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Leveraging asymmetric price limits for financial stability in industrial applications: An agent-based model

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ABSTRACT

How to upgrade business processes to improve production efficiency is an ongoing concern in industrial research. While previous studies have extensively examined various prioritization schemes at each stage of the business process, there has been a lack of investigation into the financial resources required for their implementation. The attainment of sufficient and stable financial support necessitates stability in stock prices, making the control of significant volatility in stock markets a critical issue. This study examines the effectiveness of three design schemes of price limit policy, a prevalent policy that intends to control significant volatility in financial markets and stabilize the market. Utilizing a heterogeneous agent-based model that simulates trading agents' processes of updating strategies through genetic programming algorithms and incorporates specialized designs for price limit policies, this study demonstrates that an asymmetric limit policy—consisting solely of a lower price limit (without an upper price limit)—can significantly enhance market quality by achieving lower volatility, higher market liquidity and better price effectiveness. Furthermore, we investigate the applicable conditions of asymmetric price limits. The findings suggest that an extremely restrictive limit range could lead to volatility spillover, while a 10 % range is deemed appropriate for achieving better efficiency. Additionally, the asymmetric price limit mechanism has the potential to significantly reduce market volatility by up to 12.5 % in volatile, low liquidity, and low price efficiency markets, which aligns with the declining range from bubble-crash periods to stable periods in the Chinese stock market. These results are further supported by sensitivity analysis.

1. Introduction

The optimization of business processes is a perennial concern in industrial research. Numerous studies have investigated this issue across various segments, such as design, manufacturing, production planning, and supply chain management (e.g. Ta et al., 2023; Zhang et al., 2023; Latoufis et al., 2024). These studies have proposed corresponding countermeasures and suggestions that greatly facilitate theoretical and practical development in this area. However, the enhancement of business processes requires substantial financial support for hardware and software upgrades as well as management promotion. Without strong financial backing, there is a risk of capital chain rupture, insufficient investment in process optimization, and even corporate bankruptcy (Wruck, 1990). In other words, without sufficient and stable financial support, the optimization of business processes remains unattainable even with specific solutions in place. Financial support serves as an essential underpinning for implementing process improvement schemes in the industry. The financial issue has been habitually overlooked in previous related research outputs despite its importance. Therefore, it is necessary to explore reliable ways to ensure sufficient finance in industrial companies.

Prior research has established that the performance of corporate stock, encompassing its return and volatility, can have a significant impact on the level of financing difficulty (Ahmed and Hla, 2019). Specifically, a decline in stock value and excessive volatility may undermine investor confidence, thereby leading to an increase in companies' financing costs. Consequently, to ensure stable cash flow and secure adequate financial backing for business process upgrades, appropriate measures should be implemented to mitigate abnormal fluctuations in the stock market.

Price limits are common policies that intend to control significant volatility in stock markets (Danışoğlu and Güner, 2018; Wong et al.,

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2020). Daily price limits specify the upper and lower limits that stock prices are allowed to trade within a single day. After the 2008 Global Financial Crisis, 23 of the 43 largest stock exchanges in the world adopted the price limit policy on individual stock prices to moderate the stock market volatility (Kim and Park, 2010). Until now, markets with no limiting mechanisms are becoming increasingly rare (Sifat and Mohamad, 2020). Despite its gradual prevalence in the market, research by financial economists has debated the role of price limit policies, with evidence being inconclusive. One stream of research reports a deterioration in stock market quality when price limit policies lead to volatility spillover, delayed price discovery and trading interference (e.g. Chan et al., 2005; Chang and Hsieh, 2008; Fama, 1989; Kim and Rhee, 1997; Kim and Limpaphayom, 2000; Lehmann, 1989). In contrast, an alternative stream of research indicates that price limit mechanisms can achieve their intended objectives (e.g. Huang, 1998; Huang et al., 2001; Kim et al., 2013; Ma et al., 1989a, 1989b).

To call for a more comprehensive understanding of inconsistencies in findings within and across different studies, some scholars investigate the effectiveness of price limit mechanisms under different scenarios. Among them, the difference between upper and lower limits has attracted a great deal of attention (Kim et al., 2013; Li et al., 2014). Existing empirical studies and experimental studies have shown that the effectiveness of upper and lower limits may differ. The upper limit would engender abnormal trading activities, higher volatility and delayed price discovery, while the lower limit would mitigate abnormal trading activity and constrain abnormal volatility without delaying price discovery (Kim et al., 2013; Li et al., 2014; Zhang et al., 2016).

The different effectiveness of upper and lower limits might result from the original intention of the price limit. The earliest adoption of a price limit can be traced as far back as 1988 to the *Report of the Presidential Task Force on Market Mechanisms*, following the Black Monday crash in October 1987, while the *Limit Up–Limit Down* (LULD) plan approved by the SEC in 2012 as a policy remedy to the 'flash crash' of the NYSE on 6 May 2010.[1] This price limit plan is also regarded as a three-tier price limit system[2] and it was adopted by the NASDAQ in 2013. These examples show that the evolution of price limits was often induced by stock market tumbles, indicating the design of price limits is more concerned with the lower limit rather than the upper limit. However, the conventional design of price limits in current stock markets is the symmetric price limit, i.e. with the same design for both upper and lower limits, which is designed without consideration of the difference between upper and lower limits. The effectiveness of systematic price limits in practice is also questionable, as many stock markets still experience volatility issues after implementing symmetric price limits. The four circuit breaks in the US stock markets in March 2020 suggest that the LULD was not as effective as predicted (Hong et al., 2021). China, as the world's second largest stock market, has had in place a price limit policy since the 1990s; however, major stock market bubbles and subsequent crashes continue to occur every 7–8 years (e.g., the bust of stock market bubbles in 2001, 2007, and 2015) (Li, 2019). These cases indicate that the symmetric price limit mechanism currently adopted in major stock markets might be ineffective in stabilizing stock price volatility.

In addition to the aforementioned empirical and experimental results, the asymmetric impact of the upper and lower price limits also has theoretical support. The attention-grabbing theory, put forward by Barber and Odean (2008), indicates that the attention that a stock has caught is a crucial factor in determining whether investors would buy it rather than sell it. With limited time and bounded rationality, investors are generally unable to search across and compare thousands of stocks in the stock market to decide which one to buy. In this case, they are more likely to focus on the stocks that attract their attention. On the contrary, investors are inclined to sell the stocks they already own, even in the stock markets where short selling is allowed. Thus, investors only need to limit the choices they set according to attention when buying, but not when selling, a stock. Extreme returns, as an attention-grabbing event, could be regarded as a major factor in influencing investors' trading decisions. In detail, investors are more likely to buy rather than sell the stocks with extreme returns not previously owned by them. Seasholes and Wu (2007) found that on the Shanghai Stock Exchange, individual investors are attracted to buy stocks that hit upper limits, resulting in a price increase. Hou et al. (2009) also suggested that high attention from individual investors in the upmarket could lead to price overreaction. Hence, we can speculate that when a stock reaches the upper limit, investors will be attracted to buy it, which will lead to price continuations, abnormally high trade volume, and more extreme price deviation the following day. In other words, instead of limiting further increases in stock prices and stabilizing the market, the upper limit could result in overreaction and volatility spillover.

The aforementioned analyses and cases suggest that the symmetric price limit mechanism, which includes an upper limit, does not effectively achieve the goal of stabilizing stock markets. Therefore, exploring a more efficient design scheme for price limit policy has become imperative to stabilize the stock market and ensure sufficient financial support for optimizing business processes. Considering the asymmetric effects between upper and lower limits, we propose that implementing an asymmetric price limit - retaining the lower limit while abolishing the upper limit - could effectively control abnormal volatility in stock markets. However, although the asymmetric price limit is rooted in attention-grabbing theory, it is yet to be tested or implemented in stock markets. The lack of quasi-natural experiments hinders empirical studies exploring the effectiveness of asymmetric price limits. With advancements in computational technology, agent-based models offer a new approach to address this issue.

The agent-based model, known for its effective simulation of interactions between diverse agents, has been widely utilized to replicate complex environments and systems with highly interactive agents (Laubenbacher et al., 2013). Given the multi-agent participation characteristic of business processes in the industry, the agent-based modeling approach has been extensively applied to industrial systems, such as supply chain management and manufacturing execution (e.g., Rolón and Martínez, 2012; Dorigatti et al., 2016). Furthermore, testing and implementing various schemes in business processes is costly and carries potential risks, potentially leading to production disruption if the design is inappropriate. In contrast, agent-based models can address the limitations of empirical studies by providing an experimental platform to explore and compare the performance of each scheme under different conditions. The repeatability of experiments and the ability to modify experimental parameters as needed have positioned agent-based models as a cost-effective and efficient optimization method in related research to investigate policy and trading agent behavior in financial markets. For instance, Chiarella (1992) utilized them for the examination of speculative behavior; Lux (1995) employed them to investigate herd behavior, bubbles, and crashes in speculative markets; Farmer and Joshi (2002) developed an agent-based model to explore the price dynamics resulting from various commonly used financial trading strategies. Chiarella et al. (2017) and Wei and Shi (2020) utilized them to investigate investor sentiment in limit order markets; Mizuta (2019) and Yang et al. (2020) adopted agent-based models to study tick size systems.

Given the advantages of agent-based models, they have been extensively utilized to examine policy and trading agent behavior in financial markets, including the assessment of price limit effectiveness and the optimization of price limit design. For example, Westerhoff (2004) conducted a comparison of the efficacy of price limit ranges

[1] The NYSE experienced a 'flash crash' on 6 May 2010, which was reflected in the most significant daily point decline in the Dow Jones Industrial Average of 998.5 points, followed by a regaining of 600 points after 20 minutes (Dalko, 2016).

[2] There are three percentage parameters to determine price bands according to the previous closing price of stocks. More details can be found in SEC (2019).

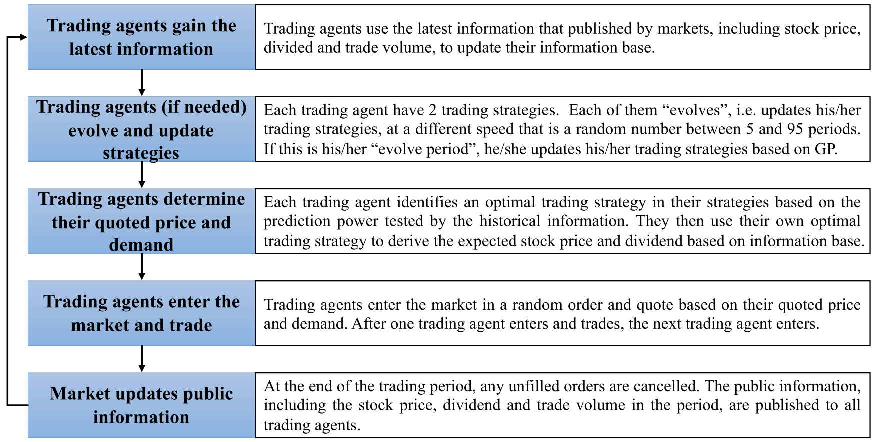

Fig. 1. The basic trading process in each trading period.

spanning from 0 to 5 percent using a nonlinear stochastic asset pricing model. The simulated findings suggest that as the price limit increases, volatility steadily rises until it reaches its maximum value without any price limits. Additionally, deviations from fundamental values decrease as the price limit range expands from 0 to 0.4 percent, but then increases thereafter. Yeh and Yang (2010) developed a heterogeneous agent-based model, expanding the research scope from 0 to 5 percent to 0–10 percent in comparison with Westerhoff (2004). Their findings suggest that the introduction of price limits has both positive and negative implications. However, the adoption of price limits may help to reduce volatility and price distortion, as well as improve liquidity and welfare to some extent when compared with a market without such limits. Yeh and Yang (2013) further explored the impacts of price limits on market quality using the same model, and found even though a price limit would not cause volatility spillover, the inapposite level of price limits might lead to delayed price discovery and trading interference. Mizuta et al. (2013a), (2013b), (2016) developed an agent-based model to investigate the appropriate parameters for a limited time span and limited price range. Their findings indicate the effectiveness of price limit policies is contingent upon the appropriate time span and limit range. Zhang et al. (2016) also examined the impact of price limits using an agent-based model. They discussed the effectiveness of upper and lower limits separately, revealing that while the implementation of upper limits may delay the price discovery process, lower limits do not exert any influence on this process. Their findings, as a supplement to the empirical results, also show the necessity to discuss upper and lower limits, respectively. These studies not only emphasize the significance of price limit design in stock markets, but also illustrate the effectiveness and appropriateness of agent-based models in examining the performance of price limit policies. However, the aforementioned studies mainly focused on the price limit range, with few investigating the effectiveness of asymmetric price limits. Thus, this study utilizes a heterogeneous agent-based model to conduct experiments and simulate the performance under different price limit designs, encompassing scenarios without price limits, with symmetric price limits, and with asymmetric price limits.

This study diverges from previous research that has focused on the detailed prioritization scheme at various stages of the business process, instead directing attention to the financial support within this process. The study emphasizes the paramount role of financial support in industrial business processes while discussing the relationship between finance and industry, which has been neglected in previous studies. Furthermore, by employing a heterogeneous agent-based model, we integrate the study of finance, industry, and computer science within a unified research framework, providing interdisciplinary insights into industrial production. In detail, we explore the designs of price limit policy in order to control abnormal volatility in the stock market and ensure sustained and stable investment support for business process upgrades. While agent-based models have been widely utilized to optimize the design of price limit policy, previous studies have mainly focused on the price limit range. Taking into account the asymmetric impact of upper and lower price limits on market quality, this study proposes an asymmetric price limit design. Our results provide evidence that the proposed asymmetric price limit is more effective in promoting market quality, including controlling volatility, improving liquidity and helping price discovery, than the symmetric price limit and no price limit. In addition, the heterogeneous agent-based model developed in this study serves as a versatile platform for simulating and analyzing stock market policies, applicable not only to price limit policies but also to other types of stock market policies. Using the price limit policy as an example, this study demonstrates how this platform can be utilized to compare the effectiveness of different policy designs.

The remainder of this paper is organized as follows: Section 2 describes the design of the heterogeneous agent-based model and tests the reliability and credibility of the model; Section 3 presents the experimental results and conducts further analysis; Section 4 does the sensitivity analysis; and Section 5 concludes this study.

2. The model

Due to the limited research on the efficacy of asymmetric price limit design, it is imperative to initially investigate the fundamental impact of asymmetric price limits on the quality of general stock markets. In other words, the model established in this study should replicate a simplified and generalized stock market environment that is representative of the majority of global stock markets, rather than taking into account specific market characteristics in a particular region. Failure to do so may result in findings that are influenced by specific characteristics and cannot provide universal recommendations for general stock markets. Therefore, we adhere to the framework of models designed to mimic a generalized stock market environment, as exemplified by Yeh and Yang (2010), Yang et al. (2020), and Dai et al. (2023). To align with the purpose of investing fundamental impacts and saving computation costs, these models generally would be simplified extremely.

The basic heterogeneous agent-based model is a simulated order-driven market that offers a trading platform for heterogeneous trading agents to quote and match orders. This model employs a genetic

Table 1
Parameters for Experiments.

Agent-based model	
Initial shares of stock for each trading agent	1
Initial money supply for each trading agent	200
Initial stock price	20
Interest rate (r_f)	0.01
Average dividend of stock ($\overline{Div}$)	0.2
Number of periods	5000
Trading agents	
Number of trading agents	100
ρ	0.95
σ_μ^2	0.01
θ_0	0.7
λ	*random* (0.2)+0.5
ω	15
GP Parameters	
Function set	{ifelse; if; +; -; *; /; sqrt; sin; cos; abs; >; <; ≥; ≤; =;≠; and; or}
Terminal set	$\{P_{t-1}, \cdots, P_{t-5}, P_{t-1} + Div_{t-1}, \cdots, P_{t-5} + Div_{t-5}, \textit{trading volume}_{t-1}\}$
Number of strategies (n)	2
Probability of immigration	0.1
Probability of crossover	0.7
Probability of mutation	0.2

programming (GP) to capture the updating strategies and behaviors of trading agents.[3] and constructs a constant absolute risk aversion (CARA) utility function to determine trading agents' demands, ensuring a more precise simulation of trading agent activities. On this basis, we embed designs of price limits into the basic model to satisfy the need to investigate the effectiveness of different price limit designs in this study. In contrast, the detailed designs of symmetric and asymmetric price limits are described comprehensively in Section 2.2.

2.1. Heterogeneous agent-based model

The basic model involves two kinds of assets: one risk-free asset bond pays interests at a constant rate r_f and one risky asset stock pays dividends Div_t at period t. Following LeBaron (2006), Div_t is simulated as:

$$Div_t = \overline{Div} + \rho(Div_{t-1} - \overline{Div}) + \mu_t, \tag{1}$$

where $\overline{Div}$ is the average value of dividends. ρ is a coefficient to indicate the influence of the previous dividend Div_{t-1} on Div_t, while $\mu_t \sim N(0, \sigma_\mu^2)$. Div_t follows left-truncated distribution that $Div_t \geq 0$.

The quoted price and demand of each trading agent are determined based on their own evolvable trading strategies and public information, including stock price, dividend, and trading volume in the market. Each trading agent has their own trading strategies and they update their trading strategies based on GP in different time periods according to the recent market information. Fig. 1 outlines the basic trading process in each trading period.

Some details in the trading process should be further elaborated. The first is how GP works in step 2. Each trading strategy in this model is represented as a hierarchical tree structure. The end points of the tree are terminal points (T), which are assigned by the public information, while the rest of points are function points (F), which are assigned by mathematical operators. The concrete content can be found in Table 1. The trading strategy, i.e., hierarchical tree structure, is updated based on three genetic operations in the GP method, including mutation, crossover, and clone. Then, defining fitness of trading strategy as the difference between predicted price based on the strategy and stock price in the market,[4] the updated strategy and original strategy with better fitness are kept in the strategy pool of this trading agent and the other is discarded. The optimal trading strategy of each trading agent in step 3 is also determined based on fitness. In detail, the strategy with the smaller absolute value of fitness is the optimal trading strategy that is used by the trading agent to generate quoted price and demand in this period. Fig. 2 illustrates the decision process of the trading strategy adopted in a period. Original strategy 1 and original strategy 2, with their hierarchical tree structures shown on the left of Fig. 2, represent the initial strategies in a trading agent's strategy pool. During the evolving period, these two strategies are updated using genetic operations. Updated strategies 1 and 2 are generated from original strategies 1 and 2 through crossover and mutation operations, respectively. The fitness of both original and updated strategy 1 is then calculated and compared, with the superior fitness determining which strategy will be retained in the pool. Strategy 2 undergoes the same evaluation process as Strategy 1 to determine its inclusion in the trading agent's current period strategy pool. If this period is not the evolving period for the trading agent, then the previous period's strategy pool of this trading agent remains unchanged. Subsequently, all strategies within the strategy pool are compared based on their fitness levels, with the optimal one being selected as the trading agent's trading strategy for that particular period.

Based on the optimal trading strategy of trading agent i in period t, the expected stock price and dividend $E_{i,t}(P_{t+1} + Div_{t+1})$ is determined according to the fitness $f_{i,t}$:

$$E_{i,t}(P_{t+1} + Div_{t+1}) = \begin{cases} (P_t + Div_t)\left[1 + \theta_0 \tanh\left(\dfrac{\ln\left(1 + f_{i,t}\right)}{\omega}\right)\right] iff_{i,t} \geq 0 \\ (P_t + Div_t)\left[1 + \theta_0 \tanh\left(\dfrac{\ln\left(\left|-1 + f_{i,t}\right|\right)}{\omega}\right)\right] iff_{i,t} < 0 \end{cases}, \tag{2}$$

With the assumption that trading agents are rational, which means they would avoid negative returns, the quote price $P_{i,t}^Q$ of trading agent i at period t can be defined as:

$$P_{i,t}^Q = \begin{cases} P_t + random\left(\dfrac{E_{i,t}(P_{t+1} + Div_{t+1})}{1 + r_f} - P_t\right) \\ if E_{i,t}(P_{t+1} + Div_{t+1}) \geq (1 + r_f)P_t \\ \dfrac{E_{i,t}(P_{t+1} + Div_{t+1})}{1 + r_f} + random\left(P_t - \dfrac{E_{i,t}(P_{t+1} + Div_{t+1})}{1 + r_f}\right) \\ if E_{i,t}(P_{t+1} + Div_{t+1}) < (1 + r_f)P_t \end{cases}, \tag{3}$$

The demand $D_{i,t}$ of trading agent i at period t is determined to maximize the CARA utility function:

[3] In addition to GP, various methods, such as genetic algorithms, online learning algorithms, alternating decision trees, classifier systems, and neural networks, have been employed to replicate trading strategies of market participators and their updating mechanisms in agent-based models (Brenner, 2006; Duffy, 2006; Creamer and Freund, 2010; Murphy and Gebbie, 2021; Arifovic et al., 2022). The selection of GP in this model is based on its close resemblance to the mechanism utilized by market participants for updating their trading strategies in real stock markets. Specifically, the process of updating a hierarchical tree structure through genetic operations in GP mirrors the strategy updating process involving random attempts made by market participants. Furthermore, the fitness-based evaluation method within GP simulates the assessment process used by market participants to determine whether an updated strategy outperforms the current one.

[4] Regarding the formation of trading strategy (called functions in GP), the fitness function, and the implementation of GP, the readers should refer to http://geneticprogramming.com/ and Esfahanipour and Mousavi (2011) as examples.

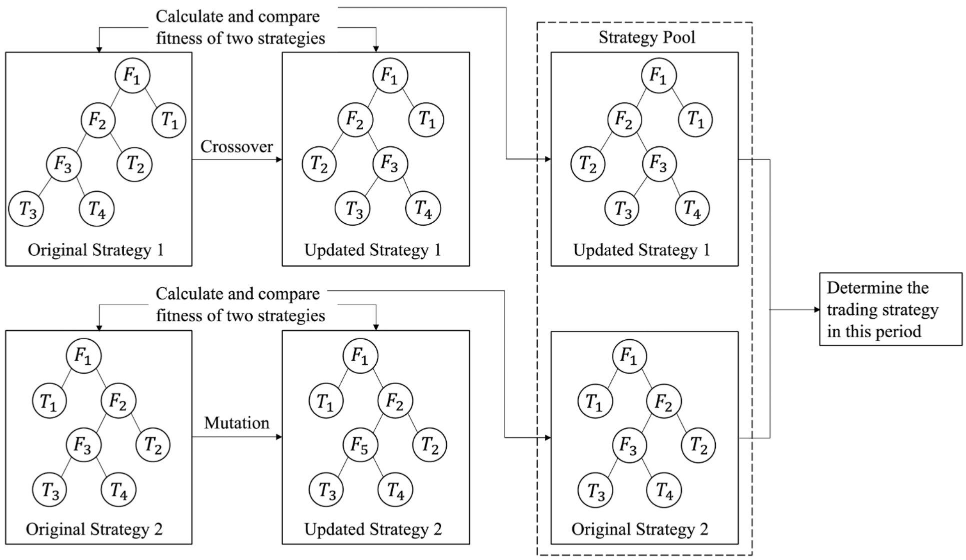

Fig. 2. The decision process of trading strategy (an example).

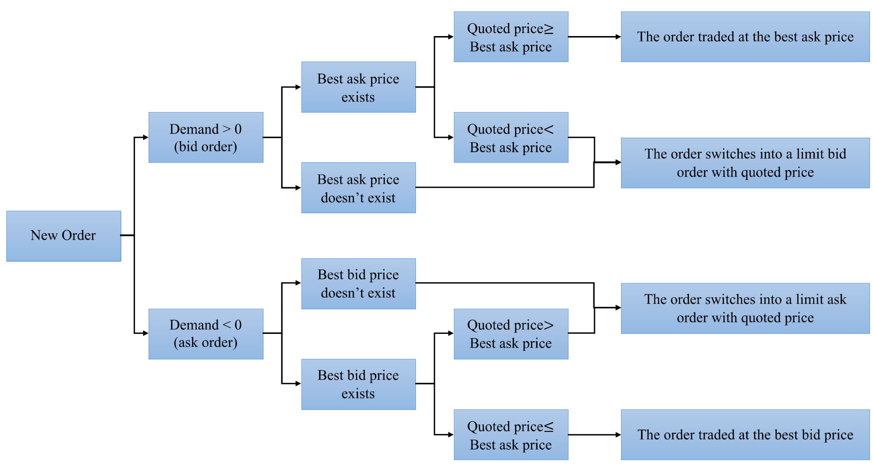

Fig. 3. Order matching rule in the agent-based model.

$$\mathrm{U}(W_{i,t}) = -\exp(-\lambda W_{i,t}), \tag{4}$$

where λ is the degree of absolute risk aversion. $W_{i,t}$, is the wealth of trading agent i at period t. $W_{i,t}$ can be calculated as the sum of the value of stock and bond that the trading agent owned, which is:

$$W_{i,t+1} = (1 + r_f)W_{i,t} + [P_{t+1} + Div_{t+1} - (1 + r_f)P_t]h_{i,t}, \tag{5}$$

In Eq. (5), $h_{i,t}$ is the quantity of the risky asset (total number of stocks) held by trading agent i at period t. From Eq. (5), trading agents can determine their optimal holdings of the risky assets to maximize their expected utility:

$$h^*_{i,t} = \frac{E_{i,t}(P_{t+1} + Div_{t+1}) - (1 + r_f)P_t}{\lambda V_{i,t}(1 + r_{f,t+1})}, \tag{6}$$

The demand of the risky asset, the quantity that trading agent i quote at period t in orders, is the difference between their optimal holdings and the actual holdings:

$$D_{i,t} = h^*_{i,t} - h_{i,t}, \tag{7}$$

After determining the quoted price and demand of trading agent i in period t, the trading agents enter the market in a random order to mimic the varying quotation times of each trading agent in the real stock market. If the current entered trading agent can trade based on the order matching rule, then he/she will engage in trading with other trading agents. In cases where he/she is unable to trade or can only partially fulfill their order, his/her unfilled order will remain in the market and be queued according to the price-time priority rule. Subsequently, the next trading agent enters and engages in trading activities. The detailed order matching rule is shown in Fig. 3. Demand < 0 (> 0) represents a sell (buy) order. If the best bid (ask) price exists in the market and is $\geq$ ($\leq$) price that the trading agent intends to sell (buy), then the trading agent will place a market order, and this order will trade at the best bid (ask) price. Otherwise, the trading agent will place a limit order in the market with the quoted price $P^Q_{i,t}$ and the demand $D_{i,t}$.

After the entry of 100 trading agent s into the market, the trading system is subsequently shut down in this period, and all unfilled orders are canceled, as shown in step 6. Moreover, the stock price of this period, defined as the transaction price of the last trading in this period, dividend, and total trading volume are published to all trading agents. Then, trading agents will update their information base using the above public information in step 1 in the next period.

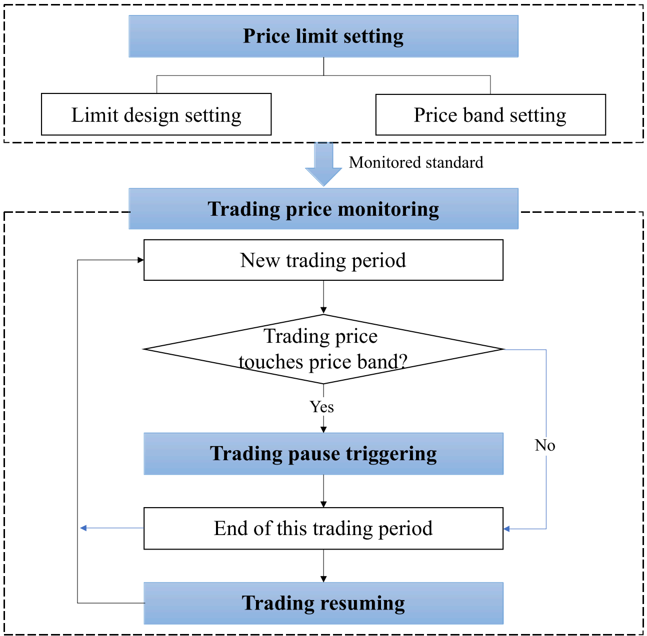

Fig. 4. The process of the trading halt system.

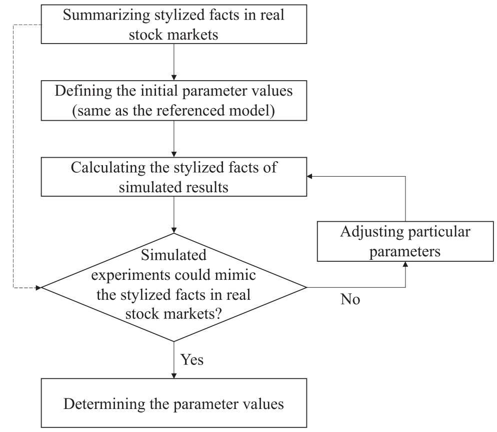

Fig. 5. The process of calibration.

2.2. *Price limit design*

Three price limit mechanisms—no price limit, symmetric and asymmetric price limits—are designed and investigated in this study. The no-price limit mechanism for stock markets represents the basic design in this study to provide a benchmark for analysis of market quality under markets adopting price limit policies. The traditional price limit mechanism in current stock markets is the symmetric price limit, with both upper and lower limits. The asymmetric price limit, with a lower limit but no upper limit, is the price limit mechanism proposed based on the results of previous studies but has not been applied in real stock markets.

The simulations of symmetric price limit and asymmetric price limit are achieved based on the embedment of the trading halt system into the basic heterogeneous agent-based model. The trading halt system mainly comprises four sections: (1) price band setting, (2) trading price monitoring, (3) trading pause triggering and (4) trading resuming. The process of the trading halt system is depicted in Fig. 4.

To be specific, price limit setting is the basic design of price limit policy, including limit design and price band setting. For limit design, it refers to the position where the price limit is embedded in the model. In detail, if the price limit is embedded in both sides of the price, it will be defined as the design of a symmetric price limit, while if only on the lower side of the price, it will be defined as the design of an asymmetric price limit. The price band is defined as:

$$\textit{Price band} = \textit{Reference Price} \pm \quad (x\% * \textit{Reference Price}), \tag{8}$$

where the x% is the limit range in experiments. In the whole process of the experiment, each trading price in each period is monitored by the trading halt system based on the price limit setting. The market will trigger a trading pause once the trading price touches the price band. For example, if the closing price in the previous period is 10, the upper price band in this period is 11, while the lower price band is 9. Therefore, a trading pause will be triggered if the trading price is larger than or equal to 11 or smaller than or equal to 9. Once the trading pause is triggered, the market will resume trading in the next trading period. Otherwise, if the trading pause is not triggered, the simulated market operates normally, as introduced in Section 3.1. Corresponding to the price limit policy adopted in current stock markets, each trading period in agent-based models is regarded as the same time notion with the length of the trading pause in stock markets.

Table 2
Statistical Properties of Experiments.

Indicator	Mean	Skewness	Kurtosis	Max Return	Min Return	|Return|	Jarque-Bera statistics
Policy							
DJIA	4.11E−04	−1.0696	29.3877	0.1108	−0.2261	0.0072	257020.5
NASDAQ	4.40E−04	−0.0945	9.8140	0.1417	−0.1135	0.0081	23877.6
S&P500	3.74E−04	−0.1398	9.0312	0.1158	−0.0903	0.0073	12245.3
HSI	4.28E−04	−1.2165	34.7274	0.1882	−0.3333	0.0106	343548.8
Russell2000	4.02E−04	−0.2360	6.5478	0.0927	−0.1185	0.0086	4303.1
Seed1	3.98E−04	−2.7480	16.6243	0.0887	−0.1243	0.0066	44964.2
Seed2	2.29E−04	−1.0947	9.2399	0.1226	−0.1213	0.0081	9110.5
Seed3	3.18E−04	−1.6580	9.0547	0.1123	−0.1206	0.0089	9928.1
Seed4	4.42E−04	−1.5200	8.4333	0.1206	−0.1131	0.0092	8075.6
Seed5	4.11E−04	−1.3491	8.0525	0.1567	−0.1206	0.0091	6834.9
Mean	3.60E−04	−1.6740	10.2809	0.1202	−0.1200	0.0084	15782.7
Median	3.98E−04	−1.5200	9.0547	0.1206	−0.1206	0.0089	9110.5
Stock price (30)	2.95E−04	−0.8528	4.8282	0.1351	−0.1317	0.0121	1302.3
Wealth (400)	2.58E−04	−1.2281	6.1809	0.0937	−0.1073	0.0087	3364.8
Interest rate (0.005)	9.28E−05	−1.1793	5.9827	0.0923	−0.1167	0.0093	3012.4
Risk aversion (0.3)	1.10E−04	−1.3536	6.6179	0.1189	−0.1064	0.0094	4253.8
Yeh and Yang (2010)	-	−1.8300	13.1900	0.2135	−0.2326	0.0048	-
Yeh and Yang (2013)	-	-	44.7400	0.2049	−0.2348	0.0051	-
Zhang et al. (2016)	2.71E−06	2.8180	56.0748	-	-	-	2.37E+05
Dai et al. (2023)	-	−0.6300	30.1100	0.0649	−0.0406	0.0035	-

In this study, three basic experiments are designed to investigate the effectiveness of the mechanisms of the price limits as follows:

1) No limit—a stock market without price limits;
2) Symmetric price limit policy—a stock market with both upper and lower price limits;
3) Asymmetric price limit policy—a stock market with only a lower price limit.

2.3. Model calibration

The reliability and credibility of the model are the insurance of the accuracy of the simulated results. With the increasing adoption of agent-based models in financial research, the calibration techniques for these models, such as direct observation, analytical methods, and simulation-based approaches, have undergone substantial expansion. Apart from direct observation, the fundamental principle behind analytical and simulation-based methods is to "select model parameters that result in dynamics that are as close as possible to those observed in a particular dataset" (Platt, 2020). In other words, there should be a true set of parameters serving as the target in these calibration methods. The agent-based model developed in this study is designed to simulate a generalized stock market environment rather than a specific one. Given the diverse nature and developmental stages of various stock markets, selecting one representative of general stock markets poses a challenge. As a result, the aforementioned calibration methods are not directly applicable to our model due to the absence of a target value. To overcome this limitation, previous studies have proposed a specific calibration method tailored for agent-based models aiming to replicate generalized stock market environments (Mizuta et al., 2016; Yeh and Yang, 2010; Zhang et al., 2016).

The detailed processes of our calibration method can be categorized into four main steps: (1) calculating and summarizing the stylized facts in representative stock markets globally; (2) assigning initial parameter values consistent with the referenced model; (3) conducting experiments and calculating the stylized facts of simulated results; (4) assessing whether the stylized facts of simulated results are able to replicate those of real stock markets, and if not, adjusting specific parameters and repeating step 3 until the model is able to mimic. The calibration process is illustrated in Figure 5[5].

We first calculate the stylized facts in real stock markets. Chen et al. (2012) summarised 30 stylized facts replicated in previous agent-based model studies, including return, trading volume, trading duration, transaction size, and bid-ask spread. Among the basic stylized facts pertaining to the return, skewness, kurtosis, and the range of returns have received the most attention (e.g. Chen and Yeh, 2001; He and Li, 2015; Yeh and Yang, 2010, 2013; Zhang et al., 2016; Yang et al., 2020). Following previous research, seven indicators generally used to calibrate agent-based models are chosen to test their performance. The first five rows of Table 2 present consistent stylized facts observed in five stock indices, including fat tails of returns, i.e. Kurtosis >3, negative skewness, large Jarque-Bera statistics and the relatively stable range of returns. Thus, the selection of parameter values should ensure that the simulated results of models are capable of replicating the aforementioned stylized facts.

The experimental setup employed the following simulation environment: 1.8 GHz Dual-Core Intel Core i5 Processor, 8 GB of 1600 MHz DDR3 Memory, and Intel HD Graphics 6000 with 1536 MB. The software environment utilized was MacOS Monterey, and the experiments were conducted using Netlogo (version 5.3.1).

After conducting the calibration process outlined in Fig. 5, a set of parameter values has been determined and is presented in Table 1. Table 2 summarises five typical simulations based on basic models without price limits. Consistent results for fat tails of returns, negative skewness, large Jarque-Bera statistics and a reasonable range of return are observed. Moreover, Fig. 6 compares the distribution of returns from Nasdaq and simulations with different limit mechanisms. Both quantile-quantile plots and density plots present our model with each limit mechanism that could provide an acceptable fit to the empirical features.

To further validate the credibility of our model, we conducted an examination of the statistical properties with varying values of key parameters. Four parameters - stock price, trading agent wealth, interest rate, and degree of absolute risk aversion - were selected due to their variability across diverse stock markets. The consistent statistical properties observed across experiments with different parameter values suggest that the simulated results may have general applicability to diverse stock market scenarios. Additionally, a comparison was made between the performance of our model and other agent-based models of stock markets. The statistical properties of four representative models are detailed in their original papers. Our findings indicate that our model addresses certain shortcomings identified in previous models, such as inaccuracies in simulating skewness (Zhang et al., 2016) and relatively smaller absolute returns compared to real stock markets (Yeh and Yang, 2010, 2013; Dai et al., 2023).

To further ensure the agent-based models with the embedment of price limit designs are still reliable and credible, we compare the statistical properties of simulations based on models that embedded a 10 % symmetric price limit with CSI 300; the stock market has adopted a 10 % symmetric price limit since December 1996. Fig. 7 compares the distribution of returns from CSI300 and simulations with symmetric price limit mechanisms. The quantile-quantile plots and density plots show that both returns of CSI300 and the experiment with symmetric price limit have similar distributions with left skewness and fat tails. Moreover, although there is no reference for an experiment with an asymmetric price limit, as all stock markets around the world have yet to adopt it, we still examine the time series properties of the experiment without an asymmetric price limit. Its returns also obey the left-skewed distribution with fat tails. All of these findings indicate that the heterogeneous agent-based models used in this study can simulate the essential features of real stock markets.

[5] Compared to the aforementioned calibration methods, the advantage of this method and its suitability for our research lies in the following fact. Instead of replicating specific stylized facts within a particular stock market, this method has the capability to replicate stylized facts observed across general stock markets. Our simulated results closely align with the stylized facts observed in real stock markets. Specifically, despite huge variations in the absolute value of these indicators, all experiments consistently demonstrate negative skewness, kurtosis greater than 3, and rational ranges of returns (as illustrated in Table 2). Therefore, the simulated results based on different seeds could provide insights into the effects of price limit designs on stock markets with varying performance. Their average results thus offer insights into the general impacts of price limit designs across most stock markets. Moreover, the sensitivity analysis results presented in Section 4 demonstrate that our core findings remain robust even when certain parameter values are altered. This indicates that our models are not significantly sensitive to certain parameters and further validates the credibility of both our models and results. However, it is also important to acknowledge the limitations of this calibration method. Due to the absence of a target value, there exist numerous sets of parameter values that could replicate the stylized facts observed in real stock markets. Although our sensitivity analyses demonstrate the effectiveness of asymmetric price limits under various parameter values, the magnitude of volatility reduction is different with different parameter values. In this case, predicting the practical magnitude of volatility reduction following the implementation of asymmetric price limits in a real stock market becomes challenging. Thus, before introducing asymmetric price limits in an actual stock market, further targeted research may be necessary.

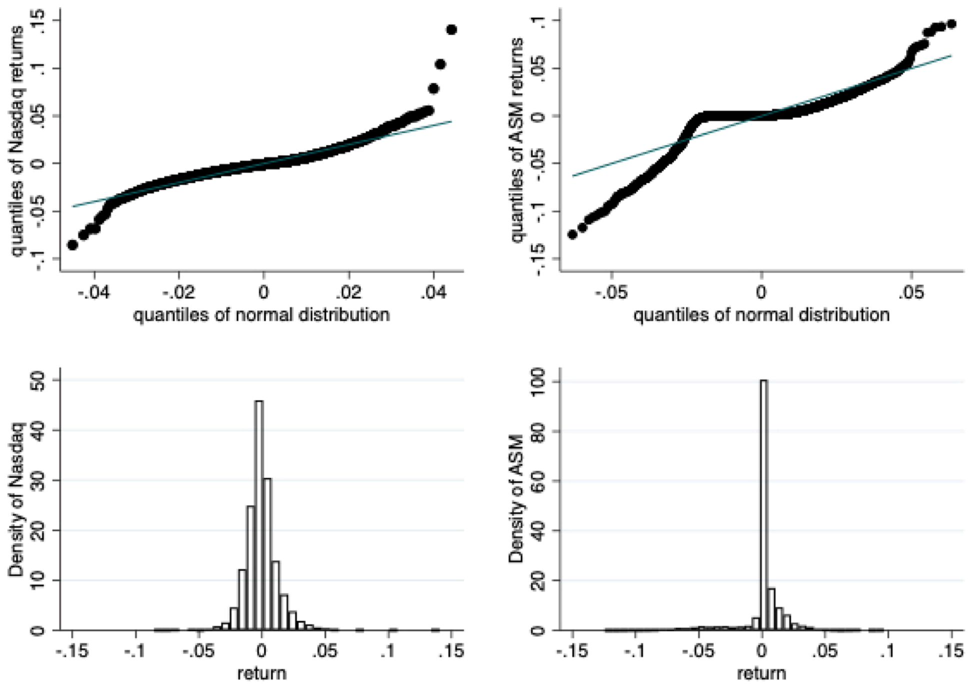

Fig. 6. Time series properties of Nasdaq and experiment without limit.

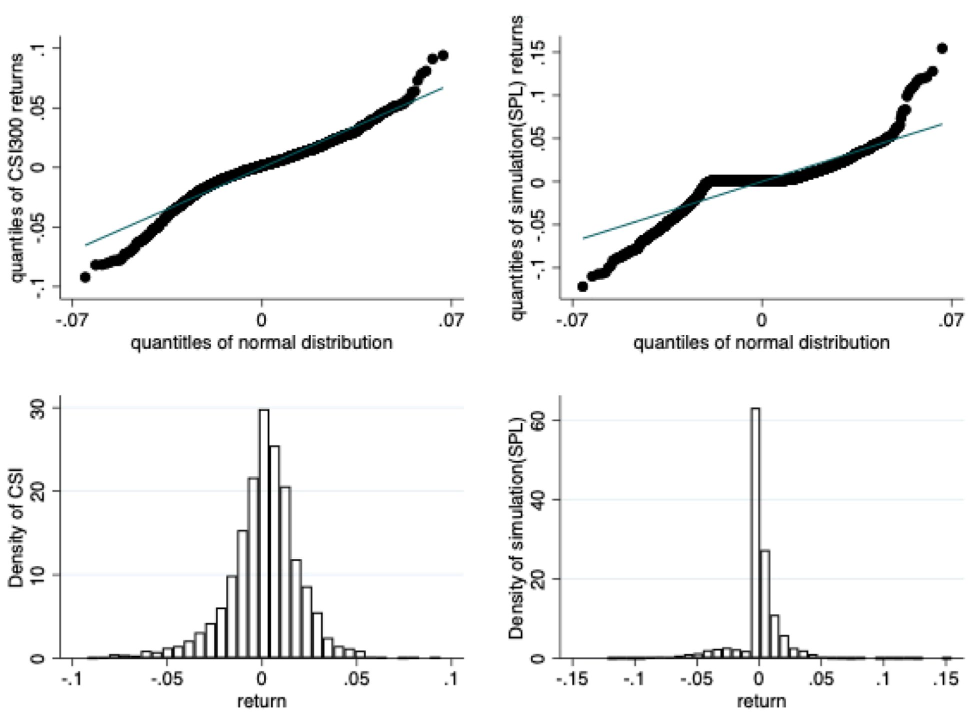

Fig. 7. Time series properties of CSI300 and experiment with a symmetric limit.

3. Results

3.1. Basic results

This study examines the effectiveness of price limit policies from market liquidity, price deviation, and market volatility. We run 10 simulations for each experiment and each simulation takes 5000 trading periods.[6] Fig. 8 shows the stock price under three different price limit designs of a typical seed. The results reported in Table 3 are the average of the simulation results in no limit, symmetric price limit, and asymmetric price limit experiments, respectively. In addition, Fig. 9 depicts the range and average value of each indicator under three price limit

[6] Results were collected from simulations after the first 1000 trading periods to avoid data distortion.

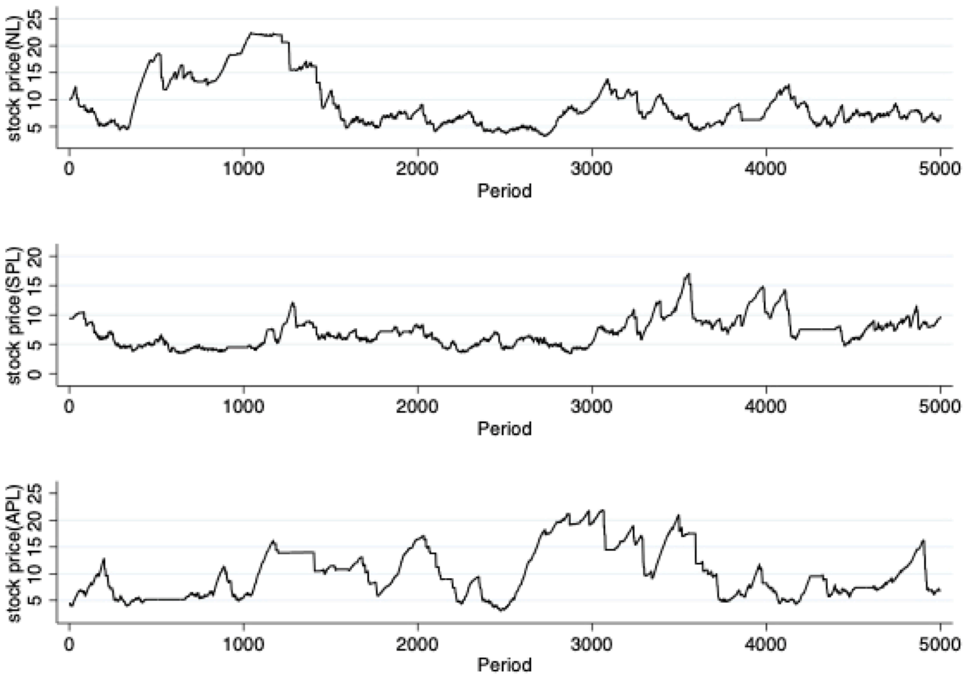

Fig. 8. Stock price under different price limit designs (results of atypical seed).

Table 3
Market quality in different price limit designs.

	NL		APL	t-value
Rolling Volatility	0.0134	>>	0.0132	2.209
	(0.133,0.134)		(0.132,0.133)	
Trade Volume	5.165		5.255	−1.678
	(5.094,5.236)		(5.177,5.333)	
Dollar Volume	43.271	<<<	45.219	−3.723
	(42.617,43.925)		(44.458,45.979)	
Quoted Spread	0.082	>>>	0.072	3.231
	(0.077,0.087)		(0.068,0.076)	
Effective Spread	0.089	>>>	0.081	2.645
	(0.085,0.094)		(0.076,0.085)	
% Quoted Spread	0.894	>	0.846	1.725
	(0.854,0.933)		(0.808,0.883)	
% Effective Spread	0.990		0.958	1.100
	(0.950,1.031)		(0.918,0.999)	
Market Depth	3.622	<<	3.776	−2.247
	(3.540,3.705)		(3.683,3.868)	
Price Deviation	0.589	>>>	0.583	4.976
	(0.588,0.590)		(0.581,0.584)	
	SPL		**APL**	**t-value**
Rolling Volatility	0.0137	>>>	0.0132	8.480
	(0.0136,0.0138)		(0.0132,0.0133)	
Trade Volume	4.952	<<<	5.255	−6.135
	(4.882,5.023)		(5.177,5.333)	
Dollar Volume	40.968	<<<	45.219	−9.501
	(40.348,41.588)		(44.458,45.979)	
Quoted Spread	0.073		0.072	0.393
	(0.069,0.077)		(0.068,0.076)	
Effective Spread	0.083		0.081	0.695
	(0.079,0.087)		(0.076,0.085)	
% Quoted Spread	0.876		0.846	1.120
	(0.838,0.914)		(0.808,0.883)	
% Effective Spread	1.002		0.958	1.453
	(0.958,1.047)		(0.918,0.999)	
Market Depth	3.608	<<<	3.776	−3.702
	(3.520,3.697)		(3.683,3.868)	
Price Deviation	0.595	>>>	0.583	14.501
	(0.594,0.596)		(0.581,0.584)	

Note: <<< and >>> significant at 1 % level, << and >> significant at 5 % level, < and > significant at 10 % level; the numbers in parentheses are 95 % confidence intervals.

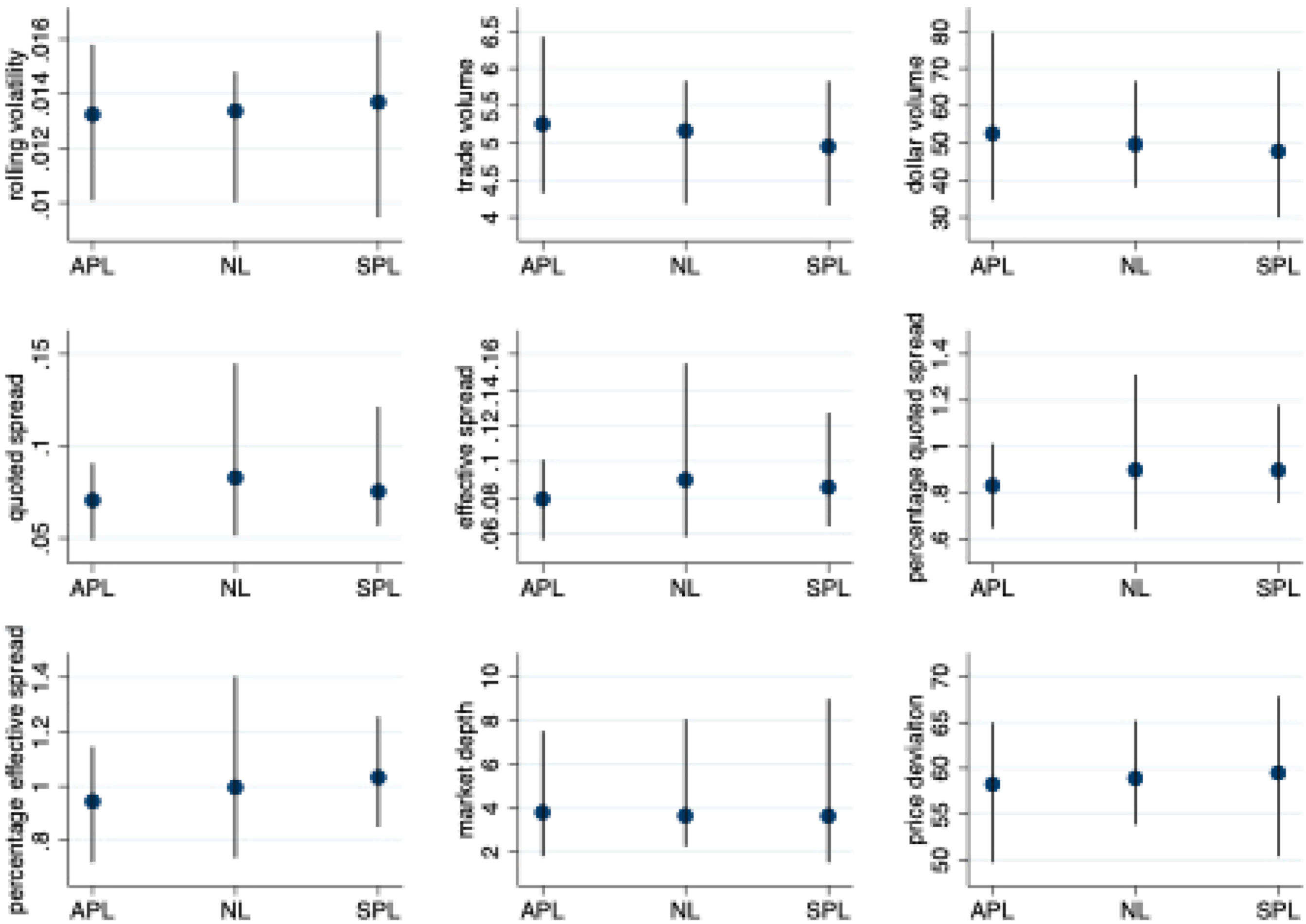

Fig. 9. Market quality under APL, NL and SPL.

designs.

Controlling market volatility is the essential objective of setting price limit policies in stock markets. In this study, the average rolling 20 periods of volatility of stock returns is employed to measure market volatility. The results are provided in the last row of Table 3. On average, the lowest volatility, 0.0132, occurs under the asymmetric price limit. Taking market volatility under no limit as the benchmark, it is clear that a symmetric price limit cannot control volatility in stock markets. This result is in agreement with the findings of opponents that traditional price limit policies would cause volatility spillover. Previous researchers (e.g. Fama, 1989; Kim and Rhee, 1997; Lehmann, 1989; Li et al., 2014) explained volatility spillover as the result of a delayed price discovery process. According to the price limit policy mechanism, trading pauses are triggered when there are large price changes. However, these trading pauses prevent immediate corrections to the order imbalance and delay the price discovery as transactions must be transferred to the subsequent trading period. As a result, volatility would be distributed over a longer period, leading to volatility spillover and larger volatility in stock markets. Fig. 8 makes this point more visually. Even though asymmetric price limit and symmetric price limit keep the stock price within a narrower range compared with no limit as the compulsory intervention of price limit, the curve of stock price under asymmetric price limit is much smoother than under symmetric price limit, i.e., the daily fluctuation of stock price under symmetric price limit is much bigger than under asymmetric price limit. It demonstrates the existence of volatility spillover under a symmetric price limit. Overall, the smallest volatility under an asymmetric price limit shows the effectiveness of an asymmetric price limit in controlling volatility.

Trade and dollar volumes are measured to analyze the trading activity under different price limit policies. Trade volume and dollar volume are defined as the average trade volume, and the product of trade volume and price, respectively, for each trading period. The first two rows in Table 3 show that the stock market that adopts an asymmetric price limit has the largest dollar and trade volumes, at 52.561 and 5.255, respectively. Focusing on trade activity under no limit, the results show that asymmetric price limits generally promote trading activity in stock markets. Unlike previous research that focused on the change in trade volume after hitting price limits and regarded lower trade volume as an effective indicator of price limits, we pay attention to the average trade volume in the whole observed period. Surprisingly, our results suggest that asymmetric price limits do not limit trading activity, but can promote it. A possible explanation for this might be that even though the price limit policy may occasionally suspend trading, a stable market can provide a more reliable trading environment, attracting larger orders from trading agents.

The bid-ask spread is used to evaluate the difference between the traded and best-quoted prices. Quoted spread, effective spread, percentage quoted spread and percentage effective spread are chosen to analyze bid-ask spread under different price limit policies, which are calculated as follows:

$$\textit{Quoted Spread} = \textit{BestAskPrice} - \textit{BestBidPrice}, \tag{9}$$

$$\textit{Effective Spread} = 2 \times |\textit{StockPrice} - m|, \tag{10}$$

$$\textit{Percentage Quoted Spread} = 100 \times \left[\frac{\textit{BestAskPrice} - \textit{BestBidPrice}}{m}\right], \tag{11}$$

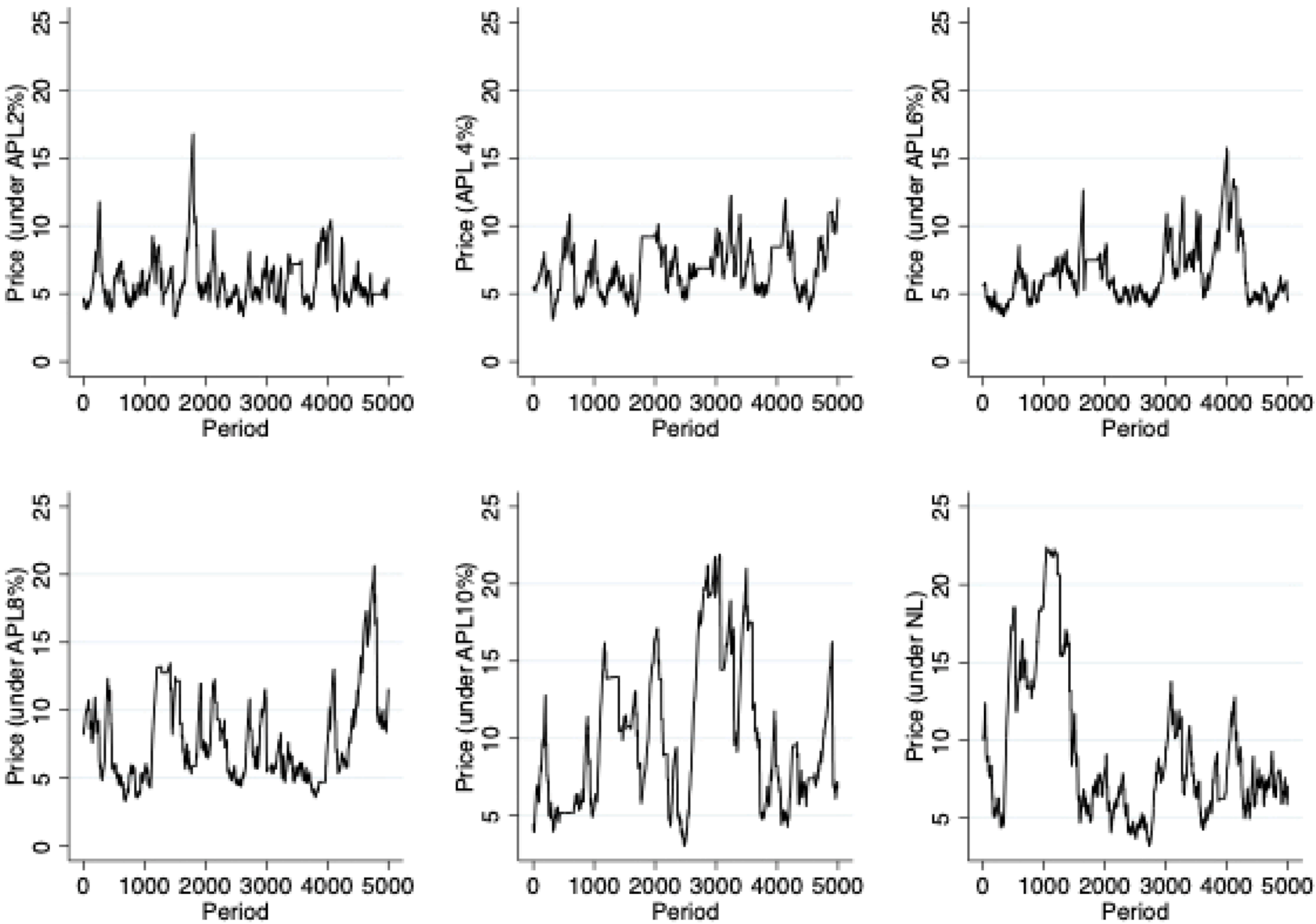

Fig. 10. Price dynamics under APL 2 %, 4 %, 6 %, 8 %, 10 % and NL.

$$Percentage\ Effective\ Spread = 200 \times \left[\frac{|StockPrice - m|}{m}\right], \tag{12}$$

where m is defined as $(best\ ask\ price + best\ bid\ price)/2$. Rows 3–6 in Table 3 consistently show that the asymmetric price limit narrows the bid–the ask spread relative to the other two price limit policies.

The market depth is defined as the average order size at the best bid price and best ask price. The seventh row in Table 3 shows that the greatest market depth, 3.776, is achieved under the asymmetric price limit. A greater market depth indicates that the stock price would experience a smaller fluctuation with the same trading activity. The results also reveal that traditional price limit policies are of limited use to control volatility effectively.

This study employs price deviation, i.e. differences between the stock price and the fundamental value of the stock (dividend divided by interest rate), to measure the pricing efficiency. The eighth row in Table 3 shows that the price deviation in asymmetric price limit is significantly lower than no limit and symmetric price limit. Compared with traditional price limit policies, the symmetric price limit, adopted by stock markets, asymmetric price limit can decrease price deviation by around 2.1 %. This result further validates the effectiveness of asymmetric price limit on calming down the overactive market by providing sufficient time to irrational investors for price discovery (Danışoğlu and Güner, 2018).

The results in Table 3 and Fig. 9 indicate that the asymmetric price limit can control market volatility without negatively affecting market liquidity. Moreover, it can promote price efficiency. This combination of findings provides some support for the conceptual premise that an asymmetric price limit policy could be a more effective policy for controlling volatility in stock markets, compared with symmetric price limits. It is important to note that while there is a noticeable decrease in market volatility in the presence of asymmetric price limits, the reduction is limited to approximately 1.5 % compared to not having any price limits and about 3.6 % compared to having symmetric price limits. In this context, we further investigate the efficacy of asymmetric price limits with varying design parameters, represented by limit ranges, and across diverse market environments to ascertain the conditions under which the asymmetric price limit mechanism is applicable.

3.2. The range of asymmetric price limit

Previous studies about symmetric price limits indicated the price limit range is a significant factor that impacts the effectiveness of the price limit policy (Zhang et al., 2022). Based on our basic results, asymmetric price limits could stabilize the market and also achieve better market quality in both market liquidity and price efficiency. We further test the effectiveness of asymmetric price limit designs with different price limit ranges. According to the magnitude of large price variations and their frequencies in experiments without price limit, five limit ranges, including the limit range of 10 % that was adopted in the basic experiment, are chosen from 2 % to 10 % with a step of 2 %.

Fig. 10 displays the price dynamics under markets with asymmetric price limits of range 2 %, 4 %, 6 %, 8 %, 10 %, and without price limits for a typical run. It is evident that a smaller limit range can control stock price in a narrower range, but the smoother curve under a larger limit range indicates that a limit that is too restrictive may also result in volatility spillover. Fig. 11 compares the market quality under

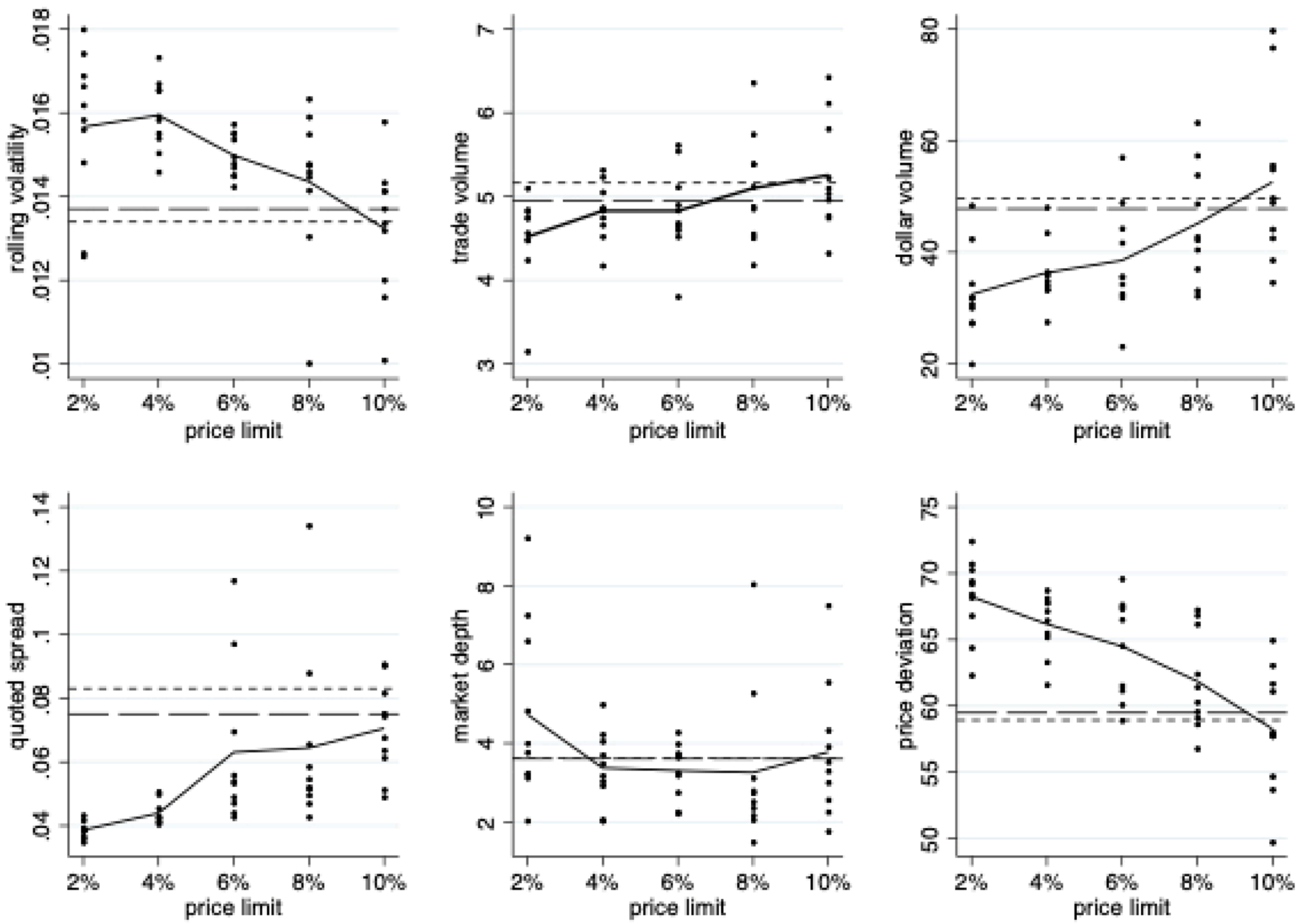

Fig. 11. Market quality under APL 2 %, 4 %, 6 %, 8 % and 10 %.

asymmetric price limit with ranges from 2 % to 10 %, and the long-dash line and short-dash line are the market performance under symmetric price limit and no limit respectively. The rolling volatility registers a small rise from 2 % to 4 % and then declines from 4 % to 10 %. The results indicate the effectiveness of price limits on market volatility is the balance between controlling intraday price fluctuation and volatility spillover in the following days. Even though a restrictive price limit could control the intraday price fluctuation directly, it would also result in severe volatility spillover, while the degree of spillover tends to be weaker with the price limit increasing.

Fig. 11 shows that the asymmetric price limit with a 10 % range achieves the smallest rolling volatility compared with the asymmetric price limit with other ranges, symmetric price limit, and no limit. In addition, asymmetric price limit with 10 % range can achieve optimal or suboptimal performance in price deviation and market liquidity except quoted spread. The narrow bid-ask spread under restrictive price limits is due to the shrinking space of quotation, which is only a result of compulsory intervention instead of the substantial improvement of market liquidity. Moreover, the narrower bid-ask spread under restrictive price limits is at the expense of market stability and price efficiency. Thus, the results reveal that 10 % is an appropriate range for asymmetric price limits.

3.3. Heterogeneous effects of asymmetric price limit

The initial validation of the effectiveness of asymmetric price limits is demonstrated through experiments utilizing heterogeneous agent-based models. In this section, we further investigate whether the efficacy of asymmetric price limits is contingent upon specific market conditions. Consistent with market quality considerations, the market conditions are categorized based on market volatility, market liquidity, and price efficiency. The diverse performance under each condition offers a more comprehensive understanding of which types of stock markets are better suited for asymmetric designs.

3.3.1. Market volatility

We select the median rolling volatility of simulations without price limits as the dividing line between stable and volatile markets. In detail, the stable and volatile markets are defined as those simulations with rolling volatility below and above average rolling volatility respectively. Table 4 reports the market quality under no limit and asymmetric price limit in stable markets and volatile markets. It is evident that the asymmetric price limit is still effective in volatile markets by significantly reducing the rolling volatility from 0.0144 to 0.0126, which is consistent with the basic results. However, when the market is stable, asymmetric price limits lead to heightened volatility, instead of calming down the market. Moreover, asymmetric price limits also damage most aspects of market quality, including trading volume, market depth, and price deviation in a stable market. On the contrary, asymmetric price limits achieve higher trading volume, deeper market depth and smaller price deviation in volatile markets, and the degree of performance improvement is much higher than in basic results. These results indicated that the price limit policy is inapplicable to a stable market but is an effective measure to stabilize the market and promote market liquidity and price efficiency in a volatile market. This finding is reasonable as basic volatility is the guarantee of market liquidity.

Table 4
Effectiveness of APL under stable markets and volatile markets.

	Stable market			
	NL		**APL**	**t-value**
Rolling Volatility	0.0124 (0.0123,0.0125)	<<<	0.0139 (0.0138,0.0140)	−18.555
Trade Volume	5.106 (5.005,5.206)		5.187 (5.084,5.290)	−1.143
Dollar Volume	49.874 (48.650,51.077)	>>>	47.411 (46.208,48.615)	2.991
Quoted Spread	0.092 (0.084,0.010)	>>>	0.075 (0.069,0.082)	3.165
Effective Spread	0.098 (0.090,0.106)	>>	0.085 (0.078,0.092)	2.540
% Quoted Spread	0.968 (0.900,1.036)		0.900 (0.837,0.962)	1.450
% Effective Spread	1.050 (0.981,1.120)		1.025 (0.958,1.092)	0.519
Market Depth	4.249 (4.125,4.373)	>>>	3.180 (3.074,3.287)	12.027
Price Deviation	0.572 (0.570,0.574)	<<<	0.600 (0.598,0.603)	−21.800
	Volatile market			
	NL		**APL**	**t-value**
Rolling Volatility	0.0144 (0.0142,0.0145)	>>>	0.0126 (0.0125,0.0127)	21.982
Trade Volume	5.224 (5.123,5.325)		5.322 (5.209,5.436)	−1.28
Dollar Volume	49.386 (48.143,50.628)	<<<	57.704 (56.020,59.388)	−7.852
Quoted Spread	0.076 (0.068,0.083)		0.069 (0.063,0.755)	1.221
Effective Spread	0.083 (0.075,0.091)		0.077 (0.071,0.084)	1.076
% Quoted Spread	0.871 (0.806,0.936)	>	0.794 (0.736,0.851)	1.741
% Effective Spread	0.973 (0.906,1.041)	>	0.889 (0.829,0.949)	1.840
Market Depth	2.996 (2.908,3.083)	<<<	4.371 (4.249,4.494)	−17.458
Price Deviation	0.606 (0.604,0.608)	>>>	0.565 (0.562,0.567)	23.146

Note: <<< and >>> significant at 1 % level, << and >> significant at 5 % level, < and > significant at 10 % level; the numbers in parentheses are 95 % confidence intervals.

Table 5
Effectiveness of APL under high and low liquidity markets.

	High liquidity market			
	NL		**APL**	**t-value**
Rolling Volatility	0.0134 (0.0133,0.0135)	<<<	0.0136 (0.0135,0.0137)	−3.267
Trade Volume	5.616 (5.512,5.719)		5.513 (5.402,5.625)	1.344
Dollar Volume	57.927 (56.562,59.291)		57.788 (56.212,59.364)	0.132
Quoted Spread	0.092 (0.085,0.099)	>>>	0.071 (0.066,0.076)	4.765
Effective Spread	0.010 (0.093,0.107)	>>>	0.080 (0.074,0.086)	4.286
% Quoted Spread	0.951 (0.895,1.006)	>>>	0.824 (0.774,0.873)	3.356
% Effective Spread	1.047 (0.990,1.105)	>>>	0.935 (0.883,0.988)	2.816
Market Depth	2.931 (2.849,3.012)		2.935 (2.845,3.026)	−0.075
Price Deviation	0.563 (0.561,0.565)	<<<	0.578 (0.576,0.580)	−10.037
	Low liquidity market			
	NL		**APL**	**t-value**
Rolling Volatility	0.0134 (0.0133,0.0135)	>>>	0.0129 (0.0127,0.0130)	6.121
Trade Volume	4.714 (4.618,4.810)	<<<	4.997 (4.888,5.106)	−3.826
Dollar Volume	41.323 (40.304,42.341)	<<<	47.327 (45.997,48.658)	−7.069
Quoted Spread	0.069 (0.063,0.074)		0.072 (0.067,0.077)	−0.869
Effective Spread	0.076 (0.070,0.081)		0.081 (0.075,0.086)	−1.227
% Quoted Spread	0.813 (0.764,0.862)		0.871 (0.820,0.922)	−1.615
% Effective Spread	0.908 (0.857,0.959)	<<	0.984 (0.928,1.039)	−1.977
Market Depth	4.314 (4.182,4.447)	<<<	4.617 (4.483,4.750)	−2.920
Price Deviation	0.615 (0.614,0.617)	>>>	0.587 (0.585,0.590)	16.402

Note: <<< and >>> significant at 1 % level, << and >> significant at 5 % level, < and > significant at 10 % level; the numbers in parentheses are 95 % confidence intervals.

Without excessive volatility, there is no need for stable markets to prevent fluctuations. The adoption of a price limit policy thus would restrict the basic volatility in a stable market and further result in volatility spillover and a decline in market liquidity.

3.3.2. *Market liquidity*

The trading volume in each experiment is utilized to classify the samples into high and low liquidity markets. Table 5 presents a comparison of the heterogeneous effectiveness of asymmetric price limits within both high and low liquidity markets. It is evident that asymmetric price limits are more effective in relatively inactive markets than active ones. Furthermore, the asymmetric design also has the potential to enhance market performance in terms of both market liquidity and price efficiency within low-liquidity markets, indicating its suitability for relatively inactive markets. The observed outcome is justifiable given that the price limit policy exerts a more pronounced impact, namely by restricting a greater number of transactions on active markets than on inactive ones. This consequently leads to a heightened spillover effect in active markets following the limit hit. This perspective is reinforced by the volatility observed in active markets that have adopted symmetric price limits.[7] The introduction of symmetric price limits further amplifies the volatility of high liquidity markets to 0.0141, attributable to the heightened spillover effect.

3.3.3. *Price efficiency*

The samples are categorized into markets with high price efficiency and those with low price efficiency based on the median of price efficiency in simulations without a price limit. Table 6 demonstrates the heterogeneous impact of asymmetric price limits in markets with varying levels of price efficiency. It is evident that asymmetric price limits can effectively stabilize markets with low price efficiency, as evidenced by reduced rolling volatility. Conversely, in high-price efficiency markets, asymmetric price limits lead to a slight increase in volatility and also result in greater price deviation, indicating that this design may not be suitable for markets demonstrating excellent performance in terms of pricing efficiency. This finding aligns with the original purpose of price limit design, which aims to mitigate abnormal volatility by allowing irrational investors sufficient time for price discovery (Danışoğlu and Güner, 2018). Therefore, it is essential to implement price limit policies in markets with low price efficiency, characterized by high price deviation, if aiming to modify irrational trading behavior.

The findings in this section suggest that there are specific conditions under which the adoption of asymmetric price limits is effective, particularly in volatile, low liquidity, and low price efficiency markets. Fig. 12 visually presents a comparison of rolling volatility under APL and NL in each market condition. These results align with the original purpose of price limits, which is to mitigate abnormal volatility and modify

[7] The complete results are provided upon request.

Table 6
Effectiveness of APL under markets with high and low price efficiency.

	High price efficiency market			
	NL		**APL**	**t-value**
Rolling Volatility	0.0127	<	0.0129	−1.873
	(0.0126,0.0128)		(0.0127,0.0130)	
Trade Volume	5.431	<	5.585	−1.948
	(5.325,5.536)		(5.472,5.536)	
Dollar Volume	56.899	<<<	59.863	−2.714
	(55.429,58.368)		(58.263,61.463)	
Quoted Spread	0.091	>>	0.079	2.435
	(0.084,0.098)		(0.073,0.085)	
Effective Spread	0.099	>>	0.088	2.276
	(0.091,0.106)		(0.081,0.094)	
% Quoted Spread	0.907		0.868	1.007
	(0.852,0.963)		(0.815,0.921)	
% Effective Spread	1.007		0.970	0.920
	(0.950,1.065)		(0.915,1.025)	
Market Depth	3.889	>>>	3.594	3.205
	(3.773,4.005)		(3.464,3.724)	
Price Deviation	0.558	<<<	0.564	−3.269
	(0.555,0.561)		(0.562,0.566)	
	Low price efficiency market			
	NL		**APL**	**t-value**
Rolling Volatility	0.0140	>>>	0.0136	5.386
	(0.0139,0.0141)		(0.0135,0.0137)	
Trade Volume	4.899		4.925	−0.363
	(4.802,4.996)		(4.818,5.033)	
Dollar Volume	42.351	<<<	45.253	−3.321
	(41.305,43.396)		(43.905,46.600)	
Quoted Spread	0.075	>>>	0.064	2.976
	(0.069,0.080)		(0.060,0.068)	
Effective Spread	0.081	>>	0.073	2.074
	(0.076,0.087)		(0.068,0.078)	
% Quoted Spread	0.898	>	0.830	1.894
	(0.845,0.950)		(0.782,0.877)	
% Effective Spread	0.991		0.951	1.040
	(0.937,1.045)		(0.898,1.004)	
Market Depth	3.356	<<<	3.958	−7.980
	(3.258,3.454)		(3.851,4.065)	
Price Deviation	0.620	>>>	0.601	10.463
	(0.619,0.622)		(0.599,0.604)	

Note: <<< and >>> significant at 1 % level, << and >> significant at 5 % level, < and > significant at 10 % level; the numbers in parentheses are 95 % confidence intervals.

irrational trading behavior. The simulated results demonstrate that asymmetric price limits can potentially reduce volatility by up to 12.5 %. In comparison to the real stock market, this reduction in magnitude is akin to the decrease in volatility observed in the Chinese stock market from the period of 2014.07–2017.10 (a period characterized by a bubble-crash) to the subsequent period of 2018.07–2021.10 (a relatively stable period), highlighting the significant stabilizing impact of asymmetric price limits on stock markets. Conversely, implementing asymmetric price limits in stable and efficient markets may lead to volatility spillover.

4. Sensitivity analysis

In order to understand how the simulation results are sensitive to the parameters chosen in Table 1, we perform the sensitivity analysis with a higher initial stock price, a higher initial trading agents' wealth, a lower interest rate and a lower degree of absolute risk aversion. The results shown in Table 7 reveal that the asymmetric price limit remains the most effective in three experiments with a higher stock price of 30, a higher wealth of 400, a lower interest rate of 0.005 and a lower degree of absolute risk aversion random (0.2)+0.3. This indicates that our basic results are still valid with various parameter settings, where asymmetric price limits present a better performance in improving market liquidity, controlling market volatility, and enhancing price discovery. Furthermore, compared to the basic results, the simulated findings suggest that an asymmetric price limit mechanism is more effective in stock markets characterized by lower stock prices, higher initial trading agent wealth, lower interest rates, and lower trading agents' risk aversion.

5. Conclusion

The study presented in this paper was designed to determine the impact of different price limit policies on market quality based on a heterogeneous agent-based model. From a point of stock performance, this study investigates the ways to guarantee financial support for prioritization schemes in industrial business processes. Our findings contribute to a deeper understanding of the effectiveness of price limits and offer practical implications for their design. The results indicate that asymmetric price limits indeed significantly control market volatility, as well as improve market liquidity and price efficiency. In particular, our simulated results suggest that an asymmetric price limit design could lead to a significant reduction in market volatility compared to both no price limit and symmetric price limit scenarios, with the potential for a 12.5 % decrease under certain conditions. In terms of economic significance, this reduction is consistent with the difference in volatility between bubble-crash periods and stable periods observed in the Chinese stock market. Compared with the previous studies that mainly focus on the size of price limits, we pay attention to its design. This study reflects pioneering research analysis to make the public aware that proposing the asymmetric price limit policy provides a deep understanding of the asymmetric effects of the upper and lower limits and supports the idea of the existence of volatility spillover.

In order to gain a more comprehensive understanding of the efficacy of asymmetric price limits and offer more nuanced and practical guidance on their implementation in real-world stock markets, this study also investigates their application conditions, including the selection of limit ranges and the appropriate market environment. Specifically, in line with previous research on symmetric price limits, this study emphasizes the importance of limit ranges in determining the effectiveness of asymmetric price limits. Overly restrictive limits are found to lead to volatility spillover, with 10 % identified as a relatively optimal range for asymmetric price limits. With regard to the market environment, our findings suggest that the mechanism of asymmetric price limits is effective in markets characterized by high volatility, low liquidity, and low price efficiency. This study offers a novel price limit design validated through simulated experiments, which provides policymakers with an effective tool for further controlling volatility and enhancing market quality in stock markets. Specially, policymakers and market regulators in stock markets, particularly those in emerging markets characterized by high volatility, low liquidity, and low price efficiency, could consider reforming their current price limit design to an asymmetric price limit design. Taking into account the diverse backgrounds and specific characteristics of individual markets, policymakers could adapt the models based on the unique features of each market and conduct re-simulation to determine a more customized price range for the asymmetric price limit design. Investigating the specific impacts of asymmetric price limits on different stock markets and providing more tailored advice for each market is also the direction of our future studies, which will be further discussed in the limitation of this study.

On the other hand, this study offers a general platform for researchers and policymakers to investigate the efficacy of various stock market policies beyond price limits. The basic heterogeneous agent-based model developed in this study is capable of replicating the trading mechanism and stylized facts observed in real stock markets, serving as an experimental platform to simulate the effects of different market policies on market quality, which can help identify potential issues and refine policy prior to implementation. Currently, there remains a lack of consensus regarding the effectiveness of certain stock market policies, such as settlement cycles and transaction taxes. These policies can all be examined and analyzed within this simulation platform.

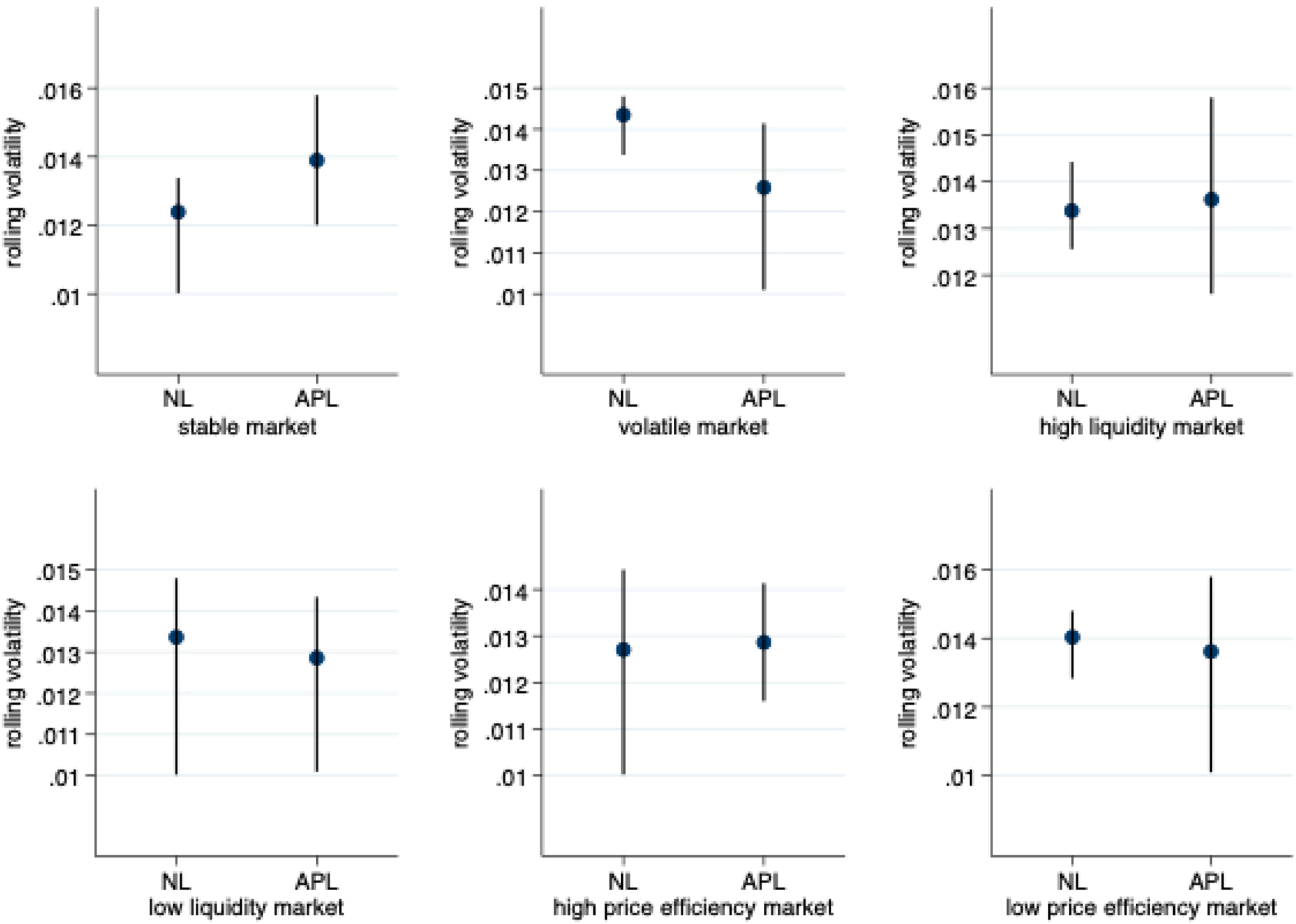

Fig. 12. Rolling volatility under APL and NL in different market conditions.

The stability of stock prices is a crucial factor in ensuring the sufficient financial resources of corporations, while stock market policies play a vital role in stabilizing stock markets. The proposed asymmetric price limit design in this study has the potential to effectively control market volatility and provide financial support for industrial companies, thereby facilitating the smooth implementation of prioritization schemes for business processes. Furthermore, this study provides a testbed for various designs of stock market policies, which can be applied to other contentious policies to enhance market quality and offer more robust financial guarantees for industrial companies.

The findings from this study have significant implications for industrial firms seeking to optimize their business processes. By ensuring a stable financial market environment, companies can more confidently invest in upgrading their manufacturing and supply chain technologies. This stability, fostered by well-designed market mechanisms like the asymmetric price limit, can provide the necessary foundation for long-term strategic investments in Industry 4.0 initiatives.

Some limitations of this study may encourage several directions for future research. First, the objective of this study is to investigate the fundamental effects of asymmetric price limit policy on stock markets. To achieve this, we constructed models to simulate a simplified and generalized stock market environment. As a result, our results could only provide general recommendations for stock markets. However, it is crucial to acknowledge that each stock market possesses its own distinct characteristics, which may pose potential challenges when implementing asymmetric price limits based on these general conclusions. To address this issue, before implementing the asymmetric price limit in a specific market, it is necessary to adapt the models according to the unique trading mechanism in the market and select parameters based on its specific characteristics. In comparison with the calibration method utilized in this research, the approaches summarized by Platt (2020) would be more effective when there is a target market to emulate. Subsequently, re-simulation should be carried out in the updated model to facilitate the development of a more targeted design scheme for the asymmetric price limit. Second, as a special phenomenon induced by price limits, the magnet effect has a negative effect on market quality. Although asymmetric price limits could promote market quality, they are unable to weaken the magnet effect. Thus, to further improve the effectiveness of asymmetric price limits, it is necessary to explore the generative mechanism of the magnet effect and develop coping strategies. Third, in this model, we have simplified the stock market participants to a single type of trading agent based on the CARA utility function. However, real stock markets consist of various types of market participants with different utility functions and trading strategies. Therefore, in order to enhance the accuracy of our model, it is essential to further differentiate between types of trading agents and incorporate other types of market participants into the simulation.

Author statement

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for

Table 7
Results of sensitivity analysis.

	Price (30)			
	NL		**APL**	**t-value**
Rolling Volatility	0.0162 (0.0161,0.0163)		0.0160 (0.0159,0.0162)	1.279
Trade Volume	6.448 (6.336,6.559)	<	6.586 (6.467,6.706)	−1.671
Dollar Volume	79.454 (77.959,80.949)	<<<	84.600 (82.870,86.330)	−4.442
Quoted Spread	0.120 (0.111,0.128)		0.111 (0.103,0.119)	1.529
Effective Spread	0.133 (0.124,0.141)		0.129 (0.120,0.138)	0.586
% Quoted Spread	0.892 (0.843,0.942)		0.873 (0.825,0.922)	0.529
% Effective Spread	1.010 (0.959,1.061)		1.021 (0.967,1.075)	−0.279
Market Depth	1.102 (1.079,1.126)	<<<	1.449 (1.413,1.485)	−15.790
Price Deviation	0.597 (0.596,0.599)	>>>	0.583 (0.581,0.585)	11.589
	Wealth (400)			
	NL		**APL**	**t-value**
Rolling Volatility	0.0142 (0.0140,0.0143)	>>>	0.0128 (0.0127,0.0129)	19.299
Trade Volume	5.099 (4.994,5.203)	<	5.213 (5.110,5.316)	−1.675
Dollar Volume	41.812 (40.818,42.806)	<<<	46.028 (45.025,47.032)	−6.326
Quoted Spread	0.066 (0.060,0.071)		0.060 (0.055,0.065)	1.532
Effective Spread	0.073 (0.067,0.078)		0.068 (0.063,0.073)	1.179
% Quoted Spread	0.806 (0.758,0.853)	>>>	0.716 (0.670,0.762)	2.659
% Effective Spread	0.907 (0.857,0.957)	>>	0.817 (0.768,0.866)	2.529
Market Depth	3.310 (3.207,3.414)	<<<	4.114 (4.008,4.220)	−10.303
Price Deviation	0.609 (0.606,0.611)	>>>	0.571 (0.569,0.573)	24.278
	Interest rate (0.005)			
	NL		**APL**	**t-value**
Rolling Volatility	0.0148 (0.0147,0.0149)	>>>	0.0146 (0.0145,0.0147)	3.074
Trade Volume	4.983 (4.884,5.082)	<<<	5.591 (5.479,5.704)	−8.170
Dollar Volume	48.034 (46.907,49.160)	<<<	57.247 (55.882,58.613)	−10.942
Quoted Spread	0.094 (0.087,0.101)	>>>	0.073 (0.068,0.079)	4.376
Effective Spread	0.105 (0.097,0.112)	>>>	0.083 (0.077,0.089)	4.519
% Quoted Spread	0.961 (0.905,1.017)	>>>	0.739 (0.695,0.784)	6.063
% Effective Spread	1.089 (1.030,1.149)	>>>	0.838 (0.791,0.884)	6.538
Market Depth	2.506 (2.423,2.589)	<<<	3.446 (3.335,3.556)	−12.995
Price Deviation	0.767 (0.765,0.769)	>>>	0.754 (0.752,0.755)	16.848
	Risk aversion (0.3)			
	NL		**APL**	**t-value**
Rolling Volatility	0.0138 (0.0137,0.0139)	>>>	0.0135 (0.0134,0.0136)	3.999
Trade Volume	6.381 (6.263,6.499)	<<<	7.048 (6.918,7.177)	−7.543
Dollar Volume	69.209 (67.518,70.900)	<<<	85.032 (82.862,87.202)	−11.752
Quoted Spread	0.087 (0.080,0.094)	>>>	0.071 (0.065,0.077)	3.610
Effective Spread	0.095 (0.088,0.102)	>>>	0.080 (0.074,0.086)	3.261
% Quoted Spread	0.853 (0.801,0.906)	>>>	0.703 (0.658,0.748)	4.275
% Effective Spread	0.954 (0.899,1.008)	>>>	0.803 (0.755,0.850)	4.085
Market Depth	4.996 (4.849,5.142)	>>	4.780 (4.636,4.925)	2.204
Price Deviation	0.537 (0.535,0.539)	>>>	0.514 (0.511,0.517)	15.158

Note: <<< and >>> significant at 1 % level, << and >> significant at 5 % level, < and > significant at 10 % level; the numbers in parentheses are 95 % confidence intervals.

publication elsewhere. We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We understand that the Corresponding Author is the sole contact for the Editorial process. He is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs.

CRediT authorship contribution statement

Qing Ye: Writing – review & editing, Supervision. **Jie Zhang:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition, Formal analysis. **Xinhui Yang:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Victor Chang:** Writing – review & editing, Validation, Resources, Project administration, Funding acquisition, Formal analysis.

Declaration of Competing Interest

This is hereby certify that the paper is original, neither the paper nor a part of it is under consideration for publication anywhere else. Also, we have no conflicts of interest with anyone to disclose. We confirm that the manuscript has been read and approved by all named authors.

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Data availability

The authors do not have permission to share data.

References

Ahmed, Z., Hla, D.T., 2019. Stock return volatility and capital structure measures of nonfinancial firms in a dynamic panel model: Evidence from Pakistan. Int. J. Financ. Econ. 24, 604–628.

Arifovic, J., He, X.Z., Wei, L., 2022. Machine learning and speed in high-frequency trading. J. Econ. Dyn. Control 139, 104438.

Barber, B.M., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Rev. Financ. Stud. 21 (2), 785–818.

Brenner, T., 2006. Agent learning representation: advice on modelling economic learning. In: Tesfatsion, L., Judd, K. (Eds.), Handbook of Computational Economics, vol. 2. Elsevier, Oxford, UK, pp. 617–631.

Chan, S.H., Kim, K.A., Rhee, S.G., 2005. Price Limit Performance: Evidence from Transactions Data and the Limit Order Book. J. Empir. Financ. 12 (2), 269–290.
Chang, C.H., Hsieh, S.L., 2008. Is the daily price limit of the taiwan stock exchange effective? Fundamentals of listed stocks and investors' perception of fair price. Korean J. Financ. Stud. 37 (4), 675–726.
Chen, S.H., Chang, C.L., Du, Y.R., 2012. Agent-based economic models and econometrics. Knowl. Eng. Rev. 27 (02), 187–219.
Chen, S.H., Yeh, C.H., 2001. Evolving traders and the business school with genetic programming: a new architecture of the agent-based artificial stock market. J. Econ. Dyn. Control 25 (3-4), 363–393.
Chiarella, C., 1992. The dynamics of speculative behaviour. Ann. Oper. Res. 37 (1), 101–123.
Chiarella, C., He, X.Z., Shi, L., Wei, L., 2017. A behavioural model of investor sentiment in limit order markets. Quant. Financ. 17 (1), 71–86.
Creamer, G., Freund, Y., 2010. Automated trading with boosting and expert weighting. Quant. Financ. 10 (4), 401–420.
Dai, X., Zhang, J., Chang, V., 2023. Noise traders in an agent-based artificial stock market. Ann. Oper. Res.
Dalko, V., 2016. Limit up–limit down: an effective response to the "flash crash"? J. Financ. Regul. Compliance 24 (4), 420–429.
Danışoğlu, S., Güner, Z.N., 2018. Do price limits help control stock price volatility? Ann. Oper. Res. 260 (1-2), 129–157.
Dorigatti, M., Guarnaschelli, A., Chiotti, O., Salomone, H.E., 2016. A service-oriented framework for agent-based simulations of collaborative supply chains. Comput. Ind. 83, 92–107.
Duffy, J., 2006. Agent-based models and human subject experiments. In: Tesfatsion, L., Judd, K. (Eds.), Handbook of Computational Economics: Agent-Based Computational Economics, vol. 2. Elsevier, Oxford, UK, pp. 949–1011.
Esfahanipour, A., Mousavi, S., 2011. A Genetic Programming Model to Generate Risk-adjusted Technical Trading Rules in Stock Markets. *Expert Syst. Appl.* 38, 8438–8445.
Fama, E.F., 1989. Perspectives on October 1987, or, What did We Learn from the Crash? In: Kamphuis Jr., R.W., Kormendi, R.C., Watson, J.W.H. (Eds.), Black Monday and the Future of Financial Markets. Mid America Institute for Public Policy Research, Chicago, IL, pp. 71–82.
Farmer, J.D., Joshi, S., 2002. The price dynamics of common trading strategies. J. Econ. Behav. Organ. 49, 149–171.
He, X.Z., Li, Y., 2015. Testing of a Market Fraction Model and Power-law Behaviour in the DAX 30. J. Empir. Financ. 31, 1–17.
Hong, H., Bian, Z., Lee, C.C., 2021. Covid-19 and instability of stock market performance: evidence from the U.S. Financ. Innov. 7 (1), 12.
Hou, K., Xiong, W., & Peng, L. (2009). *A tale of two anomalies: The implications of investor attention for price and earnings momentum.*
Huang, Y., 1998. Stock Price Reaction to Daily Limit Moves: Evidence from the Taiwan Stock Exchange. J. Bus. Financ. Account. 469–483.
Huang, Y.S., Fu, T.W., Ke, M.C., 2001. Daily Price Limits and Stock Price Behavior: Evidence from the Taiwan Stock Exchange. Int. Rev. Econ. Financ. 10 (3), 263–288.
Kim, K.A., Limpaphayom, P., 2000. Characteristics of stocks that frequently hit price limits: empirical evidence from Taiwan and Thailand. J. Financ. Mark. 3 (3), 315–332.
Kim, K.A., Liu, H., Yang, J.J., 2013. Reconsidering Price Limit Effectiveness. J. Financ. Res. 36 (4), 493–518.
Kim, K.A., Park, J., 2010. Why Do Price Limits Exist in Stock Markets? A Manipulation-based Explanation. Eur. Financ. Manag. 16 (2), 296–318.
Kim, K.A., Rhee, S.G., 1997. Price limit performance: evidence from the tokyo stock exchange. J. Financ. 52 (2), 885–901.
Latoufis, K.C., Vassilakis, A.I., Grapsas, I.K.K., Hatziargyriou, N.D., 2024. Design Optimization and Performance Evaluation of Passive Filters for Acoustic Noise Mitigation in Locally Manufactured Small Wind Turbines. IEEE Trans. Ind. Appl. 60 (3), 4350–4365.
Laubenbacher, R., Hinkelmann, F., Oremland, M., 2013. Agent-based models and optimal control in biology: a discrete approach. In: Robeva, R., Hodge, T.L. (Eds.), Mathematical concepts and methods in modern biology. Academic Press, Boston, pp. 143–178.
LeBaron, B., 2006. Agent-based computational finance. In: Tesfatsion, L., Judd, K.L. (Eds.), Handbook of computational economics, 2. Elsevier, pp. 1187–1233.
Lehmann, B.N., 1989. Commentary: Volatility, Price Resolution, and the Effectiveness of Price Limits. J. Financ. Serv. Res. 3 (2-3), 205–209.
Li, Y., 2019. Multifractal view on china's stock market crashes. Phys. A 536, 122591.
Li, H., Zheng, D., Chen, J., 2014. Effectiveness, Cause and Impact of Price Limit—Evidence from China's Cross-listed Stocks. J. Int. Financ. Mark., Inst. Money 29, 217–241.
Lux, T., 1995. Herd Behaviour, Bubbles and Crashes. Econ. J. 105 (431), 881–896.
Ma, C.K., Rao, R.P., Sears, R.S., 1989a. Volatility, price resolution, and the effectiveness of price limits. In Regulatory Reform of Stock and Futures Markets. Springer, Dordrecht, pp. 67–101.
Ma, C.K., Rao, R.P., Sears, S., 1989b. Limit Moves and Price Resolution: The Case of the Treasury Bond Futures Market. J. Futures Mark. 9 (4), 321.
Mizuta, T. (2019). An Agent-based Model for Designing a Financial Market that Works Well. arXiv.
Mizuta, T., Izumi, K., & Yoshimura, S. (2013b). Price variation limits and financial market bubbles: artificial market simulations with agents' learning process. *2013 IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr)*, Singapore, 1–7. https://doi.org/10.1109/CIFEr.2013.6611689 (accessed 24 September 2024).
Mizuta, T., Izumi, K., Yagi, I., Yoshimura, S., 2013a. Design of financial market regulations against large price fluctuations using by artificial market simulations. J. Math. Financ. 3, 15–22.
Mizuta, T., Kosugi, S., Kusumoto, T., Matsumoto, W., Izumi, K., Yagi, I., Yoshimura, S., 2016. Effects of Price Regulations and Dark Pools on Financial Market Stability: an Investigation by Multiagent Simulations. Intell. Syst. Account., Financ. Manag. 23 (1-2), 97–120.
Murphy, N.J., Gebbie, T.J., 2021. Learning the dynamics of technical trading strategies. Quant. Financ. 21 (8), 1325–1349.
Platt, D., 2020. A comparison of economic agent-based model calibration methods. J. Econ. Dyn. Control 113, 103859.
Presidential Task Force on Market Mechanisms (1988). Report of the Presidential Task Force on Market Mechanisms. US Government Printing Office.
Rolón, M., Martínez, E., 2012. Agent-based modeling and simulation of an autonomic manufacturing execution system. Comput. Ind. 63, 53–78.
Seasholes, M.S., Wu, G., 2007. Predictable behavior, profits, and attention. J. Empir. Financ. 14 (5), 590–610.
Securities and Exchange Commission (SEC) (2019). SEC Approves Proposals to Address Extraordinary Volatility in Individual Stocks and Broader Stock Market, 1 June 2012, available at: ⟨www.sec.gov/News/PressRelease/Detail/PressRelease/1365171482422⟩ (accessed April 2, 2024).
Sifat, I.M., Mohamad, A., 2020. A Survey on the Magnet Effect of Circuit Breakers in Financial Markets. Int. Rev. Econ. Financ. 69, 138–151.
Ta, A., Tarakci, H., Kulkarni, S., Prybutok, V., Pavur, R., 2023. The effects of cyber threats on maintenance outsourcing and age replacement policy. Comput. Ind. 144, 103787.
Wei, L., Shi, L., 2020. Investor sentiment in an artificial limit order market. Complexity 2020.
Westerhoff, F., 2004. Speculative markets and the effectiveness of price limits. J. Econ. Dyn. Control 28 (3), 493–508.
Wong, K.M., Kong, X.W., Li, M., 2020. The Magnet Effect of Circuit Breakers and its Interactions with Price Limits. Pac. -Basin Financ. J. 61, 101325.
Wruck, K.H., 1990. Financial distress, reorganization, and organizational efficiency. J. Financ. Econ. 27, 419–444.
Yang, X., Zhang, J., Ye, Q., 2020. Tick Size and Market Quality: Simulations Based on Agent-based Artificial Stock Markets. Intell. Syst. Account., Financ. Manag. 27 (3), 125–141.
Yeh, C., Yang, C., 2010. Examining the Effectiveness of Price Limits in an Artificial Stock Market. J. Econ. Dyn. Control 34 (10), 2089–2108.
Yeh, C.H., Yang, C.Y., 2013. Do Price Limits Hurt the Market? J. Econ. Interact. Coord. 8 (1), 125–153.
Zhang, X., Ping, J., Zhu, T., Li, Y., Xiong, X., 2016. Are price limits effective? an examination of an artificial stock market. PLoS ONE 11 (8), 1–21.
Zhang, X., Wang, Z., Hao, J., He, F., 2022. Price Limit and Stock Market Quality: Evidence from a Quasi-natural Experiment in the Chinese Stock Market. Pac. -Basin Financ. J. 74, 101778.
Zhang, G., Yang, Y., Yang, G., 2023. Smart supply chain management in Industry 4.0: the review, research agenda and strategies in North America. Ann. Oper. Res. 322, 1075–1117.