertheless, imposing regulation not only influences the activities of noise traders but also the qualities of the market.

2 Literature review

A large amount of finance literature acknowledges the prominent role of noise traders in financial markets and uses noise trading to explain market anomalies. Black (1986) and DeLong et al. (1990) are the most influential early works on this topic. The risk raised by noise traders as "noise trader risk" could be a major source of volatility and increase systematic risk in the market. Researchers argue that noise traders' sentiment could change discount (DeLong et al. 1990; Bodurtha et al. 1995; Choi and Choi 2018; Park et al. 2019) and the volatility of closed-end funds (Brown 1999). Before the 1980 s, researchers paid little attention to noise traders. Mainstream neoclassical finance postulates that the market value of an asset reflects different levels of available information and assumes that all market participants are rational. However, many market anomalies, such as momentum profit, contrarian profit, overreaction or underreaction, and information pricing errors, could not be validly explained by neoclassical finance theories, such as Efficient Market Hypothesis (EMH) and Capital Asset Pricing Model (CAPM), etc. For instance, behavioral finance researchers explained the momentum profit combined with behavioral phenomena of biased self-attribution (Daniel et al. 1998), conservatism in expectations (Barberis and Vishny 1998), and selective information conditioning (Hong et al. 2000). Moreover, Chordia and Shivakumar (2002) explain that the momentum profit is based on good macroeconomic conditions and the underlying firm's size, trading volume and earnings. Behavioral finance theories step in and use noise trading to provide an adequate explanation for these observed market anomalies. Behavioral finance researchers attempt to explain contrarian profit resulting from naive traders who pay more attention to recent information than past information, and then overreaction occurs. Cerruti and Lombardini (2022) present a game theoretical model that formalizes the interactions between noise traders and fundamental traders and use to provide an interpretation framework for periods of euphoria followed by sudden collapse in stock prices. Although attention has been given to noise traders (Zhang and Kalev 2021; Hernandez-Montoya et al. 2022; Ma et al. 2022; Russ 2022), there are remaining debates on noise trader's precise role in financial markets, especially whether they can survive in the long term.

One possible explanation is the market selection hypothesis: In financial markets, arbitrageurs would drive asset prices close to fundamental values; noise traders trade with arbitrageurs would make losses in the long term, then disappear from the market. Well-known studies support the market selection hypothesis, including Alchian (1950), Friedman (1953), Fama (1965) and Sandroni (2000). By contrast, DeLong et al. (1991) showed that noise traders could earn higher returns than rational traders and dominate the financial market in the long run. They argue that noise traders who might take on more risk than traders having rational expectations result in higher expected returns. Since DeLong et al. (1991)'s paper, many studies followed up the market selection question and had different conclusions. For example, the results from Blume and Easley (1992) supported DeLong et al. (1991), while Sandroni (2000) supported the market selection hypothesis. Blume and Easley (2006) provided a possible explanation for such variation between results: the equilibrium allocations in Pareto optimal is listed in Sandroni (2000)'s model, but not Pareto optimal in DeLong et al. (1991) or Blume and Easley (1992). Luo (2018) examines the long-run survival of earnings fixed traders in a competitive securities market with one risk-free asset and one risky asset. He found that even earnings fixated traders lose money to rational traders and eventually disappear. Theoretical models were used in the studies mentioned above.

Another set of studies emphasize the impact of noise trading on the markets. Liu et al. (2021) believed that market liquidity could be significantly affected by rational and irrational trading behavior factors. They believe that rational traders fully reveal the intrinsic value of the asset while irrational traders reflect their cognitive biases in information processing. Bloomfield et al. (2009) conducted experiments that proved that noise traders improve market liquidity, such as increasing trading volume and depth and reducing the price impact of market orders. They concluded that their trading also results in weakening the ability of market prices to reveal new information. Peress and Schmidt (2020, 2021) used the method of episoding of sensational news to distract noise traders and then found that market liquidity and volatility decrease when noise traders are distracted in the market. These findings supported that noise traders contribute to complex market behaviors, both positively and negatively. DeLong et al. (1991) presented a model of portfolio allocation with an assumption that noise traders do not affect prices. However, Kogan et al. (2006) pointed out that whether noise traders can survive in the market is independent of whether they affect prices. This study demonstrated that even noise traders could not survive in the long run and they still have a persistent impact on asset prices by using a parsimonious model with no intermediate consumption. This conclusion was also stand in Lee et al. (1991). Based on incorrect beliefs, irrational investors make their investment choices by taking positions in extremely unlikely states of the economy.

Bloomfield et al. (2009) said one of the effects of the Tobin tax might be serving to drive out noise traders. However, they concluded that transaction tax would affect noise traders and reduce informed traders' activities and profitability, so tax actually could not reduce the impact of noise trading on financial markets. With a similar purpose, China sets the 10% price limit in the stock market and imposes a T + 1 settlement cycle in the market. The US Securities and Exchange Commission make an amendment to Rule 15c6-1(a) under the

Securities Exchange Act of 1934 to shorten the settlement cycle from 3 business days to 2 business days (from T+3 to T+2) for most broker-dealer transactions. Numerous existing studies investigated effects of these regulations on market qualities (e.g. Aktas et al. 2021; Burns et al. 2017; Cappelletti et al. 2017; Chen et al. 2019; Cipriani et al. 2022; Colliard and Hoffmann 2017; Deb et al. 2010; Gomber et al. 2016; Kim et al. 2013; Lien et al. 2020; Pomeranets and Weaver 2018; Veryzhenko et al. 2017), but very few of them paid attention to the effects on noise trading specifically. We find that noise traders help increase trading volume and market volatility. Similarly, it contributes to other traders' investment return while decreasing price distortion from the asset's fundamental value. Price limit, transaction tax and shortening settlement cycle would reduce the impact of noise trading on market qualities. The third research contribution is that we construct an agent-based limit order artificial stock market (ASM), as one of model of computational economics, based on the framework presented in Yeh and Yang (2010). In our simulation models, three types of traders are introduced: informed, uninformed and noise traders. Informed and uninformed traders' trading strategies are generated and updated via genetic programming (GP), while noise traders have biased beliefs about the value of the asset. It presents one application of artificial intelligence.

The first research contribution of this paper is to provide a conclusion that whether noise traders can survive in the long run because there are a lot debates on noise trader's precise role in the markets. We attempt to provide evidences by using computational experiments to simulate financial markets, which is a different method from those in literature. The second research contribution may be that we investigate how noise trading is affected by market regulation, including transaction tax, price limit and settlement cycles, in which could have some policy value. Moreover, this paper also contributes to applications of computational economics. Computational experiments are used in the research, in which allows us to set up experiments (simulations) in a controlled environment to find the results. Agent-based intelligence, as a popular technique of computational research, is applied in the investigation. The paper also contributes to employing simulation models. It captures the complex micro characteristics of investors sufficiently, including heterogeneous beliefs and trading strategies. It provides simulations of real financial markets and makes results reasonable and reliable after models are calibrated. Our paper is also contributing to investigate risk and volatility dynamics. We attempt to find that how noise traders influence market volatility, price distortion, noise trader risk, and trading volume in the market, and also their changes under financial regulations.

The rest of the paper is organized as follows. In Sect. 2, the design of our ASM and relevant settings are introduced. We also compare statistical features of our artificial stock market with real stock markets in the world. Section 3 explains the results and the sensitivity analysis. Section 4 presents the conclusion of this paper.

3 Experimental design

3.1 Methodology

There are three advantages that modeling an artificial stock market with interacting agents. The first advantage is that ASM also allows us to set up experiments (simulation) in a controlled environment to ensure the accuracy of the conclusion. ASM can also capture the complex micro characteristics of investors sufficiently, including heterogeneous beliefs and trading strategies. Due to the lack of data, empirical studies cannot easily be set up to trace noise trading. An artificial stock market would no longer have limitations of data availability. Our ASM model is based on the framework of Yeh and Yang (2010), which is followed the model of Santa Fe ASM of Arthur et al. (1997) and Lebaron et al. (1999), and the studies of Brock and Hommes (1998).

3.2 Market structure

3.2.1 Assets

Two assets are introduced in our market. One is a risk-free asset (bonds) paying interests at a constant rate. The gross return of the risk-free asset is $R = 1 + r_f$ for one period, where r_f is the risk-free interest rate. The other asset is a risky asset (stock), paying a stochastic dividend which is assumed to be a AR(1) (the first-order auto-regressive) process:

$$D_{t+1} = D + \rho(D_t - D) + \mu_{t+1} \tag{1}$$

where D is the average dividend over a long period. ρ is a coefficient to indicate how fast the dividend value approaches the average value. μ is positive white noise, $\mu_t = N(0, \sigma_u^2)$. The setting of dividends is similar to that used in Lebaron et al. (1999). This process helps to avoid the dividend process getting too close to non-stationary dividend processes.

3.2.2 Wealth

The trader i‘s wealth at t, W_t is given by

$$W_t = RB_{i,t} + (P_{t+1} + D_{t+1} - RP_t)h_{i,t} \tag{2}$$

where B_t is bonds, P_t is the current stock price per share and $h_{i,t}$ indicates the shares of the stock held by trader i at time t.

The reservation price (P_i^R) at time period t is derived based on the expectation of each trader, which follows Yeh and Yang (2010).

$$P_i^R = \frac{E_{i,t}(P_{t+1} + D_{t+1}) - \lambda h_{i,t} V_{i,t}(R_{t+1})}{R} \tag{3}$$

where R_{t+1} is the excess return at time $t+1$, i.e. $P_{t+1} + D_{t+1} - RP_t$, and $V_{i,t}(R_{t+1})$ is the forecast of trader i regarding the conditional variance at time $t+1$ given his/her information up to t.

3.2.3 Traders

In this market, we consider three types of traders.

- *Informed traders (I)*: I traders can receive private and informative signals about the dividend and fundamental value of the risky asset. They are rational investors in the market (e.g., institutional investors). I traders generate expectations of future stock prices via updated trading strategies through a learning system (namely Genetic Programming (GP), which will be further discussed later)

- *Uninformed traders (U)*: U traders are also rational agents. Like I traders, they also update trading strategies through GP. However, they do not receive any private information and hence only update their expectations using public information, such as recent dividends and stock prices (e.g., liquidity providers or hedge funds).
- *Noise traders (N)*: N traders trade on a spurious signal that they believe is correct and informative, while the signal is purely noise. They do not have a learning system but have a biased belief about next period stock price as the previous period clearing price, given by a noise term (e.g., retail investors normally have a cognitive bias (Alldredge 2020)).

3.2.4 The learning system and traders' beliefs

The dissemination and the process of information play an important role in financial markets. Different information sets can give an investor significant advantages with the technological revolution (Afzali and Martikainen 2021).

Genetic Programming (GP) is defined as a technique by running computer programs that are encoded as a set of genes that evolved using an evolutionary algorithm. Langdon and Poli (2002) provided a detailed explanation of the technical issues of GP. The GP is inspired by the natural process and considered as a computational method aiming to find the optimal solution (Vovan et al. 2021). In our model, both informed and uninformed traders study the market and update their trading strategies via GP. The function set and terminal set are displayed in Table 1. Both informed traders and uninformed traders use dividends and stock price in the recent past five periods as a terminal set, but in addition to that, informed traders also have private information about dividends (fundamental value of the stock) in the current period. Traders have heterogeneous learning frequencies between 5 to 95 periods. Informed and uninformed traders form their believes about future stock price and dividends as following:

$$E_{i,t}(P_{t+1}+D_{t+1}) = \begin{cases} (P_t + D_t)\left[1 + \theta_0 \tanh\left(\frac{\ln(1+f_{i,t})}{\omega}\right)\right] & if \ f_{i,t} \geq 0 \\ (P_t + D_t)\left[1 - \theta_0 \tanh\left(\frac{\ln(|-1+f_{i,t}|)}{\omega}\right)\right] & if \ f_{i,t} < 0 \end{cases} \tag{4}$$

where $f_{i,t}$ is determined as a forecasting accuracy indicator. θ and ω are constants.

We employ a setting for noise traders similar as Banerjee and Green (2015). Noise traders form their believes without learning, but purely utilizing a biased belief about the previous period clearing prices:

$$E_{i,t}(P_{t+1}+D_{t+1}) = P_t + D_t + \varepsilon_{i,t} \tag{5}$$

where $\varepsilon_{i,t} = N(0, \sigma_\varepsilon^2)$ is biased belief of trader i.

3.2.5 Price determination

In general, according to the different market liquidity providers, the financial market is divided into the quote-driven market based on the market-maker mechanism (Back and Baruch 2004) and the order-driven market based on the continuous double auction mechanism, which is the mechanism used in this paper. The former is provided by market makers, while the latter is provided by limit orders under a continuous double auction trading mechanism. The early financial market was mainly based on the market maker mechanism, which made the main research on the existing market microstructure mostly focused on the framework based on the market maker mechanism, thus forming a three-way game market model composed of buyers, market makers and sellers. Nowadays, the rapid development of electronic information technology has made the continuous two-way auction mechanism more and more widely used in the modern financial market, and has become the basis of automatic matching trading system in almost all the order-driven markets, including the stock exchanges in Tokyo, Toronto, Sydney, Stockholm and China's Shanghai and Shenzhen (Domowitz and Steil 1999).

The price determination of this paper is realized by a simplified continuous double auction process. The process is similar to the framework of Yeh and Yang (2010). There are N rounds of the continuous double auction process in each period, which determine trading information.

The highest price for buying (the best bid B_b) and the lowest price for selling (the best ask B_a) are observable for traders. Traders make orders, i.e. accept a bid (an ask) or submit an order based on their own reservation prices of the risky asset. The process works as follows. Traders may come across four scenarios: (1) both B_b and B_a exist; (2) only B_a exists; (3) only B_b exists; and (4) neither bid nor ask exists. In the first scenario, the trader will either post a market buy (sell) order at $B_a(B_b)$ when $P_i^R > B_a(P_i^R < B_b)$; or post a limit buy (sell) order at his reservation price when $B_b \leq P_i^R \leq B_a$ and $P_i^R \geq (B_a + B_b)/2$ ($P_i^R < (B_a + B_b)/2$). In the second scenario, the trader will post a market buy order at B_a when $P_i^R > B_a$; or he will post a limit buy order at his reservation price when $P_i^R \leq B_a$. Under the third condition, the trader will post a market order and sell at B_b when $P_i^R < B_b$;or he will post a limit sell order at his reservation price when $P_i^R \geq B_b$. Under the fourth condition, the trader will post a limit buy or a limit sell order at his reservation price in equal chance. The traders are not simultaneous entering into the market at the beginning of the market. The order of traders entering into the continuous double auction process is random in each price determination period.

Margin trading and short selling have been implemented in many countries' financial stock markets in order to provide market liquidity. Therefore, we also attempt to employ margin trading and short selling in each experiment. Each trader has the opportunity to choose margin trading or short selling before each round of their trading.

3.3 Experimental designs

Table 1 lists important parameters used in the ASM. Totally 100 traders are in the ASM and each one has initial money of 2000 bonds and 1 stock. The return for bonds is a 0.04% interest rate in each period. The average dividend is 0.01. We collect a total of 20,000 periods for each simulation run. We tried to collect data for more than 20,000 periods and found that there is no significant difference among results.

In order to investigate the impact of noise traders on financial markets, keeping other variables fixed, we design 10 basic experiments (B0, B1, B2,…, B9) with 0%, 10%, 20%, …, 90% noise traders to start with in the market respectively. The experiments are listed in Table 2. The results presented for each experiment in Sect. 3 are the average of 10 simulation runs. To study the effect of market regulation on noise trading, we also run these 10 experiments under the following pairs of scenarios:

(1) without price limit versus with 10% price limit. Ten experiments of constant 10% price limit with different proportions of noise traders are presented by PL0, PL1, PL2,…, PL9 in Table 2;
(2) without transaction tax versus with 0.1% transaction tax. Ten experiments with 0%, 10%, 20%, …, 90% noise traders in the market with 0.1% transaction tax are presented by TT0,TT1,TT2,…,TT9;

Table 1 Settings of the simulated system

The artificial stock market	
Initial bonds	2000
The Initial number of stocks	1
Stock initial price	25
Interest rate (r)	0.0004
Dividend for each period	$0.01 + 0.95(D_t - 0.0.1) + N(0, 0.02)$
Number of periods	*The survivability of noise traders*
Number of traders	100
Number of strategies of each trader	2
Evolutionary cycle	2
θ_0	0.2
ω	15
λ	0.5
Function set	$\{ifelse, +, -, \times, \div, sqrt, sin, con, abs\}$
Terminal set of informed traders	$\{P_{t-1}, ..., P_{t-5}, D_t, D_{t-1}, ..., D_{t-5}, P_f\}$
Terminal set of uninformed traders	$\{P_{t-1}, ..., P_{t-5}, D_{t-1}, ..., D_{t-5}, P_{f-1}\}$
Probability of immigration	0.1
Probability of crossover	0.7
Probability of mutation	0.2

Based on the empirical properties presented in Table 3 and the first q–q plot in Fig. 1, the model specification of our simulation is calibrated to mimic these stylized facts in the real financial stock market. The important parameters in the system are then presented in this table. Each trader in the market has an initial wealth of 2000 cash and 1 stock. The return for cash is a 0.8% interest rate during each period. The initial stock price in the system is 25. The risky asset (stock), paying a stochastic dividend which is assumed to be an AR(1) process. 20,000 periods for each simulation run are collected. The second and third parts of Table 1 present important parameters in the learning process, which is GP

Table 2 Distribution of all experiments

The proportion of noise traders	0%	10%	20%	…	80%	90%
Name of experiments						
Basic	B0	B1	B2	…	B8	B9
10% Price limit	PL0	PL1	PL2	…	PL8	PL9
0.1% Transaction tax	TT0	TT1	TT2	…	TT8	TT9
T+1 settlement cycle	SC0	SC1	SC2	…	SC8	SC9

In order to investigate the impact of noise traders on financial markets, we design 10 basic experiments (B0, B1, B2,…B9) with 0%, 10%, 20%, …, 90% noise traders to start with in the market respectively. The experiments listed in the table are under the following pairs of scenarios: (1) without price limit vs. with 10% price limit; (2) without transaction tax versus with 0.1% transaction tax; (3) T + 0 versus T + 1 settlement cycles

(3) T + 0 versus T + 1 settlement cycles. Ten experiments of 0%, 10%, 20%, …, 90% noise traders in the market, which are named SC0, SC1, SC2,…, SC9, can test the effect of the T + 1 settlement cycle.

Table 3 Stylized facts of market returns

Series	Period	r_{min}	r_{max}	$\|r\|$	Skewness	Kurtosis
Panel A: Financial markets						
Nasdaq	1971-2022	−11.32	13.17	0.62	−0.07	8.87
S&P 500	1980-2022	−19.34	11.50	0.56	−0.84	19.09
FTSE 100	1984-2022	−11.22	9.84	0.86	−0.40	7.91
HSI	1986-2022	−23.33	8.82	1.99	−1.02	31.79
Nikkei	1984-2022	−16.50	20.15	1.62	−0.16	9.57

Series	r_{min}	r_{max}	$\|r\|$	Skewness	Kurtosis
Panel B: Artificial stock market (ASM)					
Minimum	−15.67	−0.18	0.01	−6.20	3.01
Media	−8.563	5.09	0.02	−0.14	11.94
Average	−4.06	6.49	0.347	−0.63	30.11
Maximum	0.016	29.49	2.11	0.91	232.85

Panel A summarizes basic statistical properties of the Nasdaq Composite Index (Nasdaq), the S&P 500 in the U.S., and FTSE 100 index in the U.K., Hang Seng Index (HSI) in Hong Kong, and Nikkei 225 in Japan. The first column of Table 3 presents the name of these indexes and the second column shows the time periods that the stock indices are considered for analysis. The next two columns describe the minimum returns and maximum logarithmic returns in percentage. Panel B shows the results of ASM

3.4 Model calibration and statistics of stock price

This section shows several statistical properties observed in financial markets and then presents how our model replicates these features. Table 3 Panel A summarizes basic statistical properties of the Nasdaq Composite Index (Nasdaq), the S&P 500 in the U.S., and FTSE 100 index in the U.K., Hang Seng Index (HSI) in Hong Kong, and Nikkei 225 in Japan. The first column of Table 3 presents the name of these indexes and the second column shows the time periods that the stock indices are considered for analysis. The next two columns describe the minimum and maximum logarithmic returns in percentage. It is clear that the largest absolute daily returns range from 9.84 to 33.33%. We simply use the average of absolute returns to measure the market volatility shown in the fifth column. It ranges from 0.76 to 1.09%. The skewness of raw returns, which presents in the sixth column, are all negative. The kurtosis of raw returns of all financial markets is larger than three, indicating fat tails. We present the results of ASM in panel B. It illustrates those statistic properties of stock prices in our ASM from 100 basic simulation runs (10 runs for each basic experiment). The stock price shows negative skewness and fat tail on average. Positive kurtosis could suggest the distribution of price returns are fat-tail across all timescales. It is therefore suggesting that large price movements occur in trading, which is very important in financial markets (McGroarty et al. 2019). Comparing with the empirical results summarized in Panel A, our model matches several financial markets within a reasonable range.

We further provide two quantile-quantile plots (q–q plot), which aim to test whether two sets of samples come from the same distribution. It provides a visual comparison of the sample to the theoretical distribution. The two q–q plots in Fig. 1 show the comparison of the return of S&P 500 to the standard normal distribution and the comparison of the return of our ASM to the standard normal distribution, respectively. In general, the points in the two

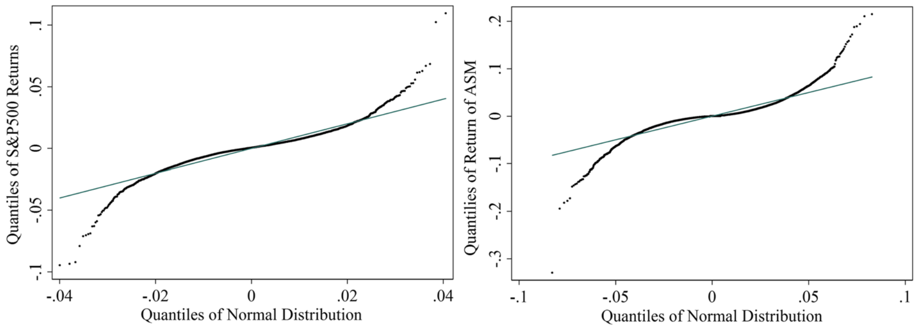


Fig. 1 Quantile–quantile plots(q–q plots) of financial market and ASM. *Notes*: The two q–q plots in Fig. 1 show the comparison of the return of S&P 500 to the standard normal distribution and the comparison of the return of our ASM to the standard normal distribution, respectively

plots fall approximately along the 45-degree reference line. It means that two sets of sample data in one q–q plot come from the same distributions.

Based on the stylized facts of daily data in the financial markets presented in Table 3 and the calibrated approaches displayed in Fig. 1, the ASM is calibrated to mimic those facts of financial markets. The ASM specifications with control parameters are then produced and displayed in Table 1.

4 Results

4.1 Survival of noise traders

We first run the experiment with 10% noise traders, 10% informed traders and 80% uninformed traders (experiment B1) to investigate how long noise traders can survive or transform to other kind of traders. Then we keep informed traders at 10%, but increase noise traders by 10% meanwhile reduce uninformed traders by 10% at a time (experiment B2) until there are 90% noise traders, 10% informed traders and 0% uninformed traders in the market (experiment B9). We allow margin trading or short selling. In order to investigate how long noise traders could survive or transform to other kind of traders, once a trader quits the market and there is no new noise traders entry, which is different from experiments below to test the impacts on the market. Within all these nine experiments, noise traders are the only type of traders that gradually disappear in the market during the first 20,000 periods. We record the last period before noise traders completely disappear or transform to other kind of traders in the market as the survival period for noise traders. We use the data starting from the first period until one type of trader is driven out from the market completely.

Figure 2 shows the survival period for noise traders in each experiment (B1,...,B9). It is generally suggested that noise traders cannot exist as noise traders in the long-term period no matter how many of them are in the financial market in the first place. They are driven out of the market or transform to other kind of traders at the end. In the 10% noise traders experiment, all noise traders lose their all wealth by around 9,000 periods. However, the period increases as the proportion of noise traders become larger. Noise traders can exist as noise traders for at least 11,000 periods (assuming 10 periods for each trading days, 11,000 periods are equivalent to (1100/252) 4.4 years) when the noise proportion is 50% or above.

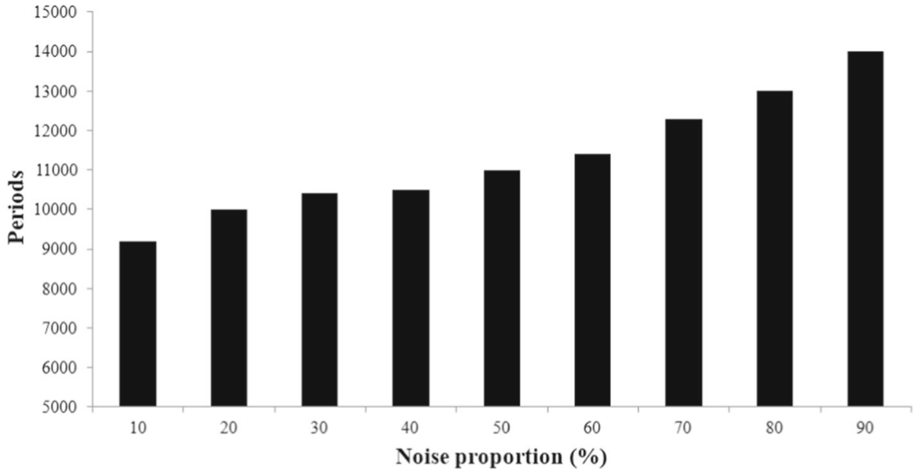


Fig. 2 Survival periods of noise trader. *Notes*: Fig. 2 shows the survival period for noise traders in each experiment (B1,...,B9)

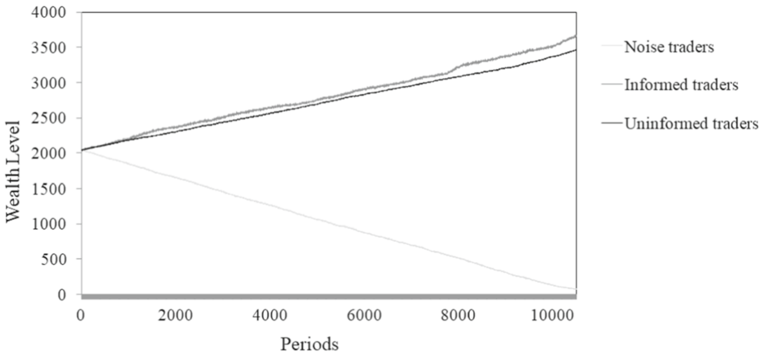


Fig. 3 Wealth levels of different types of traders. *Notes*: Fig. 3 indicates changes of wealth level overtime for three types of traders, averaging those experiments with initial 80% noise traders

Figure 3 indicates changes of wealth level overtime for three types of traders, averaging those experiments with initial 80% noise traders. Other experiments of different distributions of traders also provide similar pictures with Fig. 3. In general, noise traders tend to make a loss after entering the market and are finally being driven out of the market or transforming to other kind of traders because of inaccurate beliefs. This conclusion is consistent with the arguments of Friedman (1953), Blume and Easley (2006) and Sandroni (2000). As Bloomfield et al. (2009) concluded, in real stock markets, noise traders could be normally considered as retail investors who lack informational advantages and have inaccurate beliefs to make investment decisions. They usually act as unwise contrarians and consistently lose money in stock markets. However, they may transform from noise traders to fundamental or other kind of traders instead of disappearing. As William et al. (2006) argue that trades do not simply occur in order to generate profit, they may generate information, accelerate learning, create commitments and enhance social capital, all of which sustain traders' long term survival in the market.

4.2 The impacts on the market

Having concluded that noise traders could not survive in the long run, we proceed to gain more insight on how noise traders influence the market, as indicated by market volatility, price distortion, trade volume, price dynamics and other traders' profits. In this part's experiments, we assume that there is a new market participant once a trader quit the market, which is the different setting from the above experiment when investigating the survivability of noise traders.

4.2.1 Price dynamics, volatility, noise trader risk and distortion

The impact of noise traders on stock price dynamics is illustrated in Fig. 4. Figure 4 displays typical results of simulation runs in ten basic experiments (noise proportion rises from 0% to 90%) respectively. In the first experiment with 0% noise trader, price dynamics are relatively flat, moving just around the initial price of 25. The price ranges from 20.7 to 45.4 in the experiment with a 30% noise ratio. The price fluctuation becomes more significant when the noise ratio increases and arrived peak under a 90% noise ratio: from a minimum of 8.2 to a maximum of 63.5.

Skillful informed and uninformed traders update their trading strategies to reflect recent market information (or/and private information), but noise traders do not learn from the market and they use false information, so it is likely that informed and uninformed traders have similar expectations, but noise traders expect differently. Hence noise traders cause fluctuation in stock prices. We also examine the market volatility with heterogeneous beliefs in our artificial stock market. According to Westerhoff (2003), the market volatility (P_v) can be measured by

$$P_v = \frac{100}{N_{T-1}} \Sigma_{\mathrm{t=1}}^{N_T} \left| \frac{P_t - P_{t-1}}{P_{t-1}} \right| \tag{6}$$

where P_t is the price per share of the stock, P_{t-1} is the price of the last period and N_T is the number of periods.

The left panel of Fig. 5 presents the tracks of market volatility for all simulations under different noise trader proportions (from 0% to 90%), which helps us to visualize the influence. The solid and dashed lines represent the mean and standard deviation of the ten runs, respectively. It is obvious that market volatility increases on average when the proportion of noise trading is raised. The value is 0.03% when there are 0% noise traders and it reaches the highest point of 1.28% when there are 90% noise traders in the market. Moreover, the standard deviation of volatility also increases when there are more noise traders. This reveals that noise trading plays an important role in increased volatility. It is consistent with the results provided by Ramiah et al. (2015). They identify that noise traders can be seen as a major source of volatility. A noise trader makes the decision that buys or sells stocks based on incorrect beliefs. They have sentiment or feelings in trading without considering any fundamentals, making their investment decisions more bearish. It can explain that the market volatility goes up when there are more noise traders. Herve et al. (2019) used online search data and combined an original approach with a new measurement to find that noise traders provide an extra risk and increase volatility. Peress and Schmidt (2020) also supported that noise traders increase volatility by employing a new method of episoding of sensational news to distract noise traders.

According to the literature, "noise trader risk" is described as the risk risen by noise traders according to the literature, we aim to investigate the exact relationship between noise trader

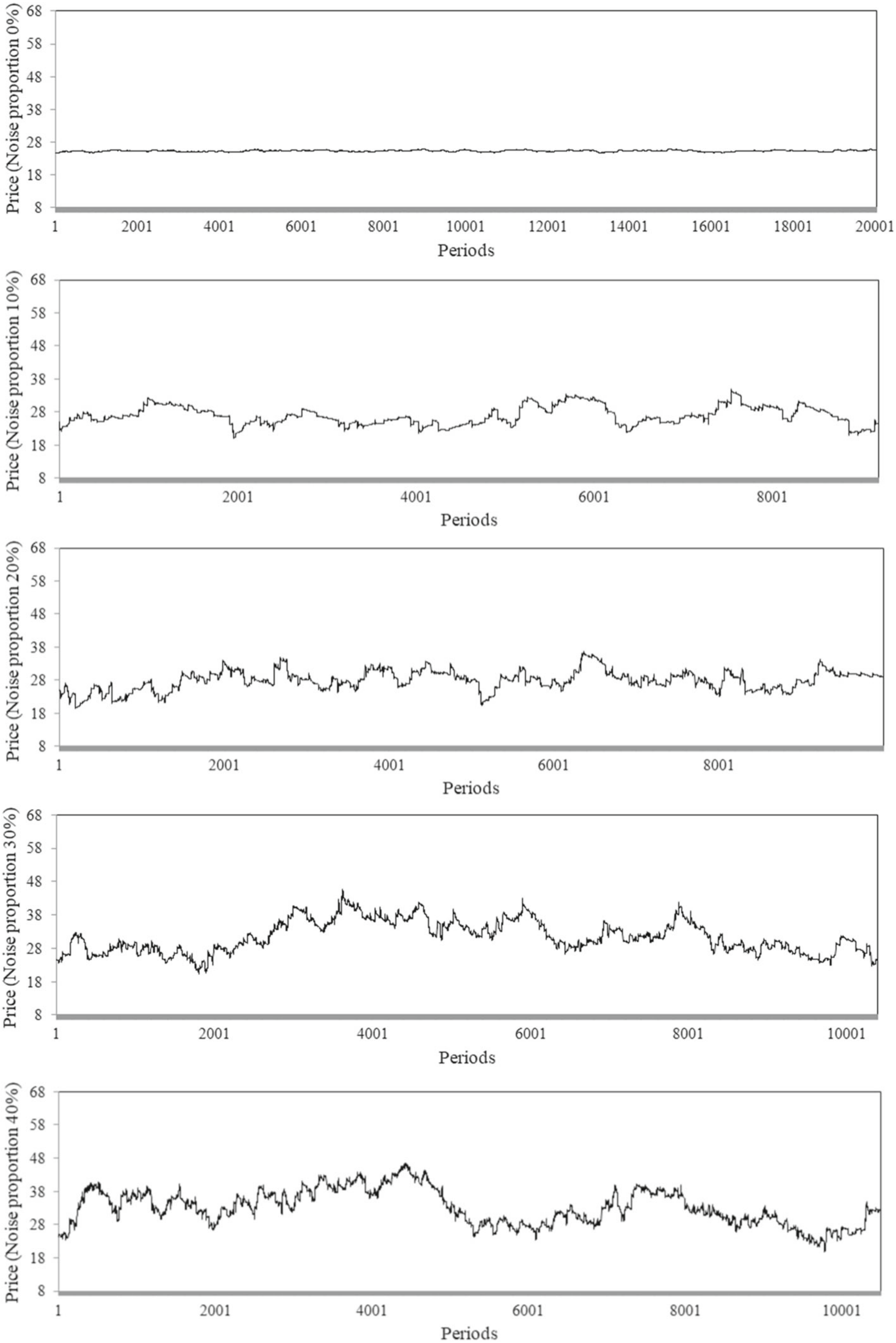


Fig. 4 Price dynamics of simulations based on different proportions of noise traders. *Notes*: Fig. 4 displays typical results of simulation runs in ten basic experiments (noise proportion rises from 0% to 90%) respectively

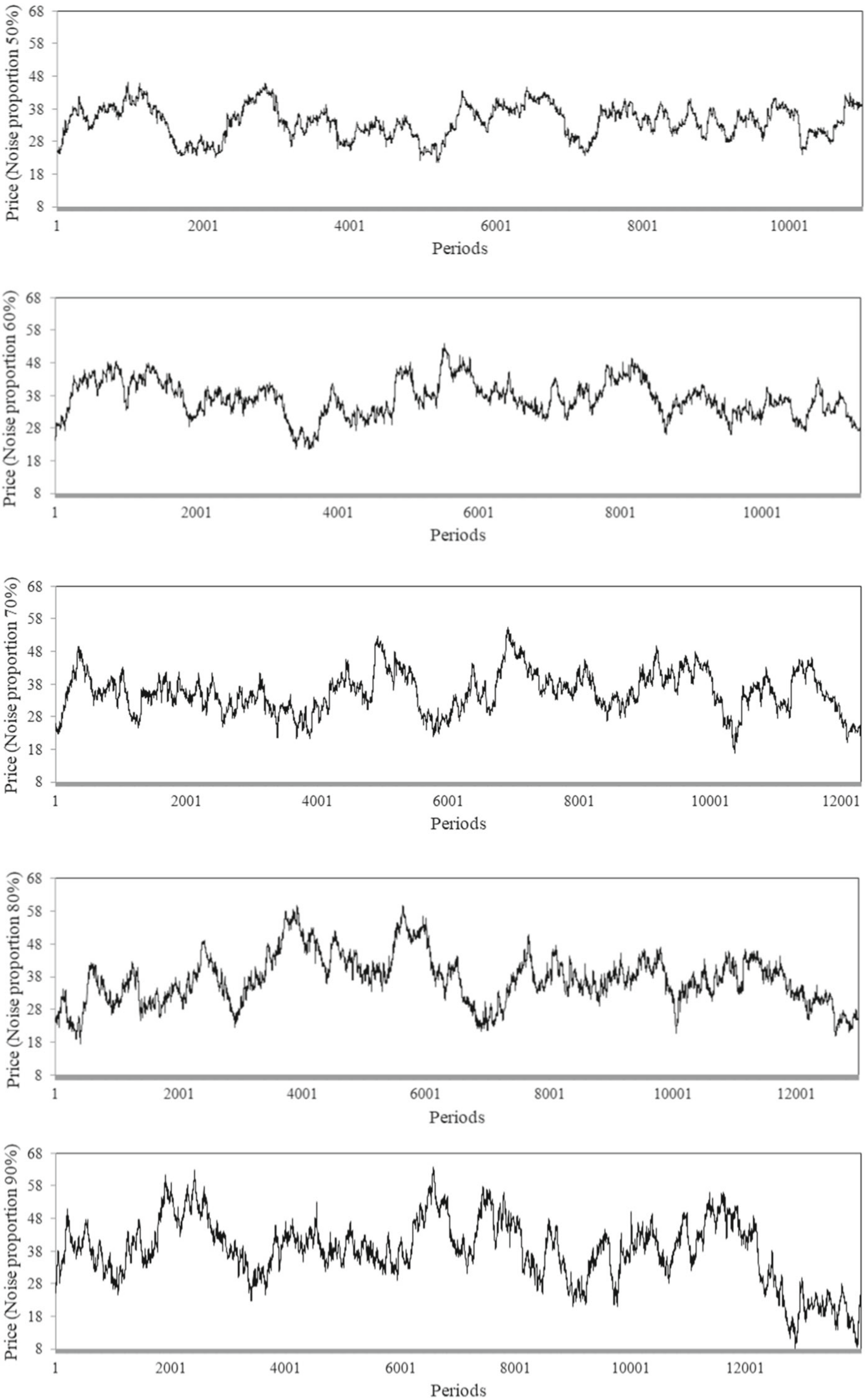


Fig. 4 continued

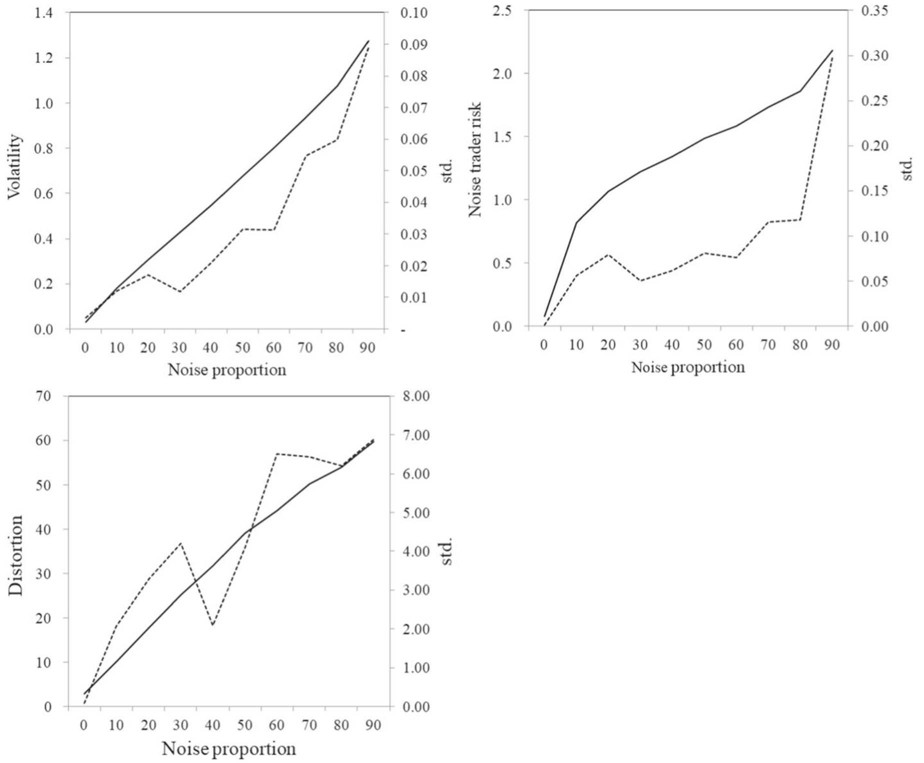


Fig. 5 Volatility, Noise trader risk and Distortion. *Notes*: The left panel of Fig. 5 presents the tracks of market volatility for all simulations under different noise trader proportions (from 0 to 90%). The second picture in Fig. 5 presents the relationship between noise trader risk and the proportion of noise traders. The last diagram in Figure 5 represents how noise traders affect price distortion. The solid and dashed lines represent the mean and standard deviation of the ten runs, respectively

risk and the proportion of noise traders (from 0 to 90%) in the market. Following the definition provided by Scruggs (2007), noise trader risk can be seen as the volatility, such as standard deviation, of return of one stock. We then examine the noise trader risk by considering the standard deviation of stock returns. The second picture in Fig. 5 presents the relationship between noise trader risk and the proportion of noise traders. It reveals that noise traders help increase the standard deviation of stock returns, which can be seen as an indicator of noise trader risk. In the market with 0% noise traders, the standard deviation is equal to 0.08% and it reaches almost 2.18% in the market with 90% noise traders. We provide evidence that the systematic risk as well as its standard deviation rise when the increasing number of noise traders in the market, which is consistent with the literature (Odean 1998; Brown 1999; Nguyen and Daigler 2005 and Herve et al. 2019). Choi and Choi (2018) and Park et al. (2019) also use empirical evidence to suggest that individual trading could be weighted as a proxy for noise trader risk because they believe that individuals have been regarded as noise traders for a long time.

The price distortion (P_D) is a straightforward way to measure the informational efficiency of a market. It considers how quickly and how well stock prices reflect true values. This measurement examines the degree of pricing error from the fundamental price, which is defined as following by Westerhoff (2003)

$$P_D = \frac{100}{N_T} \Sigma_{t=1}^{N_T} \left| \frac{P_t - P_f}{P_f} \right| \tag{7}$$

where P_f refers to the fundamental price according to $P_f = D_t/r_f$ (Gordon's dividend discount model). The last diagram in Fig. 5 represents how noise traders affect price distortion. Price distortion increases on average as noise traders become more. We find that the lowest value of price distortion is 2.91% in the market without any noise traders, while it reaches the highest point of 59.75% in the market with 90% noise traders. We conclude that the existence of noise traders reduces the informational efficiency of the market by examining the pricing error. They act the role that harms market efficiency and makes an effort to keep prices from adjusting to true values.

4.2.2 Trading volume

As an important subject of measuring market liquidity, trading volume can also be examined to investigate whether or not noise trading benefits market liquidity. Liu et al. (2021) believe that market liquidity is significantly affected by rational and irrational trading behavior factors. The upper left part of Fig. 6 illustrates the relationship between trading volume and the proportion of noise traders (from 0 to 90%) on average of all simulations, as well as the standard deviation of the ten runs. In general, trading volume increases from 38.03 to 55.50 as the proportion of noise traders from 0 to 90%. This reveals that noise traders help provide liquidity and are beneficial to the market. Peress and Schmidt (2020) also supported that noise traders increase liquidity by employing a new method of exploiting episodes of sensational news to distract noise traders. However, the speed of increasing trend is different from the different degrees of noise trading introduced by noise traders. Interestingly, trading volume increases fast when there is not much noise trading according to the convex line. The average number of trading volumes becomes somewhat stationary, around 55.50, when the noise proportion is between 60 and 90%. The decreasing standard deviation of trading volume when there are more noise traders also provides a similar conclusion. It may indicate that noise trading has little influence on market liquidity when noise trading occupies more than 60% of the market. It might be because that noise traders trade randomly and do not consider any information. The trading volume would not have significant change when the majority of traders are noise traders in the market because information would not change their investment decision.

The bottom left part of Fig. 6 shows the average trading volume given rise by each noise trader in the market. Each trader has a different trading amount in different experiments. It is generally an increasing line which indicates that the trading volume of each noise trader rises as their group becomes larger. Noise traders will trade more when there is a larger number of their group. It is because noise traders make investment decisions without considering new information or change of market structure and they trade just based on biased beliefs. More different orders are then presented in the market. Therefore, it is easier for them to make transactions when there are more noise traders in the market. The right panel of Fig. 6 presents the trading volume change provided by each of uninformed and informed traders on average, respectively. Obviously, each trader trades more as the proportion of noise traders increases, although the lines of these diagrams are not exactly the same. This result also helps to indicate that the trading activity in the market is significantly affected by noise traders.

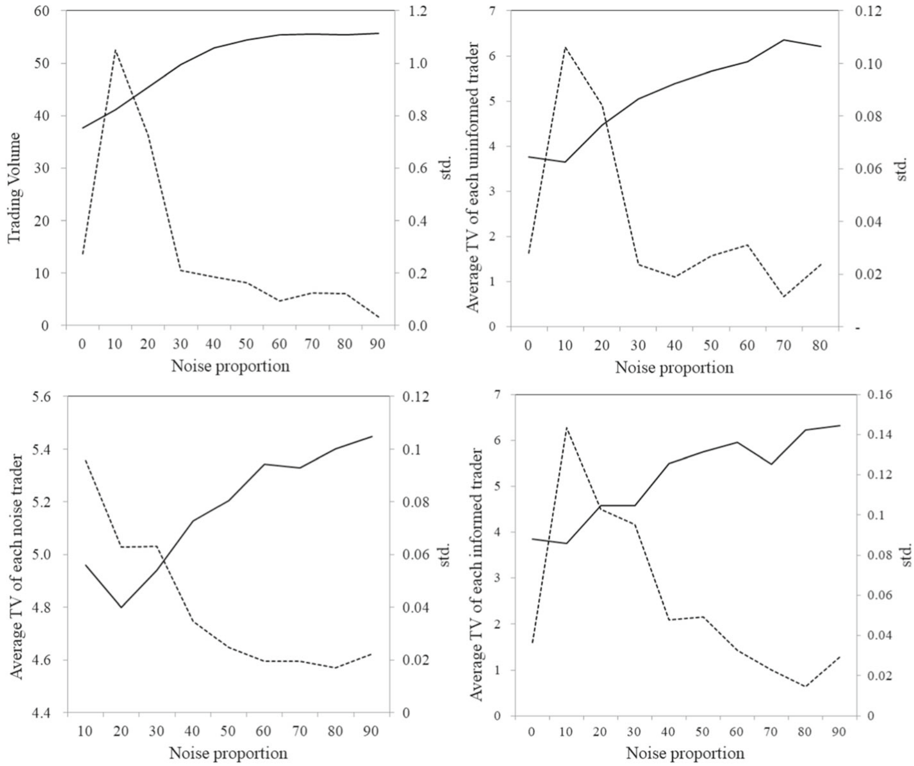


Fig. 6 Trading volume. *Notes*: The upper left part of Fig. 6 illustrates the relationship between trading volume and the proportion of noise trading on average of all simulations. The upper right part presents the change of average trading volume of each uninformed trader according to the increasing proportion of noise traders. The following two parts show each noise and informed trader's trading volume on average respectively as the increasing proportion of noise traders. The solid and dashed lines represent the mean and standard deviation of the ten runs, respectively

4.2.3 Profit analysis

The wealth effect arising from the noise traders is also an important subject that market regulators may consider. We examine the net profit on average of different kinds of traders at the last period. As we expected, noise traders who trade with no rational reason lose all their money to informed and uninformed traders. Figure 7 presents the average net profit (increased wealth / initial wealth) of informed and uninformed traders on average. The solid and dashed lines represent the net profit of informed and uninformed traders, respectively. It is clear that both these two kinds of traders earn profit, and informed traders do better. They earn more on average when the proportion of noise traders increases. Informed traders have the highest net profit of 116% when 90% of noise traders are in the market. Uninformed traders have a similar pattern with them; they reach the highest net profit of 99% when the proportion of noise traders is 80%. When noise trader proportion increases, less uninformed traders are in the market. The diagram indicates that informed traders could increase profit and it reveals that it is easier for informed traders to make profit than uninformed traders.

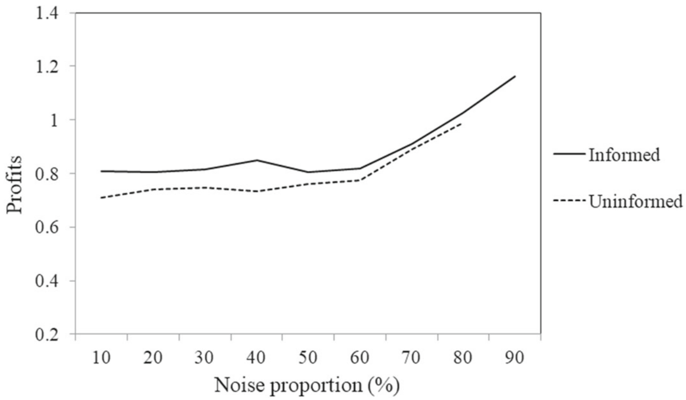


Fig. 7 Profits of informed and uninformed traders. *Notes*: Fig. 7 presents the average net profit (increased wealth/initial wealth) of informed and uninformed traders on average. The solid and dashed lines represent the net profit of informed and uninformed traders, respectively

Uninformed traders also raise their profit shows that they also benefit from trading with noise traders.

4.3 Regulatory intervention

Our results suggest that noise traders increase market volatility, price distortion and trade volume. They also help increase informed and uninformed traders' profits by losing all their wealth in the long run. We further investigate whether noise trader's activity or their influences on the market will be affected by imposing several regulations: including price limit, transaction tax and different security settlement cycles.

4.3.1 Price limit

10% price limit is imposed in the market. Figure 8 summarizes how the price limit influences noise traders' activity. The left diagram shows the different survivability of noise traders based on the simulated markets with or without considering the 10% price limit. Their survival periods shorten on average by imposing the price limit. For instance, noise traders lose all their wealth after 14,000 periods when 90% of noise traders are in the market. However, they shorten the period to 10,000 in the market with the price limit. The right panel of Fig. 8 shows the average number of price limit hits resulted from all traders' expectations for each period. We find that the number of limit hits significantly increases as the noise traders become more. For example, the average number of price limit hits is 0.15 when there are 10% noise traders, 10% informed traders, and 80% uninformed traders, while it is 2.91 when there is 90% noise traders and 10% informed traders. It suggests that noise trader's expectation, which is based on incorrect beliefs, is significantly limited by the 10% price limit imposition. The shorten survival periods may be because that their bid-ask range would be narrower and other traders then have more opportunities to make the deal in the market. Hence, noise traders lose all their wealth and are driven out of the market faster.

Figure 9 shows the effect of the 10% price limit on the noise trader risk, volatility, price distortion and trade volume. The solid and lines with the symbol ⧫ represent the results

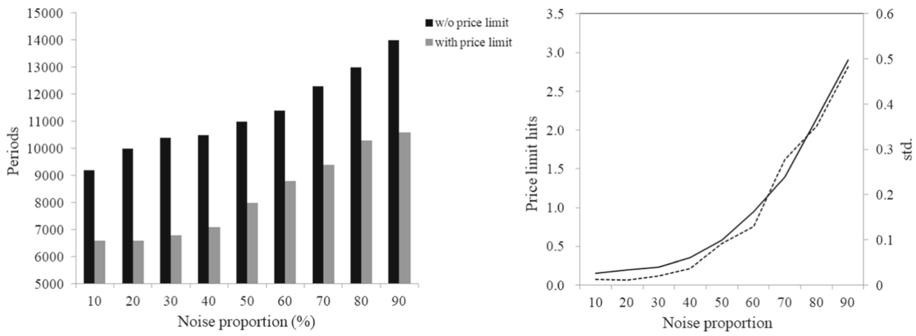


Fig. 8 Survival periods with or without considering price limit / Proportion of price limit hits of all traders' expectation for each period. *Notes*: Fig. 8 summarizes how the price limit influences noise traders' activity. The left diagram shows the different survivability of noise traders based on the simulated markets with or without considering the 10% price limit. The right panel of Fig. 8 shows the average number of price limit hits resulted from all traders' expectations for each period

without and with considering price limit, respectively. The dashed line shows the standard deviation of ten runs considering the 10% price limit. From the figure, we can find that imposition of price limit helps reduce noise trader risk and market volatility no matter the composition of traders. With 90% noise traders, noise trader risk reduces from 2.18 to 1.54% once we consider the price limit. At the same time, volatility reduced from 1.28 to 1.01%. The conclusion is consistent with the price limit hits provided in Fig. 8—the narrower of noise trader's bid range results in the shortening of price fluctuations. Hence, the market volatility is then reduced by imposing the price limit. It is consistent with one of the aims of imposing a price limit, repressing excessive speculation. Based on the same explanation, noise trader risk is also reduced because noise trader's bid range is limited by imposing price limits. Yeh and Yang (2010) investigate the influence of different levels of price limits on the market and they also find that price limit reduces market volatility.

The third diagram in Fig. 9 indicates that how the price limit affects the price distortion. Interestingly, we find that the 10% price limit increases price distortion. In other words, price limit diminishes the ability of market prices to adjust to fundamental value. This may be because not only noise traders, but also informed or uninformed traders' expectations are limited by the imposition of price limits. Imposing price limits may result in fundamental prices falling outside the price limit range.

The fourth diagram in Fig. 9 illustrates the change of trading volume with or without the 10% price limit. The influence of price limits on trading volume is not stationary, not like that on volatility and price distortion. The trading volumes are quite low when the noise trader's proportion is less than 30% in the market with a price limit, especially when there are only 10% noise traders and 90% informed and uninformed traders. The reason may be that informed and uninformed traders have similar expectations of the next period's stock price after considering market information; the difference of their forecasting values becomes smaller once we impose price limits into the market. In other words, price limit helps raise homogeneous beliefs among these traders, reducing the trading volume. Informed or uninformed traders may improve their profits by not trading at all. However, noise traders trade based on incorrect beliefs and lose their wealth on average. Not surprisingly, trading volume increases as there are more noise traders. The reducing of noise traders' bid range with price limits, which indicates by price limit hits in Fig. 9, makes trades easier for all participants and then the trading volume increases. It also explains that noise traders lose

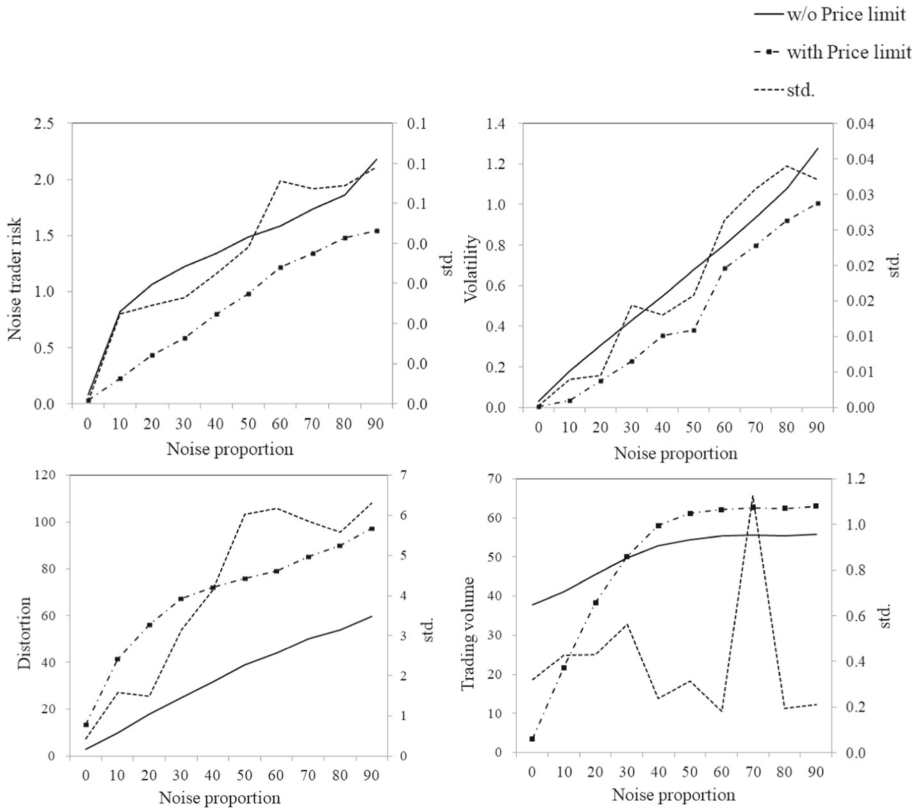


Fig. 9 Noise trader risk, volatility, price distortion and trading volume with or without imposing price limit. *Notes*: Fig. 9 shows the effect of the 10% price limit on the noise trader risk, volatility, price distortion and trade volume. The solid and lines with the symbol ⧫ represent the results without and with considering price limit, respectively. The dashed line shows the standard deviation of ten runs considering the 10% price limit

money more quickly with more transactions when we impose a 10% price limit in the market. Hence, whether or not price limit diminishes trade volume depends on different structures of market traders.

4.3.2 Transaction tax

Figure 10 shows the influence of transaction tax on markets. We introduce 0.1% of the trading value as the amount of transaction tax. The solid and lines with the symbol ⧫ represent the results without and with considering the transaction tax, respectively. The dashed line shows the standard deviation of the ten runs with considering transaction tax. We cannot clearly find a monotonic relationship between noise trader risk and the degree of noise proportion in the market. In this part, it is inappropriate to draw a conclusion that how the imposition of 0.1% transaction tax influences the market according to the figure. The second picture also shows that market volatility is not clearly and significantly influenced by imposing the transaction tax. The third part of Figure 10 shows the change of price distortion by considering tax. The relationship between transaction tax and price distortion is monotonic from this picture. The imposition of 0.1% transaction tax slightly results in higher price distortion. The conclusion

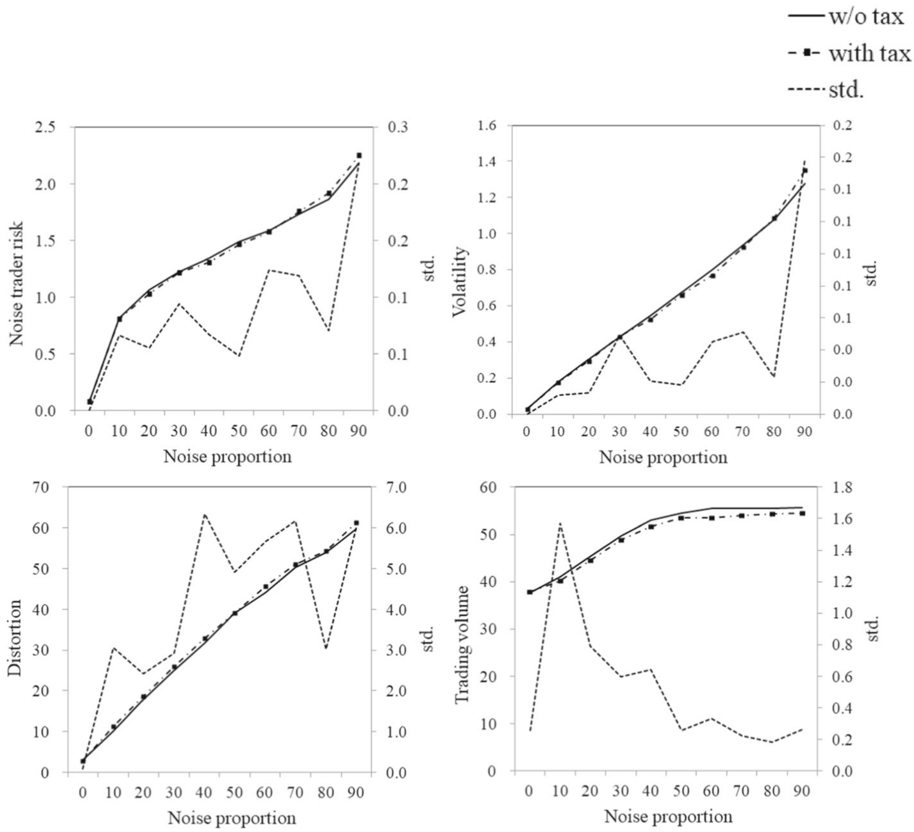


Fig. 10 Noise trader risk, volatility, price distortion and trading volume with or without imposing a transaction tax. *Notes*: Fig. 10 shows the influence of transaction tax on the noise trader risk, volatility, price distortion and trade volume of the market. The solid and lines with the symbol ⧫ represent the results without and with considering the transaction tax, respectively. The dashed line shows the standard deviation of the ten runs with considering transaction tax

is consistent with Lensberg et al. (2015), which indicated that price efficiency is lower when imposition the transaction tax into the market. The reason may be that imposing a transaction tax will encourage traders to reconsider and re-balancing their portfolios in response to new information when the transaction tax causes the trade unprofitable. Therefore, transaction tax may influence the trader's response to information and then price efficiency.

As expected, the trading volume is influenced by the presence of transaction tax, according to the third part of Fig. 10. The imposition of transaction tax reduces trading volume for most of the simulation runs. In the market with 10% noise traders, volume is not influenced by imposing transaction tax, while it is about 1.14 times greater with 90% of noise traders. It reveals that transaction tax has more restrictive effects on those markets with more noise beliefs. As noise traders trade less, they may lose their money to other traders more slowly. However, there is a tax they still need to pay. Figure 11 presents the surviving periods of noise traders with or without considering transaction tax, respectively. We find that noise traders are driven out of the market more quickly when we consider the tax in the market. The reason might be that noise traders trade randomly and do not based on any information

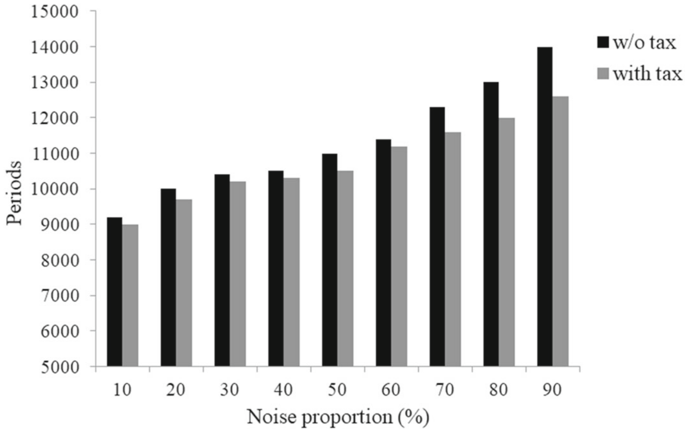


Fig. 11 Survival periods of noise traders with or without imposing a transaction tax. *Notes*: Fig. 11 presents the surviving periods of noise traders with or without considering transaction tax, respectively

advantages. It is different with informed traders that only trade on information. Therefore, informed traders would rather choose not to have the transaction after they carefully consider the net profits with transaction taxes, while noise traders might not. Noise traders would just buy or sell and pay more transaction taxes without any consideration. In this care, they might lose their money more quickly.

4.3.3 Settlement cycles

The settlement cycle is defined as a process that securities completes trading for certain securities or bonds. The cycle can be introduced as the timeline, described as the number of business days after one trade occurs. The cycle is normally described as T + 0, T + 1, T+2 or T+3, and we introduce T + 0 and T + 1 in this paper, the two most popular settings.

In Fig. 12, the solid and lines with the symbol ♦ represent the results by applying T + 0 and T + 1, respectively. The dashed line shows the standard deviation of the 10 simulation runs when considering the T + 1 cycle. We find that widening the settlement cycle from T + 0 to T + 1 helps decrease the noise trader risk and market volatility, especially when there are more noise traders. Interestingly, widening from T + 0 to T + 1 insignificantly affects noise trader risk and market volatility when there is no noise trader (10% of informed traders and 90% of uninformed traders). The reason may be that the widening of settlement cycle restricts the speculation of traders by limiting the process of completing their settlement trades. It indicates that traders cannot complete the trades and make money in a short period to make big price fluctuation by lower trading frequency.

Price distortion, provided in the third part of Fig. 12, increases by widening the settlement cycle from T + 0 to T + 1. The value of price distortion is 59.75% and 74.61% in the market, with 90% of noise traders in the markets of T + 0 and T + 1, respectively. The result is consistent with the SEC Press Release on March 22, 2017 (SEC 2017): shortening the standard settlement cycle will enhance transactional efficiency in securities markets. It reveals that the length of the settlement process will diminish more ability of market prices to adjust to new information or generally informational efficiency. Thus, regulators should consider shortening the settlement cycle to achieve this policy goal.

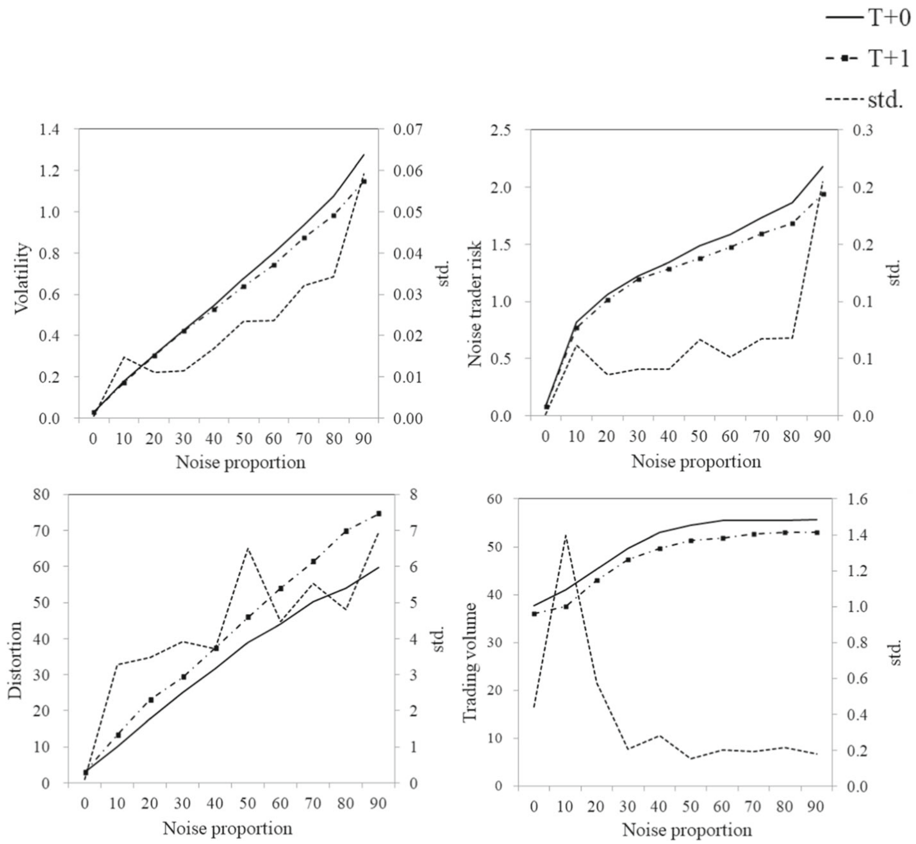


Fig. 12 Noise trader risk, volatility, price distortion and trading volume with different settlement cycles (T + 0/T + 1). *Notes*: Fig. 12 shows the influence of different settlement cycle on the noise trader risk, volatility, price distortion and trade volume of the market.The solid and lines with the symbol ⧫ represent the results by applying T + 0 and T + 1, respectively. The dashed line shows the standard deviation of the 10 simulation runs when considering the T + 1 cycle

The fourth part of Fig. 12 presents that how the settlement cycle affects the trading volume. It can be found that shortening the settlement cycle increase the market trading volume no matter how many noise traders are in the market. It is likely because that shortening the settlement cycle limits the trading frequency of rational traders to finish the deal.

Figure 13 presents the survivability of noise traders by imposing T + 0 or T + 1. It is clear that widening the settlement cycle from T + 0 to T + 1 helps noise traders survive in longer periods. In other words, noise traders are driven out of the market more quickly when we employ T + 0. This finding is consistent with the conclusion draws from Fig. 12. There is higher volatility and liquidity by using T + 0, and T + 0 also increases the ability of market prices to adjust to new information. It helps informed and uninformed traders finish their trading in a shorter period. Following that, it could help increase the efficiency and ability to make profits of informed and uninformed traders. Therefore, noise traders may take shorter periods to lose all their money to others.

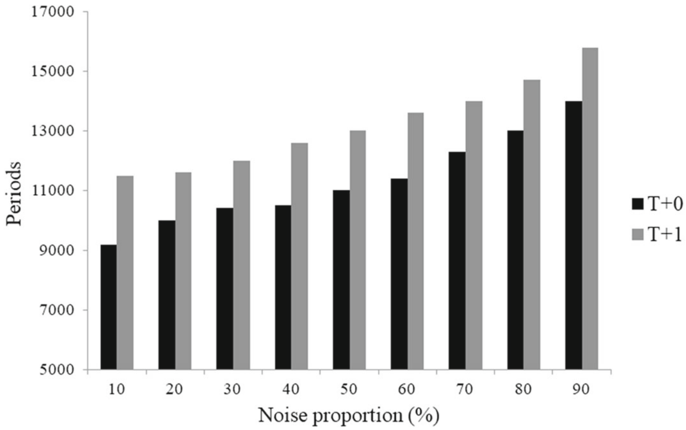


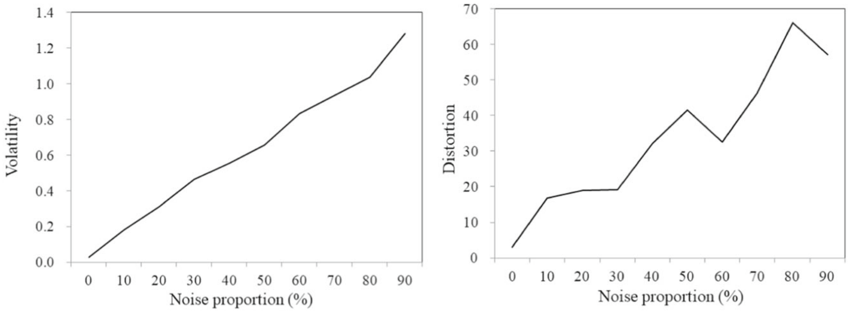
Fig. 13 Survival periods with different settlement cycles (T+0 / T+1). *Notes*: Fig. 13 presents the survivability of noise traders by imposing T + 0 or T + 1

4.4 Sensitivity analysis

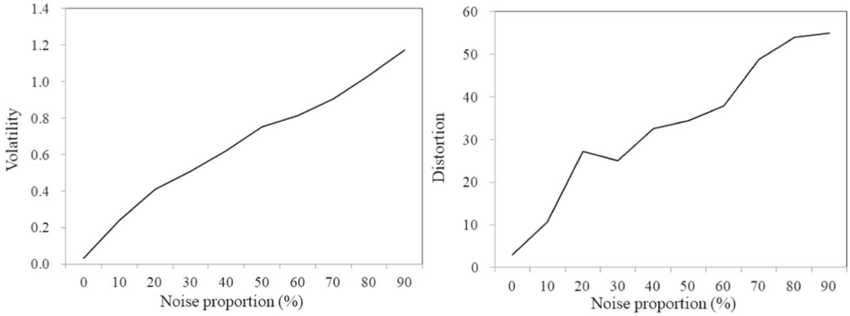
We perform the sensitivity analysis to investigate how the findings are sensitive to the parameters of the simulated model. We perform the analysis by considering different parameters, such as the initial wealth of each trader and the learning behavior of informed and uninformed traders, the probability combination of mutation and crossover in the GP. Figure 14 presents the results by considering different parameters. We test whether the results of volatility and price distortion are influenced by the change of those chosen parameters in the model. The first two pictures summarize the volatility and distortion under different wealth levels: $M_0 = 1000$ and $M_0 = 3000$, in which M_0 is the initial wealth of each trader. The following two panels display the outcomes under different probability combinations of mutation and crossover: m = 0.3; c = 0.6 and m = 0.4; c = 0.5. We find that the results do not have significantly differ from those observed in the calibrated model, indicating that noise traders increase volatility and price distortion.

5 Conclusion

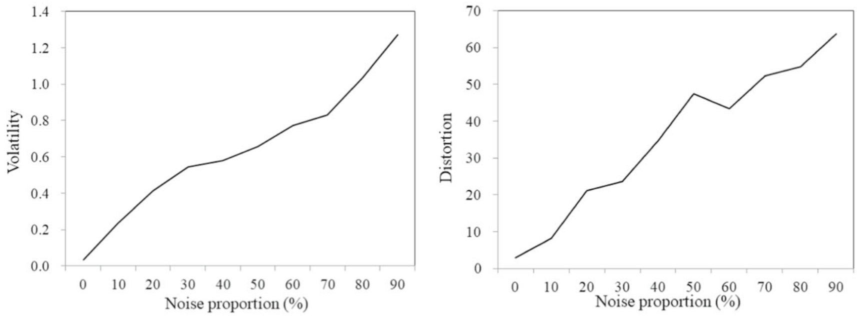
This paper constructs an agent-based limit order ASM based on the framework presented in Yeh and Yang (2010). Three types of traders are introduced in the market: informed, uninformed and noise traders. Informed and uninformed traders' trading strategies are generated and updated via GP, while noise traders have biased beliefs about the fundamental value of the asset. This paper aims to use computational method to investigate whether or not noise traders survive in the long term. We find that noise traders are eventually driven out of the market no matter how many they are in the market. We construct 10 simulated financial markets with different proportions of noise traders, from 0 to 90%, with a step size of 10%. They all provide evidence that informed and uninformed traders make money from them and noise traders lose all their money or transform to other kind of traders in the end in all simulated models. Nevertheless, the survival period becomes longer as their group is larger in the market. They can survive in the longest period when there are 90% of noise traders in the market.This is identical to real world trading environment. Since the stock market is



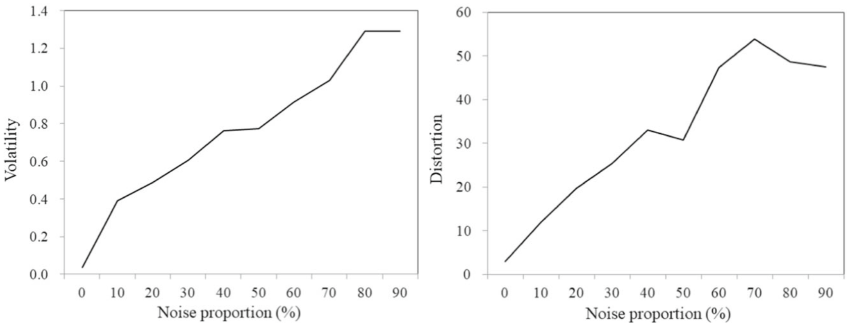
Volatility and distortion under $M_0 = 1000$.



Volatility and distortion under $M_0 = 3000$.



Volatility and distortion under $m = 0.3;\ c = 0.6$.



Volatility and distortion under $m = 0.4;\ c = 0.5$.

Fig. 14 Volatility and distortion in the sensitivity analysis. *Notes*: Fig. 14 presents the results by considering different parameters zero-sum game, informed traders may gain all the profits eventually as the result of information advantages. Furthermore, higher percentage of informed traders should be able to gain more profits from the noise traders within the same period. This could increase the speed that noise traders losing all their money. For example, developed markets like US markets are dominated by institutional investors, which refers to the informed traders in our simulation system since retail investors which refers to noise traders has been driven out of the market in the process of market self development. In emerging markets, like China, the majority market participants are retail investors.

This paper also examines how noise traders influence the financial market, including risk and volatility dynamics, price distortion and liquidity. It is found that noise traders help increase noise trader risk, volatility, trading volume in the market. However, they diminish the market ability of stock prices to adjust to new information. Furthermore, we also make an analysis of imposing price limit, transaction tax and different settlement cycles from $\mathrm{T}+0$ to $\mathrm{T}+1$. We find that noise traders are driven out of the market or transform to other kind of traders by imposing price limit and transaction tax in the market. The reason might be that noise traders' bid-ask range would be narrower and other traders then have more opportunities to make the deal in the market with price limit. Hence, noise traders lose all their wealth faster. Noise traders trade randomly and do not based on any information. It is different with informed traders that only trade on information. Therefore, informed traders would rather choose not to have the transaction after they carefully consider the net profits with transaction taxes, while noise traders might not. Noise traders would just buy or sell and pay more transaction taxes without any consideration. In this care, they might lose their money more quickly in the market with transaction tax. Nevertheless, widening the settlement cycle from $\mathrm{T}+0$ to $\mathrm{T}+1$ helps noise traders survive in longer periods. This might be that $\mathrm{T}+0$ helps informed and uninformed traders finish their trading in a shorter period. Following that, it could help increase the efficiency and ability to make profits of informed and uninformed traders. Therefore, noise traders may take shorter periods to lose all their money to others.

We also find that a 10% price limit contributes to limit noise trading as it helps reduce noise trader risk and volatility. Informed and uninformed traders have more opportunities to make money from a shorter range and then noise traders cannot survive extended periods with a 10% price limit, which further diminishes the ability of stock prices to adjust to new information. This means a 10% price limit influences noise trading, as well as informed and uninformed trading. The imposition of transaction tax slightly increases the price distortion while decreasing the trading volume. Noise traders are driven out of the market more quickly when we consider tax in the market. When we widen the settlement cycle from $\mathrm{T}+0$ to $\mathrm{T}+1$, we find that noise trader risk, volatility and trading volume significantly reduced. At the same time, $\mathrm{T}+1$ also diminishes the ability of informed and uninformed traders to finish their trading in a short period. In this way, it reduces the market efficiency. It eventually helps noise traders by losing money slowly to informed and uninformed traders. We find that noise traders can survive longer periods when the settlement cycle is $\mathrm{T}+1$. In sum, these three regulations do not have consistent effects on limiting noise trading and the financial market. Also, the effects of different regulations on noise traders or the financial stock market are significant distinguishing. For example, price limit, transaction tax and $\mathrm{T}+0$ settlement cycle might be imposed into stock market if regulators aim to lower the proportion of noise traders. However, regulator may not consider imposing price limit when they aim to improve market efficiency. Therefore, regulators should make appropriate regulations deliberately to achieve specific or different policy goals.

Due to the limitation of computations experiments, the settings of our ASM is more simple than real financial stock market. Therefore, future work might be the robustness test that check some aspects using data-sets from the real market, not just the generated ASM model array.

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Appendix

Genetic Programming (GP) is a technique by running computer programs that are encoded as a set of genes that evolved using an evolutionary algorithm. As an important part of artificial intelligence, GP is determined by the parse tree structure, which contains functions and terminals. Generally, the terminal set is composed of those dependent variables, such as stock prices or dividends. The elements of the function set can be explained as functions used to combine the terminals with building up the functions. For example,

$$A = 6B(C + 5) \tag{8}$$

The GP tree structure is described as follows:

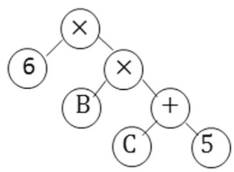

Fig. 15 GP tree strcuture. *Notes*: Fig. 15 is the description of the GP tree structure

The first function model is generated randomly according to the pre-specified terminal and function set. The performance of each function model is evaluated by the resulting fitness. GP generates new function models in three ways: immigration, crossover and mutation. They help form new functions in the following generation. Immigration is the process that gives an existed function, and thus immigration shows no innovation in creating forecasting models. The crossover procedure randomly selects one point from each of two GP trees, which are named parents here. Then exchange the whole parts below that point of the parents to generate a new function model. The procedure shows that combining two kinds of knowledge into one idea. The mutation is used to randomly change a part of the sub-tree of the original function tree. It can be regarded as an innovation relying on current knowledge.

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