Reexamining the Impact of Closing Call Auction on Market Quality : A Natural Experiment from the Shanghai Stock Exchange

Qian Han

Xiamen University, South Siming Road, Xiamen, Fujian 361005, China

Chengzhi Zhao

Xiamen University, South Siming Road, Xiamen, Fujian 361005, China

Jing Chen (corresponding author)

Cardiff University, Senghennydd Road, Cardiff CF24 4AG, UK

Qian Guo

Birkbeck College, University of London, London WC1E 7HU, UK

Abstract

Using the intraday and daily data of Chinese A shares in Shanghai and Shenzhen from May to January 2018, this paper examines the regulatory impact of the Shanghai closing call auction on market liquidity, volatility, and price effectiveness using the Difference-in-Difference (DID) method. We find that the Shanghai closing call auction has no significant impact on market liquidity, but has resulted in 1) a shift of trading volume from closing to pre-closing; 2) increased volatility at pre-closing; 3) significant improvement in the continuity of the closing price; and 4) no prominent improvement on price effectiveness. Also, the regime appears to have a pronounced impact, particularly on small-cap stocks. Our findings suggest that the introduction of the Shanghai closing call auction helps reduce the risk of small-cap stocks, meanwhile improve the continuity of closing and pre-closing prices.

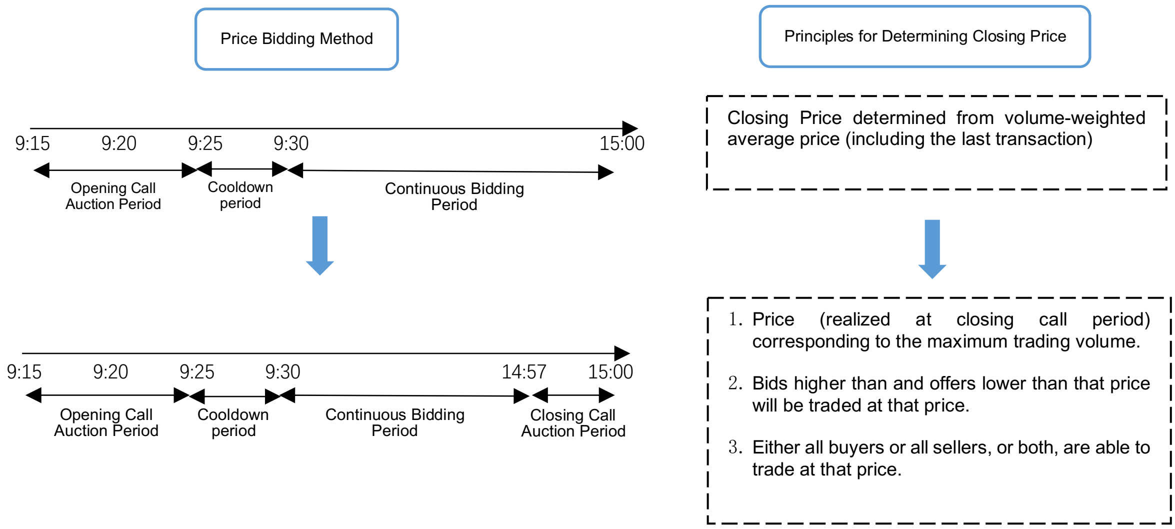
Keywords: Closing Call Auction; Market Liquidity; Market Volatility; Closing Price Manipulation

JEL: G10; G14; G18

1 Introduction

The Chinese capital market saw a nationwide infrastructure reform since the beginning of 2018. The State Council and the China Securities Regulatory Committee (CSRC) sets its agenda, with an aim to achieve a stable, robust, yet more dynamic capital market through some key regulatory changes. One of the regulatory changes is on the closing auction in the Shanghai Stock Exchange (SSE) where the continuous auction has been changed to call auction in the last three minutes of trading (one-time matching within a specified period of time) since August 20, 2018. Under such a new regime, the closing price determination changed from the previous volume-weighted average price (including the last transaction) based on all transactions in the last one minute of trading *to the price purely generated by call auction* (see Figure 1 for specifics). In fact, the way of determining the closing price with a closing call auction could be traced back to 2006 when the Shenzhen Stock Exchange (SZSE), the other stock exchange in China, first adopted such a regime. Hence, the ultimate purpose of the reform on the same closing pricing mechanism brought by SSE is to align the two major national stock exchanges in China for a more consistent trading mechanism.

Figure 1: Reform of the Closing Auction at the Shanghai Stock Exchange



Notes: Since August 20, 2018, the closing auction in the Shanghai Stock Exchange (SSE) underwent a fundamental regulatory change where the continuous auction has been changed to call auction in the last three minutes of trading (one-time matching within a specified period of time). Under such a new regime, the closing price determination is based on the price purely generated by call auction.

In accordance with the SSE's announcement and media reports, the reform aims to increase the difficulty in manipulating the closing price, maintain the price stability at the closing period of trade, reduce the adverse effect from abnormal volatility in the closing price, and thus maintain the order of trade and protect the rights and interests of investors. It is, therefore, intriguing to explore whether such a reform of the trading system has indeed achieved the desired effect and how it affects the quality of the market. To answer this question, we focus on traders' behavior - ultimately, the market quality depends on how investors trade. In light of this, the first root question we want to address is how the Close Auction System (CAS) affects trading behavior.

Aitken et al. (2005) argue that the impact of the closing call auction on trading activity lies in two aspects. First, it may lead to the inflow of new orders or outflow of original orders, resulting in an increase or decrease in the overall trading volume. Second, the trading volume may be redistributed given that the overall volume is unchanged. It is argued that traders may choose to postpone transactions that were originally earmarked for continuous auction to the call auction session because of the low transaction costs and high informational efficiency that call auction brings. Alternatively, informed traders may advance their transactions to the continuous auction session due to the weakening in the advantage of private information in the call auction and increased difficulty in leveraging insider information for price manipulation. Liquidity traders may also move trading forward to the continuous auction session due to their concerns about the overnight financial risk from the incomplete execution of the trading order. Naturally, all these changes in the trading behavior due to the introduction of closing call auction may well generate some important impact on market quality.

Even if the logical relationship between the closing call auction and trading activities is clear, however, it is not easy to testify exactly the impact of the closing call auction reform on the market quality. Theoretically, the pro-call-auction school of thought believes that the concentration of orders during call auction can reduce transaction costs and so attract more traders. Also, traders can infer the behavior of other traders based on the information revealed by the indicative prices and indicative volume. These factors help reduce information asymmetry, and price tends to reflect the intrinsic value of the stock. Others argue that there is no major difference in the pricing behavior under call auction and continuous auction, and the price discovery under continuous auction appears more efficient. This is because call auction may attract noise traders, thus enlarging the pricing errors. For instance, Kyle (1985) finds that noise traders' losses double in the continuous market when compared with a single call auction. Also, Pagano and Roell (1996) find that the call auction leads to lower expected trading costs for noise traders than in a continuous auction, because of the greater transparency of the call auction. Schnitzlein (1996) provided theoretical support to suggest that noise traders incur lower levels of adverse selection costs under a call auction. Madhavan (1992) shows that periodic auctions appear less likely to close down than a continuous trading system under severe asymmetric information.

Apart from the above theoretical studies, many empirical studies tend to render ununified results (about how the closing auction affects the trading behavior) either. The actual regulatory impact seems to depend on specific rules and regulations underpinning the closing auction and not all closing call auction systems seem to be successful. One typical empirical finding is based on the pilot version of the closing call auction system introduced by Hong Kong Exchange (HKEx) in 2008. The closing prices of many stocks became more volatile after the introduction of the new regime, leading to an end of the policy after ten months of the regime being implemented. It was not until 2016 that HKEx introduced an improved version of the closing call auction system and gradually expanded the range of pilot stocks over the next few years in a careful manner. Park et al. (2020) undertake a study on this improved version of the closing call auction system in Hong Kong. The study uses the difference-in-difference method and finds that the new version significantly alleviates the manipulation problem in the closing price. Comerton-Forte et al. (2007), however, examine the impact of the 2002 open call auction on the quality of the market in Hong Kong. Their results show that the market quality indicators decrease under the open call auction.

Aitken et al. (2005) study the impact of the closing call auction system on the Australian Stock Exchange in 1997. Under the system, the closing price is set to be the volume-weighted average price (VWAP) based on the last two transaction prices, and no indicative price is provided throughout the closing period. The study finds that the volume detected during the last two hours of the continuous auction session drifts to the call auction session, but has no significant impact on the intraday bid-ask spread. In 2002, the Australian Stock Exchange introduced another reform on the closing call auction system, providing both indicative volume and indicative prices to further improve information transparency. Moreover, the existing method of calculating the closing price was modified to prevent price manipulations. Comerton-Forde and Rydge (2006) find that the indicative prices in the call auction appear closer to actual prices than before, indicating that the closing call auction facilitates price discovery. Nevertheless, there is no significant improvement in information efficiency during the closing auction session.

The empirical literature on other markets also seems to generate diverse findings of how the closing auction affects trading behavior. In the case of France, the Paris Stock Exchange first introduces the closing call auction system in 1996, which is initially applied to illiquid Class B stocks and later extends to liquid Class A stocks. Pagano and Schwartz (2003) examine the impact of such an event and find that investors moved their trading in the first 15 minutes of the continuous trading session to the closing call auction session, making the closing price more efficient and thus facilitating price discovery.

Chinese scholars have also carried out many enriched studies about the closing auction mechanism. Trading System Research Group (2016) [1] shows that the closing auction implemented in the Shenzhen Stock Exchange effectively prevents the behavior of "phishing"

[1] The article is in Chinese and published in a Chinese academic journal.

manipulation. Additionally, the closing call auction system of the Shenzhen Stock Exchange appears unsuitable for mechanisms such as random closing of the market. Li et al. (2018)[2] build theoretical models characterizing the closing price manipulation to empirically test the impact of the manipulation indicators on market liquidity. The results show that manipulation of the closing price leads to higher transaction costs and lower liquidity, which appears prominent in a volatile market.

Generally speaking, the literature tends to support that the closing call auction helps alleviate the problem of closing price manipulation and improve price continuity. However, the impact of the regime on market quality remains largely inconclusive.

One common phenomenon in the literature we explained above is that the adoption of different approaches has led to different conclusions, which may be one of the reasons why there is inconsistency in their empirical findings (apart from the reason of diversity in the regime itself, which inevitably leads towards that inconsistency). After all, the key to research on policy evaluation is to identify the causal relationship and eliminate the impact of confounding factors. To this end, we make full use of the fact that mainland China has two national stock exchanges (Shanghai and Shenzhen) where Shenzhen implemented the closing call auction system before Shanghai. On the basis of this, a difference-in-difference method (DID) is employed to empirically analyze and explain the impact of closing call auction on market liquidity, volatility, and price effectiveness. Our empirical results show that after the closing call auction is applied to the Shanghai Stock Exchange, 1) no significant change to the market liquidity in the last 15 minutes of closing is detected, 2) percentage of closing volume

[2] The article is in Chinese and published in a Chinese academic journal.

in the all-day trading volume has decreased significantly, 3) there exists a tendency for the closing volume to shift towards the 3-minute interval before the start of the closing call auction (i.e. the last 3-minute session of the continuous auction), 4) volatility increases prominently 15 minutes before closing, and then declines prominently from the continuous auction session to the closing of trade, 5) there is no significant improvement on price effectiveness. The reason for these empirical observations may be that informed traders avoid the increased overnight financial risk due to incomplete execution of trading order and increased costs of manipulating the closing price during the call auction, and therefore, will want to trade before the start of the closing call auction. This leads to an increase in the pre-closing volatility, and also, an improvement in the continuity of both closing and pre-closing prices. This, in turn, suggests that the closing call auction at the Shanghai Stock Exchange has achieved its expected regulatory objectives in general.

Our paper contributes to the literature in the following aspects. First, existing research has its tremendous focus on the closing call auction of SZSE and opening call auction of both SZSE and SSE, with a minimum focus on the closing call auction of SSE. This paper intends to generate an integrated body of research on the call auction literature, in particular, of the Chinese stock market as a whole through the provision of complementary empirical evidence of SSE. Second, a large number of studies explores the regulatory impact of the trading mechanism on the market quality, however, very few of them considers the difference-in-difference method to address the same research question. Here, we use the DID method to study the regulatory impact of the closing call auction which gets around the endogeneity problem and produces robust statistical inferences. Also, this article analyzes and explains the diverse impact of the closing call auction on stocks with different market values.

2 Data and Testable Framework

2.1 Sample Selection and Source of Data

Because the SSE began implementing the closing call auction system on August 20, 2018, we classify the sample period into two three-month episodes - one episode corresponds to the time period before the implementation of the system, and the other episode corresponds to the time period after the implementation. In other words, our total sample period is from May 21 until November 20, 2018, and the two sub-sample periods are from May 21 to August 19 and from August 20 to November 20, 2018, respectively. The data are downloaded from the China Stock Market & Accounting Research (CSMAR), including the transaction-by-transaction and intraday high-frequency data and daily data of all A shares traded in Shanghai and Shenzhen stock exchanges. The dataset excludes stocks with changed equity in the sample period, especially those stocks with special treatments, newly listed and exited stocks, stocks that do not cover the entire sample range on the trading day, and stocks with missing data. In addition, this paper excludes the Shenzhen Stock Exchange small and medium-sized board and GEM shares to ensure reasonable matching to the SSE stocks. Finally, 738 Shanghai A shares and 172 Shenzhen A shares were selected from all A shares traded during the selected sample period.

2.2 The Construction of Market Quality Indicators

We take three indicators to proxy for the financial market quality: market liquidity (ability to trade a reasonable number of financial assets efficiently at a fair price), market volatility (frequency and magnitude of price changes), and effectiveness of price discovery (ability of asset price in transmitting the information) (see Table 1).

Market Liquidity

We use relative bid-ask spread, trading volume, and quoted depth (see, for example, Han and Liang, 2017) to measure the stock market liquidity during continuous auction trading. In principle, the smaller the relative bid-ask spread, the greater the trading volume, the deeper the quoted depth, and the more liquid the stock market is. The relative bid-ask spread and quoted depth are defined as follows:

$$RSP_{i,t}^{m} = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{S_{i,j,t} - B_{i,j,t}}{(S_{i,j,t} + B_{i,j,t})/2} \times 100,$$

$$Depth_{i,t}^{m} = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{S_{i,j,t} \times SV_{i,j,t} + B_{i,j,t} \times BV_{i,j,t}}{2} \times 100.$$

where for a given trading day t, $RSP_{i,t}^{m}$ is the average relative bid-ask spread of stock i during time period m; $B_{i,j,t}$、$S_{i,j,t}$, $BV_{i,j,t}$ and $SV_{i,j,t}$ are the best bid price, best ask price, quoted volume at the best bid price, and quoted volume at the best ask price for stock i at intraday time j during period m, respectively; and N_t is the total number of time intervals of period m. The time period under our empirical examination includes the entire trading day (excluding call auction) and one 15-minute session prior to closing (14:42-14:57). To understand precisely how liquidity evolves with time, we further divide that 15-minute session prior to closing into three five-minute intervals to obtain narrow time windows for investigation.

Relative Volume

Due to the lack of trading data, this article uses the relative volume approach (see Aitken et al., 2005) to reflect traders' engagement during continuous trading. Relative volume is defined as the percentage of trading volume at a given time interval in the overall trading volume during a day.

$$dV_{i,t}^{m} = Vol_{i,t}^{m}/Vol_{i,t}^{T},$$

where $Vol_{i,t}^{m}$ is the volume traded in the time interval m on a given day t for stock i; $Vol_{i,t}^{T}$ is the total trading volume on day t for stock i. The higher the ratio, the more liquid the stock market is, and the more active the traders are at the given time interval. In particular, the relative volume at the closing, $dV_{i,t}^{C}$, captures the liquidity of the market during the closing period. The higher the value of $dV_{i,t}^{C}$, the more active the traders are, and the more liquid the market is at the closing.

Price Volatility

We use Andersen et al.'s（2003）realized volatility to model the unobservable volatility of asset prices during continuous auction trading, using high-frequency 1-minute data. The Andersen et al.'s（2003）realized volatility is defined as follows:

$$Rv_{i,t}^{m} = \sqrt{\sum_{j=1}^{n} r_{i,j,t}^{2}} \times 100,$$

where $r_{i,j,t}$ is the logarithmic return for i'th stock traded on t'th day in j's minute during m'th time interval. n refers to the total minutes in m'th time interval. More specifically, m=15 with $Rv_{i,t}^{15}$, which is the realized volatility 15 minutes before closing, well captures the price fluctuation before closing call auction. In light of the approaches in modelling volatility of asset price by Ko et al. (1995) and by 2014 Shanghai Stock Exchange's study of the closing trading mechanism, we use price deviation to characterize volatility during the closing, which is defined as follows:

$$Pv_{i,t} = \frac{|P_{i,t}^{C} - VWAP_{i,t}|}{VWAP_{i,t}},$$

where $P_{i,t}^{C}$ is the closing price for i'th stock traded on t'th day; $VWAP_{i,t}$ is the volume-weighted average price 15 minutes before closing for i'th stock on t'th day. Hence, the price deviation, $Pv_{i,t}$, measures the deviation of the closing price away from a reference price (we choose the volume-weighted average price 15 minutes before closing as the reference price). The smaller the price deviation, that is, the smaller the deviation of the closing price from the pre-closing average price, the smaller the fluctuation in the closing price, and the higher the price continuity.

Effectiveness of Price Discovery

We use Amihud et al.'s (1997) relative return dispersion approach as a descriptive measure to evaluate the efficiency of a trading mechanism. In particular, we define the relative return dispersion $RRD_{i,t}$ as the absolute value of the residuals of the following multiple regression model, performed on stock i traded on day t:

$$R_{i,t} = \alpha + \beta_1 R_{m,t} + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{i,t},$$

$$RRD_{i,t} = |\varepsilon_{i,t}|$$

where $R_{i,t}$ is the return on the i'th stock on t'th day; $R_{m,t}$ is the daily return on the market portfolio m; SMB_t captures the return on the firm size on day t; and HML_t represents the return on market-to-book ratio on the t'th day. The smaller the relative return dispersion, the more efficient the price discovery process.

We also use Stoll's (2000) relative volatility of the opening – a volatility measure to measure trading frictions at the opening:

$$OV_{i,t} = |P_{i,t}^O - P_{i,t-1}^O| - |P_{i,t}^C - P_{i,t-1}^C|,$$

where $OV_{i,t}$ is the opening volatility relative to volatility at the close for stock i traded on day t; $P_{i,t}^O$ and $P_{i,t}^C$ are the opening and closing prices for the same stock i traded on day t, respectively. The closer the $OV_{i,t}$ approaches 0, the smaller the trading frictions at the opening, and the more effective the trading mechanism is.

Table 1: Approaches to Measuring Liquidity, Volatility, and Price Effectiveness

Market Quality Proxy	Dependent Variable	Variable Construction
Liquidity	Relative Bid-Ask Spread	$RSP_{i,t}^{m} = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{S_{i,j,t} - B_{i,j,t}}{(S_{i,j,t} + B_{i,j,t})/2} \times 100$
	Trading Volume	$Vol_{i,t}^{m}$
	Quoted Depth	$Depth_{i,t}^{m} = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{S_{i,j,t} \times SV_{i,j,t} + B_{i,j,t} \times BV_{i,j,t}}{2} \times 100$
	Relative Volume	$dV_{i,t}^{m} = Vol_{i,t}^{m}/Vol_{i,t}^{T}$
Volatility	Realized Volatility	$Rv_{i,t}^{m} = \sqrt{\sum_{j=1}^{n} r_{i,j,t}^{2}} \times 100$
	Price Deviation	$Pv_{i,t} = \frac{\lvert P_{i,t}^{C} - VWAP_{i,t}\rvert}{VWAP_{i,t}}$
Price Discovery	Relative Return Dispersion	$R_{i,t} = \alpha + \beta_1 R_{m,t} + \beta_1 SMB_t + \beta_1 HML_t + \varepsilon_{i,t}$ $RRD_{i,t} = \lvert\varepsilon_{i,t}\rvert$
	Excess Volatility	$OV_{i,t} = \lvert P_{i,t}^{O} - P_{i,t-1}^{O}\rvert - \lvert P_{i,t}^{C} - P_{i,t-1}^{C}\rvert$

2.3 Testable Framework

A standard DID analysis is applied to the following panel data regression:

$$Y_{i,t} = \alpha + \mu_i + \lambda_t + \varphi D_i \times D_t + \beta X_{i,t} + \varepsilon_{i,t},$$

where $Y_{i,t}$ is the dependent variable characterizing the market liquidity, volatility, and price discovery. μ_i and λ_t represent the stock and time fixed effects, respectively. $X_{i,t}$ is a vector of control variables. D_i is a dummy variable representing the treatment group, i.e. $D_i = 1$ if stock i is a component stock of Shanghai A shares, and $D_i = 0$ otherwise. D_t is a dummy variable representing the treatment period, i.e., $D_t = 1$ if t falls under any day after the introduction of the closing call auction system, and $D_t = 0$ otherwise. By design, the coefficient ϕ indicates the net effect of the introduction of the closing call auction on the dependent variable. Standard deviations are clustered at the stock level.

We base our selection of the control variables on the existing literature (see Table 2). For example, our selection of the control variables for the liquidity indicators is primarily based on Han and Liang's (2017) approach. In particular, we use realized volatility, trading volume, and logarithmic average transaction prices as the control variables for the *relative bid-ask spread*, because they are supposed to be highly correlated with the relative bid-ask spread. More specifically, the higher the volatility, the greater the risk a trader faces in trading, and the higher the transaction cost induced by the bid-ask spread. Also, the higher the volume, the smaller the transaction cost of altering the order that a trader places, and the smaller the bid-ask spread. Moreover, faced with limited funds, the number of shares that a trader can invest in is determined directly by the stock price. The higher the nominal price, the higher the transaction cost, and the higher the bid-ask spread.

In addition, the higher the volatility, the larger the firm size, and the higher the stock return, which reflects high volume. In light of these, this paper uses realized volatility, firm size and stock return as the control variables for the *trading volume*.

And finally, the lower the volatility, the larger the size of the firm, the greater the volume of trading, and the deeper the depth of the quote. Therefore, this paper uses realized volatility, firm size and volume as the control variables for *quoted depth*.

For relative volume, we use Aitken et al.'s (2005) approach by taking return, realized volatility, logarithmic daily trading volume, and logarithmic firm size as the control variables.

In general, the larger the firm size, the greater the volume, and the greater the number of transactions, and so, the greater the volatility. Hence, in the regression equation of realized volatility, we use the logarithmic firm size, volume, and the number of transactions as the control variables. For the price deviation, the higher the realized volatility 15 minutes before closing, the higher the closing return and hence the higher the price deviation. Additionally, the closing volume has an impact on price deviation too. Therefore, we use the realized volatility 15 minutes before closing, logarithmic closing volume and the absolute value of closing return as the control variables for the regression equation of price deviation.

In terms of the effectiveness of price discovery, this paper uses the logarithmic daily volume as the control variable for the regression equation of relative return dispersion. We also use the logarithmic closing price and logarithmic daily volume as the control variables of excessive volatility.

Table 2: Control Variables for Regression Analyses

<table>
<tr><th>Market Quality Proxy</th><th>Dependent Variable</th><th>Control Variables</th><th>Definition of the Control Variables</th></tr>
<tr><td rowspan="4">Liquidity</td><td>Relative Bid-Ask Spread (RSP)</td><td>$Rv^m_{i,t}$, $\ln Vol^m_{i,t}$, $\ln P^m_{i,t}$</td><td rowspan="6">$Rv^m_{i,t}$ realized volatility for a given time interval m

$Rv^{15}_{i,t}$ realized volatility 15 minutes before closing

$\ln P^m_{i,t}$ logarithm of the arithmetic average of the transaction prices for a given time interval m

$\ln P^C_{i,t}$ logarithmic closing price

$\ln FSize_{i,t}$ logarithmic firm size,</td></tr>
<tr><td>Trading Volume (Vol)</td><td>$Rv^m_{i,t}$, $Return^m_{i,t}$, $\ln FSize_{i,t}$</td></tr>
<tr><td>Quoted Depth ($Depth$)</td><td>$Rv^m_{i,t}$, $\ln Vol^m_{i,t}$, $\ln FSize_{i,t}$</td></tr>
<tr><td>Volume Ratio (dV)</td><td>$Rv^m_{i,t}$, $\ln Vol^T_{i,t}$, $\ln FSize_{i,t}$, $Return^m_{i,t}$ or $Return^C_{i,t}$</td></tr>
<tr><td rowspan="2">Volatility</td><td>Realized Volatility (Rv)</td><td>$\ln Vol^{15}_{i,t}$, $\ln NT^{15}_{i,t}$, $\ln FSize_{i,t}$</td></tr>
<tr><td>Pricing Deviation</td><td>$Rv^{15}_{i,t}$, $\ln Vol^C_{i,t}$, $|Return^C_{i,t}|$</td></tr>
</table>

	(Pv)		proxied by the market value of tradable, circulating shares
Price Discovery	Relative Return Dispersion (RRD)	$\ln Vol_{i,t}^{T}$	$Return_{i,t}^{m}$ m-period logarithmic return (difference between logarithmic end price and logarithmic starting price for a given time interval m)
	Excess Volatility (OV)	$\ln Vol_{i,t}^{T}$, $\ln P_{i,t}^{C}$	$Return_{i,t}^{C}$ closing return (difference between logarithmic closing price and logarithmic average closing price 15 minutes before closing) $\ln Vol_{i,t}^{m}$ logarithmic trading volume for a given time interval m $\ln Vol_{i,t}^{C}$ logarithmic closing volume $\ln Vol_{i,t}^{T}$ logarithmic daily trading volume $\ln NT_{i,t}^{15}$ logarithmic number of transactions 15 minutes before closing

2.4 Stock Matching

In light of the diverse characteristics between Shanghai and Shenzhen stock markets, it is quite difficult for all Shenzhen A shares to form a counterfactual control group corresponding to Shanghai A shares. So, we use stock matching to generate the treatment and control groups that satisfy the parallel trend assumptions and then proceed with the DID analysis. Based on Bae et al. (2004) and Xie and Mo (2014), we use the stock information from May 20 to August 19, 2018 (i.e. before the implementation of the SSE closing call auction system) to match Shanghai A shares with Shenzhen A shares. We first run the following regressions to get an estimated coefficient of α:

$$Y_i = \alpha_0 + \alpha \cdot X_i + \varepsilon_i$$

where Y_i is the time series average of the measurement of liquidity, volatility, and price effectiveness for stock i before August 20, 2018, and X_i is a control variable vector with each element being the time series average of the control variables for stock i before August 20, 2018. We then calculate the distance between the i'th stock and j'th stock:

$$Distance_{i,j} = (X_i - X_j)'\hat{\alpha}'\hat{\alpha}(X_i - X_j),$$

where stock i is the Shanghai A shares, and stock j is the Shenzhen A shares. Finally, according to the 2012 China Securities Regulatory Commission (CSRC) Class One Securities Industry Code (SIC), the stock pair (i, j) is restricted to the same industry, using the latest industry classification standard of 2012. We then construct matched pairs of stocks by minimizing the distance between the two stocks. If a Shenzhen stock appears close to a few different Shanghai stocks, we pair the closest Shanghai stock with that Shenzhen stock, and remove the matched Shanghai stock from the pool, and repeat the above process for the remaining Shanghai stocks until all A shares of Shenzhen match with Shanghai A shares. After the matching is accomplished, we obtain 170 pairs of Shanghai-Shenzhen stock pairs.

3 Empirical Analyses

3.1 Descriptive Statistics

Table 3 presents descriptive statistics and t-tests on the major control variables of liquidity, volatility, and price effectiveness for the 340 stocks traded on the Shanghai and Shenzhen stock exchanges after matching. It should be noted that it is impossible to generate the treatment effect around the transfer of SSE to closing call auction trading by looking at the Shanghai Stock Exchange alone. Rather, we focus on the changing trading environment across Shanghai and Shenzhen stock exchanges before and after the move to the closing call auction trading.

Market Liquidity Indicators

The change in the relative bid-ask spread (RSP) and quote depth ($\ln Depth$) before and after the introduction of the closing call auction remains similar across the Shanghai and Shenzhen stock exchanges, indicating that the closing call auction may have no significant effect on the two liquidity indicators. On the other hand, there is a striking difference in the volume 15 minutes before closing ($\ln Vol$), closing volume ($\ln Vol^C$), and closing volume ratio (dV) before and after the move to the call auction across the two stock markets. For example, the decrease in the volume of SSE detected 15 minutes of closing is less than that of SZSE, while the decrease in the volume of SSE at the closing is significantly greater than that of SZSE. Also, the closing volume ratio of SSE falls significantly more than SZSE, while the daily trading volume ($\ln Vol^T$) of the two stock exchanges falls by a similar margin. This seems to reflect that the introduction of the closing call auction has led to an increase in pre-close trading volume and a decrease in the volume at the closing period of trading.

Market Volatility Indicators

The Shanghai A shares exhibit a significant increase in realized volatility 15 minutes before closing (Rv), while the Shenzhen stocks have a significant decrease in the same variable. Also, the price deviation (Pv) of Shanghai A shares exhibits a significant decline, while that of the Shenzhen A shares does not change prominently. This may reflect the fact that the introduction of the closing call auction has led to an increase in pre-close volatility and a decrease in price volatility in closing, and there is an increase in the continuity of closing prices.

Price Effectiveness Indicators

The change in the relative return dispersion (RRD) and excessive volatility (OV) before and after the introduction of the closing call auction remains similar in both Shanghai and Shenzhen, indicating that the closing call auction may have no significant impact on the effectiveness of prices.

Table 3: Descriptive Statistics for Stocks Traded on the Shanghai and Shenzhen Stock Exchanges Before and After the Introduction of the Closing Call Auction

Category	Variable	Shanghai Stock Exchange: Average Value Pre- Policy Change	Shanghai Stock Exchange: Average Value Post- Policy Change	Shanghai Stock Exchange: Difference	Shenzhen Stock Exchange: Average Value Pre- Policy Change	Shenzhen Stock Exchange: Average Value Post- Policy Change	Shenzhen Stock Exchange: Difference
Liquidity Indicator	RSP	0.194(0.101)	0.212(0.11)	0.019***	0.193(0.099)	0.208(0.106)	0.015***
	$\ln Vol$	13.015(1.108)	12.963(1.142)	-0.052***	13.025(1.079)	12.921(1.128)	-0.104***
	$\ln Depth$	12.265(0.938)	12.266(0.971)	0.001	12.13(0.875)	12.143(0.919)	0.012
	$\ln Vol^C$	11.758(1.222)	10.862(1.43)	-0.896***	11.081(1.316)	10.938(1.39)	-0.143***
	$\ln Vol^T$	15.502(1.058)	15.46(1.097)	-0.042***	15.430(1.06)	15.369(1.107)	-0.061***
	dV	0.030(0.028)	0.015(0.017)	-0.016***	0.018(0.02)	0.017(0.018)	-0.001***
Volatility Indicator	Rv	0.657(0.368)	0.68(0.391)	0.023***	0.705(0.448)	0.693(0.392)	-0.012**
	Pv	0.259(0.305)	0.231(0.265)	-0.029***	0.25(0.274)	0.246(0.282)	-0.003
Price Effectiveness Indicator	RRD	.011(.012)	.01(.011)	-0.001***	.012(.013)	.011(.012)	-0.001***
	OV	.166(.34)	.138(.276)	-0.028***	.178(.344)	.14(.267)	-0.038***
	$\ln FSize$	22.757(1.072)	22.633(1.078)	-0.124***	22.399(0.966)	22.279(0.966)	-0.120***
	lnP	1.994(0.711)	1.868(0.694)	-0.127***	2.002(0.689)	1.881(0.669)	-0.121***
	$Return$	0.016(0.556)	0.029(0.55)	0.013*	0.022(0.655)	0.048(0.575)	0.026***
	$Return^C$	0.064(0.416)	0.052(0.395)	-0.012**	0.035(0.425)	0.063(0.411)	0.029***
	N	10799	10206		10717	10171	

*Note: a) Table 3 presents descriptive statistics and t-tests on the major control variables of liquidity, volatility, and price effectiveness for the 340 stocks traded on the Shanghai and Shenzhen stock exchanges after matching. The closing call auction 1) has no significant effect on liquidity; 2) has led to an increase in pre-close trading volume and a decrease in the volume at the closing period of trading; 3) has associated with an increase in pre-close volatility and a decrease in price volatility in closing, and there is an increase in the continuity of closing prices; 4) has no significant impact on the effectiveness of prices. b) *，**，and *** signify the statistical significance levels at 10%, 5%, and 1%, respectively. c) The standard deviation is in parentheses.*

3.2 Diagnostic Test on the Parallel Trends

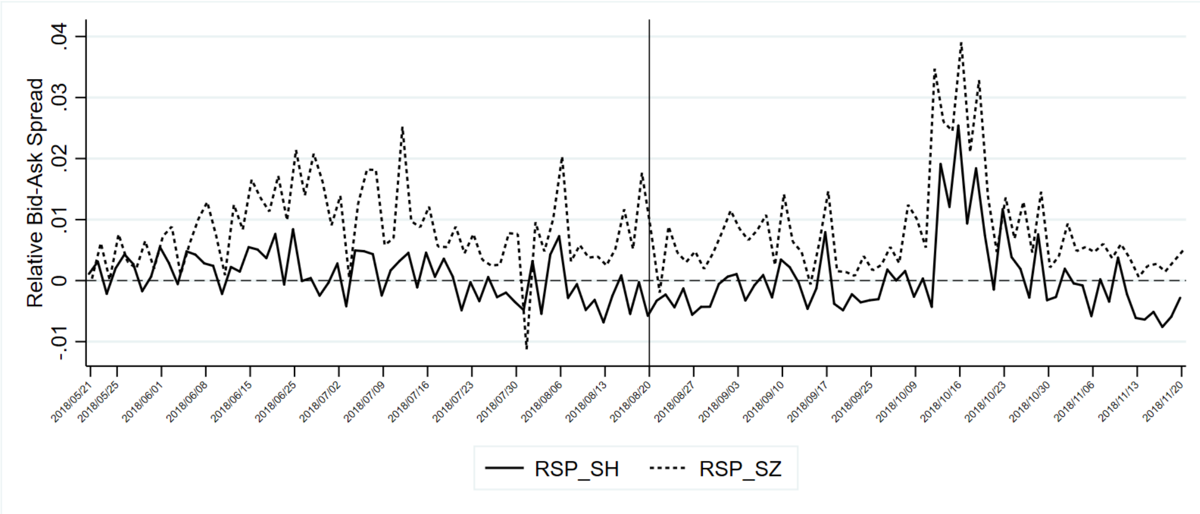
Before the DID regression can be implemented, we check for consistency in the parallel trends using the time series of the matched 340 stocks. To do this, we first perform the following regression equation on the matched 170 stocks traded on the Shanghai Stock Exchange:

$$Y_{i,t} = \alpha + \mu_i + \lambda_t + \beta X_{i,t} + \varepsilon_{i,t}.$$

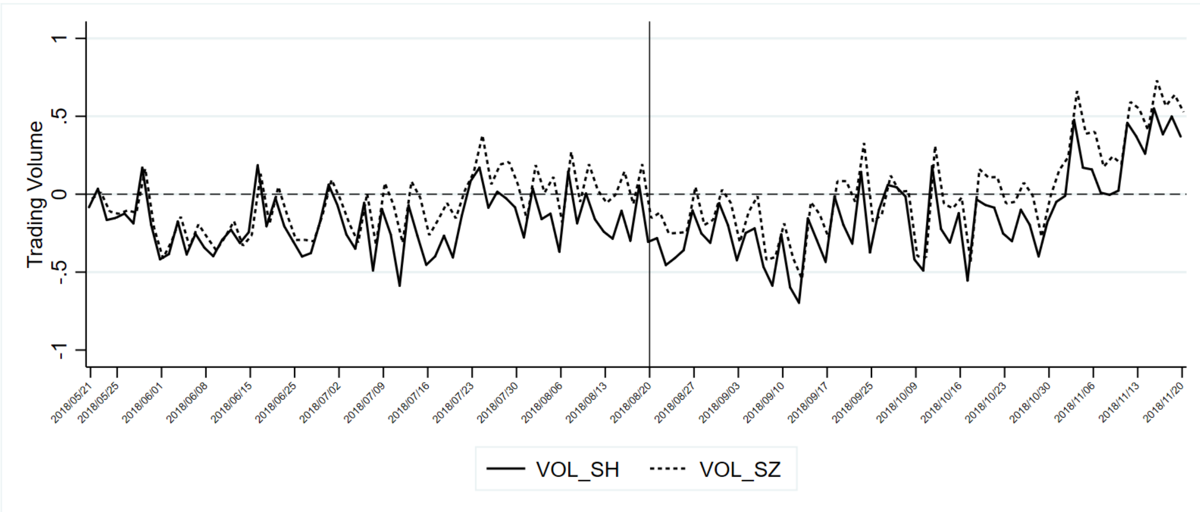
where $Y_{i,t}$ is a vector of the liquidity, volatility, and price effectiveness indicators, λ_t is a daily time dummy used to control the time fixed effect, $X_{i,t}$ is a vector of the control variables pre-determined by the model, μ_i is an individual stock dummy used to control the stock fixed effect. We then plot the estimated coefficient λ_t and examine how those market quality indicators change with time. The same procedure is applied to the matched 170 stocks traded on SZSE to generate the estimated coefficient λ_t. Figure 2 (Panels 1-8) shows the time series plots of the estimated coefficient λ_t, which corresponds to the chosen market quality indicators for the Shanghai and Shenzhen Stock Exchanges.

Figure 2 Parallel Trends

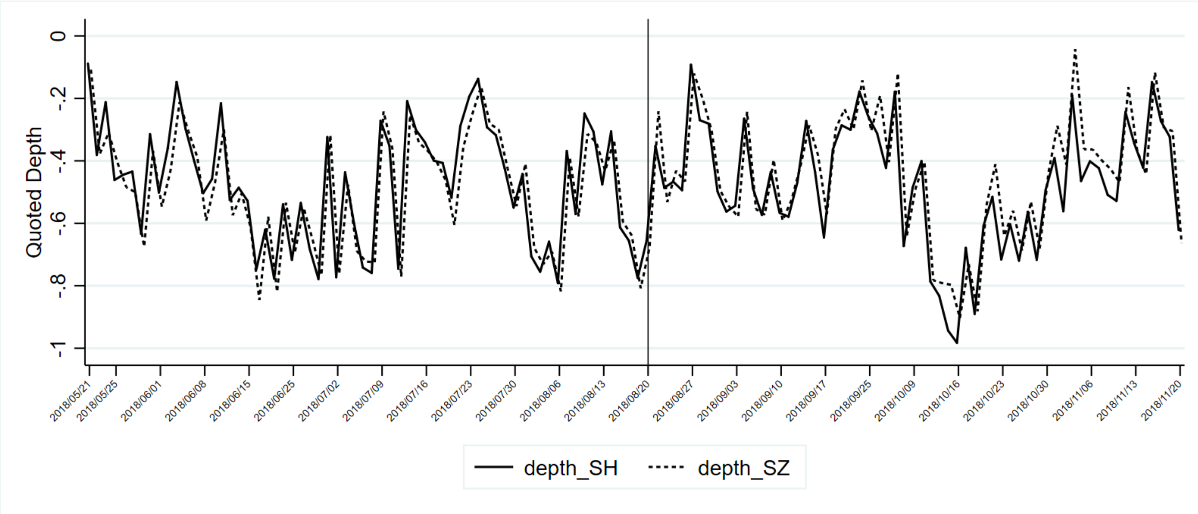
Panel1: Parallel Trends of Relative Bid-Ask Spread 15 Minutes Pre-Closing



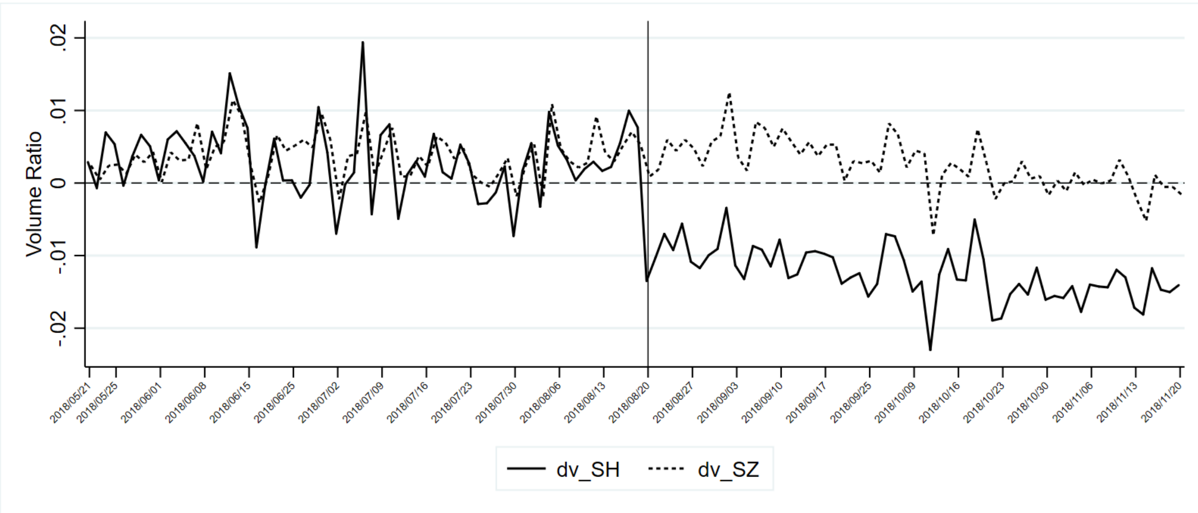
Panel 2: Parallel Trends of Trading Volume



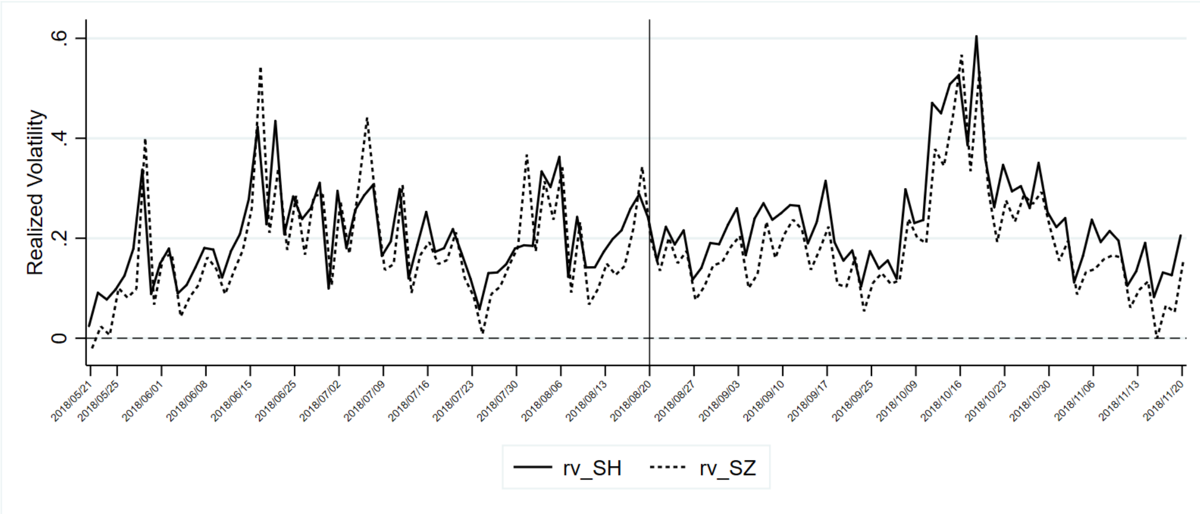
Panel 3: Parallel Trends of Quoted Depth 15 Minutes Pre-Closing



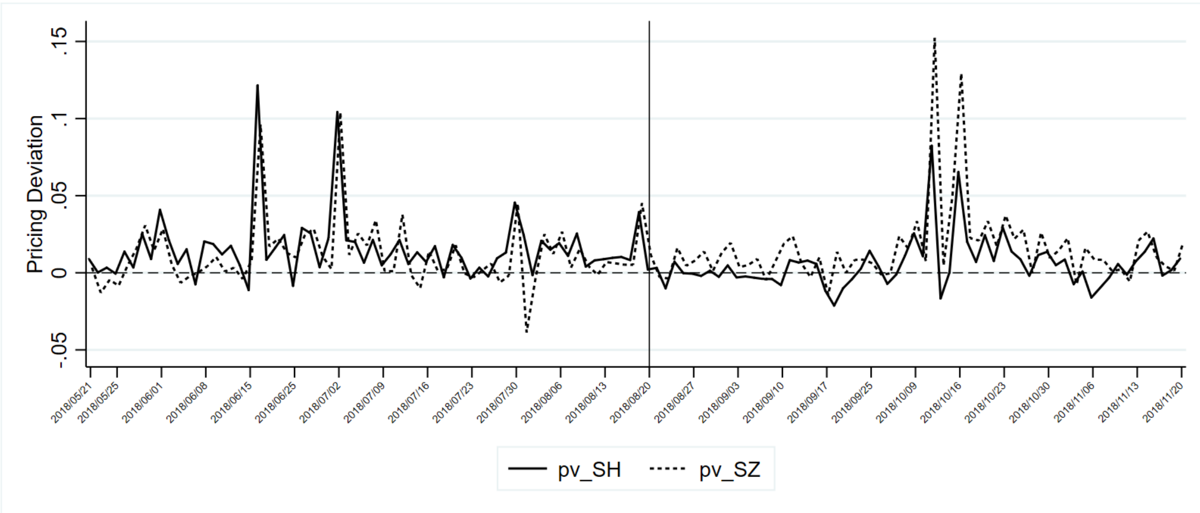
Panel 4: Parallel Trends of Volume Ratio at the Close



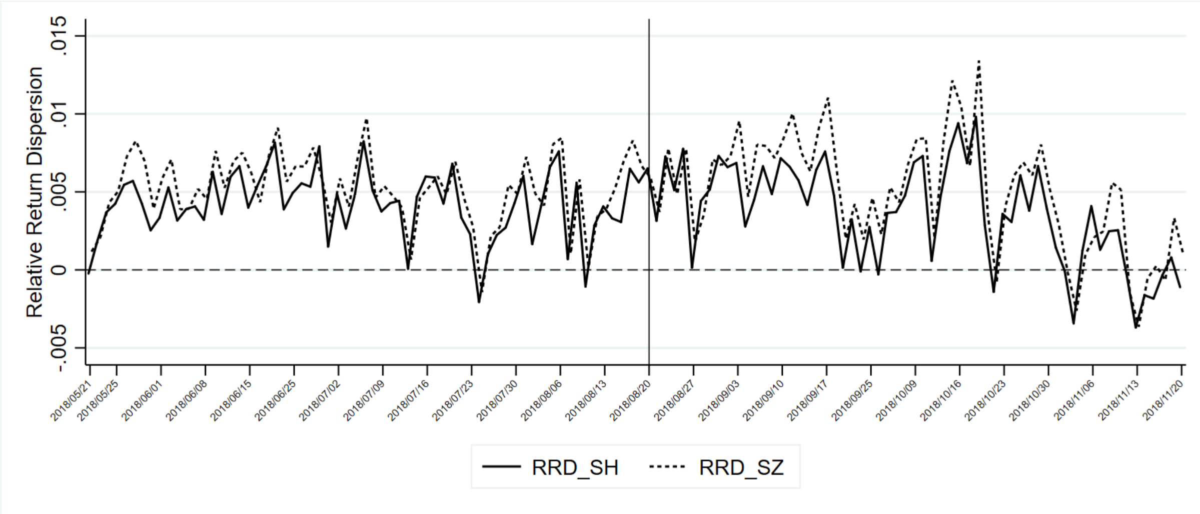
Panel 5: Parallel Trends of Realized Volatility 15 Minutes of Closing



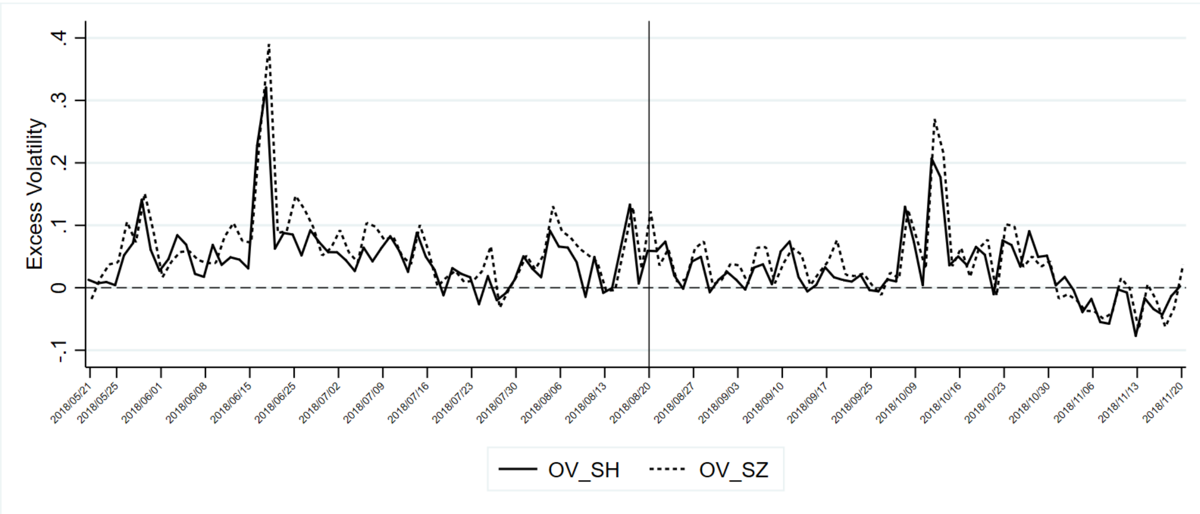
Panel 6: Parallel Trends of Pricing Deviation



Panel 7: Parallel Trends of Relative Return Dispersion



Panel 8: Parallel Trends of Excess Volatility



Notes: a) Panels 1-8 show the time series plots of the estimated coefficient λ_t, which corresponds to the chosen eight market quality indicators for the Shanghai and Shenzhen Stock Exchanges. b) The vertical lines in these figures indicate the time when the Shanghai closing call auction was implemented, and SH and SZ signify the Shanghai and Shenzhen markets, respectively. c) For the first three chosen liquidity indicators, namely, the relative bid-ask spread, volume and quote depth calculated 15 minutes before closing, each indicator's deviation in one trading platform away from the other trading platform remains almost the same both before and after the cutting off period where the Shanghai closing call auction is implemented (Panels1-3). d) The volume ratio detected at the closing in Shanghai differs significantly from Shenzhen after the introduction of the closing call auction; it also exhibits a downward trend (Panel 4). e) The difference in the realized volatility (and also in the price deviation) calculated for the two sets of stocks is very small before the introduction of the closing call auction but widens slightly afterwards (Panels 5-6). f) For the two price effectiveness indicators, that is, relative return dispersion and excess volatility, there is no major difference in each of these indicators across the two trading platforms before and after the cutting off period of the Shanghai closing call auction (Panels 7-8).

The vertical lines in these figures indicate the time when the Shanghai closing call auction was implemented, and SH and SZ signify the Shanghai and Shenzhen markets, respectively. From Figure 2 (Panels 1-8), there is compelling evidence that the matched pairs for the two stocks share a parallel trend before the reform. In particular, for the first three chosen liquidity indicators, namely, the relative bid-ask spread, volume and quote depth calculated 15 minutes before closing, each indicator's deviation in one trading platform away from the other trading platform remains almost the same both before and after the cutting off period where the Shanghai closing call auction is implemented (see Figure 2, Panels 1-3). It is interesting to note, however, that the volume ratio detected at the closing in Shanghai differs significantly from Shenzhen after the introduction of the closing call auction (see Figure 2, Panel 4). More specifically, it exhibits a prominent decline following the adoption of the closing call auction. The findings here have meaningful implications: Table 4 shows that the absolute total trading volumes during both the all-day continuous session and the 15-minute session before closing have not experienced significant changes. In contrast, Table 5 suggests that the relative trading volume during the closing session (dV^c) has significantly declined (which validates Figure 2, Panel 4) whereas the relative volume during the pre-close 15-minute session (dV^{15}) has significantly increased. This means that the absolute trading volume does not see significant changes day on day. However, the trading volume has seen a significant redistribution between different trading sessions within the trading day, namely the closing auction and the pre-close 15-minute session.

Furthermore, the difference in the realized volatility (and also in the price deviation) calculated for the two sets of stocks is very small before the introduction of the closing call auction but widens slightly afterwards (with the price deviation of SSE stocks being smaller than that of the SZSE stocks) (see Figure 2, Panels 5-6). And finally, for the two price effectiveness indicators, that is, relative return dispersion and excess volatility, there is no major difference in each of these indicators across the two trading platforms before and after the cutting off period of the Shanghai closing call auction (see Figure 2, Panels 7-8).

3.3 Empirical Results

3.3.1 Regression of Market Liquidity Indicators

In our empirical analyses, we evaluate whether the closing call auction has indeed improved market liquidity. To do this, we first take the all-day continuous auction session (excluding call auction), calculate and regress the three liquidity indicators - relative bid and ask spread, volume and quoted depth (see columns 2-4 of Table 4) on the chosen control variables explained in Table 2. The estimated coefficients of the interactive items, $\boldsymbol{D_i} \times \boldsymbol{D_t}$, are positive in the relative bid-ask spread and volume equations and negative in the quoted depth equation, but are all statistically insignificant. Admittedly, the introduction of the closing call auction has not significantly increased the market liquidity in continuous auctions of the day.

Because the closing call auction may have an impact primarily on the market during the closing of trade, we restrict the panel to include a time series of the three liquidity indicators calculated from a time interval of 15 minutes before closing. The same regression is performed, and the results are outlined in columns 5-7 of Table 4. These results are consistent with those under the all-day continuous auction trading, indicating that the introduction of the closing call auction has no significant effect on the liquidity of the market 15 minutes before closing either.

Table 4: Results of the Regression of Market Liquidity Indicators Based On All-Day Continuous Auction and one 15-Minute Trading Session Pre-Closing

Variable	All-Day Continuous Auction Session			A 15-minute Trading Session Before Closing (14:42-14:57)		
	RSP	$\ln Vol$	$\ln Depth$	RSP	$\ln Vol$	$\ln Depth$
Rv	0.015***	0.234***	-0.080***	0.070***	0.707***	-0.405***
	(0.001)	(0.009)	(0.005)	(0.005)	(0.031)	(0.029)
$\ln P$	-0.097***			-0.129***		
	(0.007)			(0.008)		
$\ln Vol$	-0.032***		0.359***	-0.013***		0.336***
	(0.002)		(0.012)	(0.001)		(0.010)
$\ln FSize$		1.135***	-0.302***		1.332***	-0.160*
		(0.196)	(0.090)		(0.254)	(0.086)
$Return$		0.024***			0.011	
		(0.002)			(0.011)	
$D_i \times D_t$	0.003	0.013	-0.009	0.001	0.036	-0.018
	(0.002)	(0.034)	(0.015)	(0.002)	(0.040)	(0.017)
Constant	0.809***	-3.220	12.050***	0.567***	-17.3658***	12.189***
	(0.029)	(3.084)	(1.322)	(0.018)	(5.760)	(1.910)
Observations	41893	41893	41893	41893	41893	41893
R^2	0.560	0.536	0.468	0.431	0.306	0.352

*Notes: a) We first take the all-day continuous auction session (excluding call auction), calculate, and regress the three liquidity indicators - relative bid and ask spread, volume, and quote depth (see columns 2-4) on the chosen control variables explained in Table 2. b) The estimated coefficients of the interactive items, $\boldsymbol{D_i} \times \boldsymbol{D_t}$, are all statistically insignificant. Admittedly, the introduction of the closing call auction has not significantly increased the market liquidity in continuous auctions of the day. c) We then restrict the panel to include a time series of the three liquidity indicators calculated from a time interval of 15 minutes before closing. The same regression is performed, and the results are outlined in columns 5-7. d) These results are consistent with those under the all-day continuous auction trading, indicating that the introduction of the closing call auction has no significant effect on the liquidity of the market 15 minutes before closing. e) *, **, and *** signify the statistical significance levels at 10%, 5%, and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

It is intriguing to note, however, that even though the new trading regime does not lead the volume to change, it may cause a reallocation of trading volume at different trading sessions. Therefore, we regress the volume ratio dV on the chosen control variables explained in Table 2, calculated from the closing period of trade and a 15-minute time interval right before closing (see columns 1 and 2 of Table 5). The results show that the estimated coefficient on the interaction term $D_i \times D_t$ in the closing auction period is negative and statistically significant, while the same coefficient in the 15-minute pre-close interval is positive and statistically significant. Hence, there is a clear tendency for the trading volume to shift to the continuous auction session, following the move to the closing call auction regime. The drift of the volume towards the end of the continuous session may be attributable to the increased costs of manipulating the closing price and increased overnight financial risk due to incomplete execution of the trading order, after the introduction of the closing call auction system, which causes the traders to move some of their trades forward.

To further explore at which time periods the volume shifts are populated, we divide the trading in the 15 minutes before closing into three 5-minute trading sessions and examine each episode one by one. The coefficient of the interaction term in the episode of 14:52-14:57 (which is the nearest to closing) is statistically significant and positive at the 5% level, while the same interaction coefficient is insignificant in the other two sub-periods. This means that the volume shifts are mainly populated within the 5-minute trading interval nearest to closing (see column 4 of Table 5). Such a point can be illustrated more clearly through Figure 3, which compares the trading volumes across the equally divided 5-minute episodes (of 14:42-14:57) and the last 3-minute call auction trading in Shanghai and Shenzhen. The volume of trading in

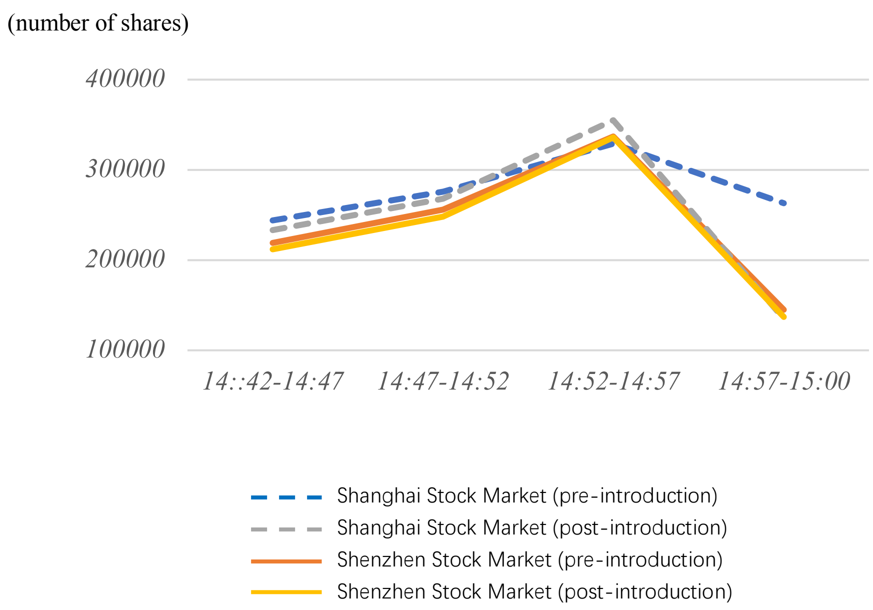
Shanghai in the last three minutes is higher than that in Shenzhen, both before and after the introduction of the new regime. However, with the move to the closing call auction regime, Shanghai's trading volume detected in the entire 18-minute episode exhibits a similar pattern as Shenzhen. In addition, the volume in the 14:52-14:57 interval for Shanghai incurs a sharp increase, followed by a sharp decline in the last three minutes, both relative to their respective volume before the introduction of the closing call auction regime.

Table 5: Results of the Regression of Volume Ratio

Variable	dV^C	dV^{15}	$dV^{5,1}$	$dV^{5,2}$	$dV^{5,3}$
$Return$		0.006***	0.006***	0.002***	0.001
		(0.001)	(0.001)	(0.001)	(0.001)
$Return^C$	0.011***				
	(0.002)				
Rv	0.002***	0.051***	0.032***	0.032***	0.028***
	(0.000)	(0.003)	(0.001)	(0.001)	(0.002)
$\ln Vol^T$	-0.003***	-0.018***	-0.007***	-0.006***	-0.005***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
$\ln FSize$	0.016***	0.030***	0.015***	0.010***	0.005***
	(0.003)	(0.006)	(0.003)	(0.002)	(0.002)
$D_i \times D_t$	-0.014***	0.002*	0.002**	0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Constant	-0.242***	-0.336**	-0.197**	-0.116	-0.028*
	(0.004)	(0.139)	(0.079)	(0.051)	(0.035)
Observations	41893	41893	41893	41893	41893
R^2	0.148	0.239	0.171	0.183	0.172

*Notes: a) We regress the volume ratio dV on the chosen control variables explained in Table 2. b) Columns 2-6 correspond to the regression based on 1) a 3-minute trading session before 15:00 (14:57-15:00); 2) a 15-minute trading session before 14:57 (14:42-14:57); 3) three equally divided 5-minute trading sessions 15 minutes before closing (14:52-14:57, 14:47-15:52, and 14:42-14:47). c) There is a clear tendency for the trading volume to shift to the continuous auction session, following the move to the closing call auction regime (see columns 1 and 2). d) The coefficient of the interaction term in the episode of 14:52-14:57 (which is the nearest to closing) is statistically significant and positive at the 5% level, while the same interaction coefficient is insignificant in the other two sub-periods. This means that the volume shifts are mainly populated within the 5-minute trading interval nearest to closing (see column 4). e) *, **, and *** signify the statistical significance levels at 10%, 5%, and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

Figure 3: Comparison of Trading Volumes Before and After the Introduction of the Closing Call Auction



Notes: a) Figure 3 compares the trading volumes across the equally divided 5-minute episodes (of 14:42-14:57) and the last 3-minute call auction trading in Shanghai and Shenzhen, both before and after the introduction of the new regime. b) The volume of trading in Shanghai in the last three minutes was higher than that in Shenzhen, both before and after the introduction of the new regime. c) With the move to the closing call auction regime, Shanghai's trading volume detected in the entire 18-minute episode exhibits a similar pattern as Shenzhen. d) The volume in the 14:52-14:57 interval for Shanghai incurs a sharp increase, followed by a sharp decline in the last three minutes, both relative to their respective volume before the introduction of the closing call auction regime.

We further divide the 15-minute trading session before closing into five 3-minute sessions and run the same regression again as we do in Table 5. The results are largely consistent with the regressions from those equally divided 5-minute trading sessions, with one exception that is the three-minute episode nearest to closing (see column 2, Table 6) where the estimated coefficient of the interaction term is statistically significant and positive. This means that the volume shifts from closing to the continuous auction session before the closing call auction, and most of the shifts are populated in the time interval closest to the beginning of the closing call auction. This also suggests that the transfer of volume has no association with how the 15-minute trading session is divided into sub-groups.

Table 6: Results of the Regression of Volume Ratio Calculated from Five Equally Divided 3-Minute Trading Sessions 15 Minutes Pre-Closing

Variable	$dV^{3,1}$	$dV^{3,2}$	$dV^{3,3}$	$dV^{3,4}$	$dV^{3,5}$
$Return$	0.005***	0.002***	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Rv	0.024***	0.022***	0.024***	0.021***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\ln Vol^T$	-0.005***	-0.004***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln FSize$	0.011*	0.006***	0.006***	0.006***	0.001
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
$D_i \times D_t$	0.002**	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.162***	-0.061	-0.061*	-0.072***	0.020
	(0.052)	(0.040)	(0.033)	(0.027)	(0.022)
Observations	41893	41893	41893	41893	41893
R^2	0.141	0.137	0.150	0.142	0.146

*Notes: a) We further divide the 15-minute trading session before closing into five 3-minute sessions and run the same regression again as we do in Table 5. b) Columns 2-6 correspond to the regression based on five equally divided 3-minute trading sessions in the 15 minutes before closing. c) The results are largely consistent with the regressions from those equally divided 5-minute trading sessions, with one exception that is the three-minute episode nearest to closing (see column 2) where the estimated coefficient of the interaction term is statistically significant and positive. This suggests that the volume shifts from closing to the continuous auction session before the closing call auction, and most of the shifts are populated in the time interval closest to the beginning of the closing call auction. d) The transfer of volume has no association with how the 15-minute trading session is divided into sub-groups. e) *, **, and *** signify the statistical significance levels at 10%, 5%, and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

3.3.2 Regression of Market Volatility Indicators

In Table 7, we regress the two volatility indicators - realized volatility 15 minutes before closing (14:42-14:57) Rv and price deviation Pv on the chosen control variables explained in Table

2. The coefficient of the interaction term in the regression specification of realised volatility is statistically significant and positive (see column 2 of Table 7). It is, however, significant and negative in the regression specification of price deviation (see column 3 of Table 7). This means the volatility increases prominently 15 minutes before closing but decreases during the closing of trade and price continuity increases. Such a point can be illustrated more clearly using Figure 4. Here, we compare the volatilities of the SSE and SZSE calculated from a time interval of 15 minutes before closing. The benchmark period for comparison is the day when the Shanghai closing call auction is implemented. Before the introduction of the closing call auction system, the volatility of SZSE was higher than that of SSE. It is interesting to note, however, that when Shanghai has joined Shenzhen in adopting the closing call auction, the volatility pattern of SSE converges with that of SZSE, and the volatility of SSE increases significantly in the last 5-minutes. This may be because the trading volume is shifted to the pre-closing period from the entire closing period. The increase in liquidity has also led to an increase in volatility, while the call auction's batch matching mechanism weakens the individual trader's influence on price and reduces the likelihood of submissions of price deviating significantly from the pre-close price, resulting in a smaller deviation in the closing price and an increase in the continuity of the pre-close price.

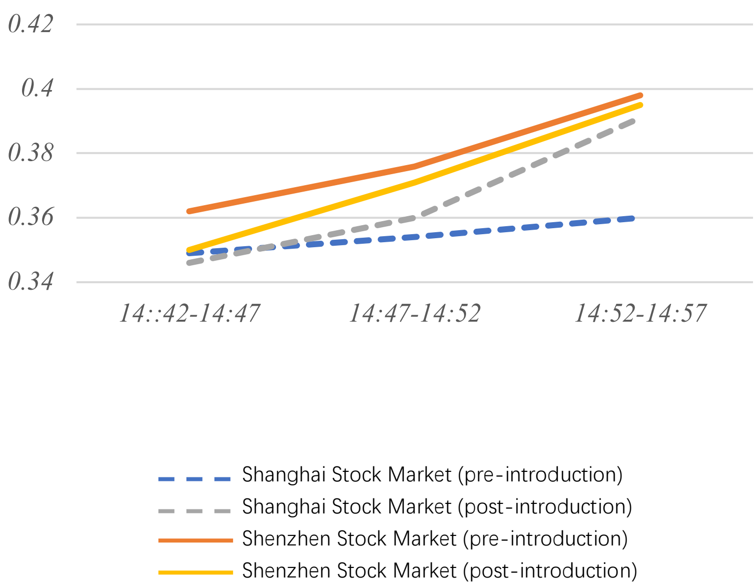
Table 7: Results of the Regression of Market Volatility Indicators

Variable	Rv	Pv
Rv		-0.035***
		(0.013)
$\ln Vol$	0.115***	
	(0.008)	
$\ln FSize$	-0.230***	
	(0.062)	

$\ln NT$	0.133***	
	(0.009)	
$\lvert Return^C \rvert$		0.822***
		(0.014)
$\ln Vol^C$		0.002
		(0.002)
$D_i \times D_t$	0.019*	-0.013***
	(0.011)	(0.002)
Constant	3.441**	0.014
	(1.389)	(0.014)
Observations	41893	41893
R^2	0.273	0.856

Notes: a) *We regress the two volatility indicators - realized volatility 15 minutes before closing (14:42-14:57)* Rv *and price deviation* Pv *on the chosen control variables explained in Table 2. b) The coefficient of the interaction term in the regression specification of realized volatility is statistically significant and positive (see column 2). It is, however, significant and negative in the regression specification of price deviation (see column 3). This suggests that the volatility increases prominently 15 minutes before closing but decreases during the closing of trade and price continuity increases. c)* *, **, *and* *** *signify the statistical significance levels at 10%, 5% and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

Figure 4: Variations of Realized Volatility Before and After the Introduction of the Closing Call Auction



Notes: a) We compare the volatilities of the SSE and SZSE calculated from a time interval of 15 minutes before closing. The benchmark period for comparison is the day when the Shanghai closing call auction is implemented. b) Before the *introduction of the closing call auction system, the volatility of SZSE was higher than that of SSE. c) When Shanghai has joined Shenzhen in adopting the closing call auction, the volatility pattern of SSE converges with that of SZSE, and the volatility of SSE increases significantly in the last 5-minutes.*

3.3.3 Regression of Price Discovery Indicators

In Table 8, we regress the two price discovery indicators – relative return dispersion RRD and excess volatility OV on the chosen control variables explained in Table 2. The estimated coefficient on the interaction term is small and statistically insignificant in the two regression specifications, indicating that the efficiency of price discovery has not changed significantly with the introduction of the closing call auction.

Table 8: Results of the Regression of Price Discovery Indicators

Variable	RRD	OV
$\ln P^c$		0.163***
		(0.032)
$\ln Vol^T$	0.011***	0.080***
	(0.000)	(0.006)
$D_i \times D_t$	-0.000	0.009
	(0.000)	(0.008)
Constant	-0.165***	-1.472***
	(0.004)	(0.136)
Observations	41893	41893
R^2	0.285	0.103

Notes: a) *We regress the two price discovery indicators – relative return dispersion RRD and excess volatility OV on the chosen control variables explained in Table 2. b) The estimated coefficient on the interaction term is small and statistically insignificant in the two regression specifications, indicating that the efficiency of price discovery has not changed significantly with the introduction of the closing call auction. c) *, **, and *** signify the statistical significance levels at 10%, 5%, and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

3.4 Further Regression Results Based on the Market Value of Stock

The introduction of the closing call auction may have different effects on liquidity and volatility of stocks with different market values (Kalay et al, 2002). In this paper, we rank all 340 stocks based on the market value of Shanghai A shares and divide them into 2 subsamples – small-cap stocks (where the stock's market value is below the median market value) and large-cap stocks (where the stock's market value is above the median market value). Such a partition will facilitate us to investigate the heterogeneity of the impact of the closing call auction on stocks with a different market capitalization.

Tables 9 and 10 report the result of the regression of the liquidity indicators, namely, relative bid-ask spread RSP, volume $\ln Vol$, quote depth $\ln Depth$, and volume ratio dV, calculated based on the small and large market capitalizations of stocks, respectively. These subsample results are consistent with those that use the whole 340 stocks, and no heterogeneity is found in terms of the impact on stocks under the closing call auction system with a different market capitalization.

Table 9: Results of the Regression of Market Liquidity Indicators Calculated from Small-Cap Stocks

Variable	RSP	$\ln Vol$	$\ln Depth$	dV^C	dV^{15}
Rv	0.078***	0.681***	-0.347***	0.002***	0.050***
	(0.007)	(0.040)	(0.037)	(0.001)	(0.003)
$\ln P$	-0.149***				
	(0.013)				
$\ln Vol$	-0.016***		0.326***		
	(0.002)		(0.011)		
$\ln FSize$		1.759***	-0.032	0.019***	0.032***
		(0.306)	(0.095)	(0.005)	(0.007)
$Return$		-0.012			0.004***

		(0.015)			(0.001)
$Return^C$				0.012***	
				(0.002)	
$lnVol^T$				-0.003***	-0.02***
				(0.000)	(0.001)
$D_i \times D_t$	0.000	-0.009	-0.016	-0.015***	0.003
	(0.003)	(0.056)	(0.022)	(0.001)	(0.002)
Constant	0.634***	-26.403***	9.280 ***	-0.344***	-0.344**
	(0.026)	(6.823)	(2.075)	(0.006)	(0.159)
Observations	20872	20872	20872	20872	20872
R^2	0.447	0.338	0.376	0.162	0.246

*Notes: a) Table 9 reports the result of the regression of the liquidity indicators, namely, relative bid-ask spread RSP, volume $lnVol$, quote depth $lnDepth$, and volume ratio dV, calculated based on the small market capitalizations of stocks. b) These subsample results are consistent with those that use the whole 340 stocks, and no heterogeneity is found in terms of the impact on stocks under the closing call auction system with a different market capitalization. c) *, **, and *** signify the statistical significance levels at 10%, 5% and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

Table 10: Results of the Regression of Market Liquidity Indicators Calculated from Large-Cap Stocks

Variable	RSP	lnVol	ln$Depth$	dV^C	dV^{15}
Rv	0.060***	0.747***	-0.503***	0.002**	0.053***
	(0.006)	(0.046)	(0.040)	(0.001)	(0.003)
ln$P$	-0.111***				
	(0.011)				
lnVol	-0.010***		0.363***		
	(0.002)		(0.016)		
ln$FSize$		0.975***	-0.273**	0.013***	0.030***
		(0.351)	(0.122)	(0.004)	(0.010)
$Return$		0.039**			0.008***
		(0.016)			(0.001)
$Return^C$				0.010***	
				(0.002)	
$lnVol^T$				-0.003***	-0.017***
				(0.001)	(0.001)
$D_i \times D_t$	0.000	0.089	-0.021	-0.013***	0.002
	(0.002)	(0.058)	(0.026)	(0.001)	(0.002)
Constant	0.492***	-9.600	14.667***	-0.244***	0.023***
	(0.022)	(8.158)	(2.746)	(0.093)	(0.007)

Observations	21021	21021	21021	21021	21021
R^2	0.435	0.290	0.347	0.153	0.207

*Notes: a) Table 10 reports the result of the regression of the liquidity indicators, namely, relative bid-ask spread RSP, volume $lnVol$, quote depth $lnDepth$, and volume ratio dV, calculated based on the large market capitalizations of stocks. b) These subsample results are consistent with those that use the whole 340 stocks, and no heterogeneity is found in terms of the impact on stocks under the closing call auction system with a different market capitalization. c) *, **, and *** signify the statistical significance levels at 10%, 5% and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

Table 11 is the result of the regression of the volatility indicators, namely, realized volatility Rv and price deviation Pv, calculated based on the small and large market capitalizations of stocks. In the regression specification of realized volatility, the results from the small-cap subsample appear more consistent with those that use the overall sample of 340 stocks (see Table 7) when comparing with the large-cap subsample results. Furthermore, the estimated coefficient of the interaction term in the regression of realized volatility, 0.019, is only significant at the 10% level when the whole sample of 340 stocks is used (see Table 7). It is interesting to note that the same coefficient becomes 0.039 and significant at 5% under the small-cap subsample. Admittedly, the introduction of the closing call auction has an effective impact on the small-cap stock's pre-close volatility. In particular, it significantly increases the pre-close volatility of small-cap stocks. On the other hand, for the subsample of large-cap stocks, the estimated coefficient of the interaction term in the regression of realized volatility is 0.003 and statistically insignificant. This means that the closing call auction system is ineffective in changing the large-cap stock's pre-close volatility.

In the regression of price deviation during the closing of trade, the estimated coefficient of the interaction term for large-cap stocks appears to be the same as the entire sample (see Table 7). Moreover, the same coefficient is smaller under the small-cap stock sample, which means the closing call auction helps improve the continuity of the closing price of small-cap stocks. Such heterogeneity is likely because large-cap stocks are more difficult to be manipulated. In other words, even though the closing call auction has been introduced and the trading volume of large-cap stocks does drift towards the pre-close trading, these trading are yet large enough to change the pre-close volatility of large-cap stocks. On the other hand, for small-cap stocks, the closing call auction increases the pre-close volatility but improves the continuity of the closing price in a prominent manner. To some extent, the introduction of the closing call auction helps reduce the risk of manipulation at the closing for small-cap stocks.

Table 11: Results of the Regression of Market Volatility Indicators Calculated from Stocks with Small and Large-Market Capitalizations

Variable	Small-Cap Stock Sample		Large-Cap Stock Sample	
	Rv	Pv	Rv	Pv
Rv		-0.033***		-0.047
		(0.010)		(0.029)
$\ln Vol$	0.132***		0.106***	
	(0.012)		(0.010)	
$\ln FSize$	-0.195**		-0.239***	
	(0.091)		(0.079)	
$\ln NT$	0.132***		0.121***	
	(0.012)		(0.013)	
$\lvert Return^C \rvert$		0.793***		0.825***
		(0.021)		(0.015)
$\ln Vol^C$		0.003		0.002
		(0.002)		(0.003)
$D_i \times D_t$	0.039**	-0.018***	0.003	-0.013***
	(0.017)	(0.004)	(0.015)	(0.003)
Constant	2.444	0.012	3.86**	0.022
	(2.005)	(0.021)	(1.80)	(0.019)
Observations	20872	20872	21021	21021
R^2	0.280	0.837	0.276	0.865

Notes: a) Table 11 shows the result of the regression of the volatility indicators, namely, realized volatility Rv and price deviation Pv, calculated based on the small and large market capitalizations of stocks. b) The introduction of the closing *call auction has an effective impact on the small-cap stock's pre-close volatility. In particular, it significantly increases the pre-close volatility of small-cap stocks. c) The closing call auction system is ineffective in changing the large-cap stock's pre-close volatility. d) The closing call auction helps improve the continuity of the closing price of small-cap stocks. e) *, **, and *** signify the statistical significance levels at 10%, 5% and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

Table 12 presents the regression results of the price efficiency indicators, RRD and OV, calculated based on the small and large market capitalization of stocks, respectively. These subsample results are generally consistent with the results based on the whole 340 stocks (see Table 8), and still, the coefficient of the interaction term remains statistically insignificant for both subsamples. This means the introduction of the closing call auction has no significant effect on the efficiency of price discovery no matter how large or small the stock's market value is.

Table 12: Results of the Regression of Price Discovery Indicators Calculated From Stocks with Small and Large Market Capitalizations

Variable	Small-Cap Stock Sample		Large-Cap Stock Sample	
	RRD	OV	RRD	OV
lnP^c		0.221***		0.136***
		(0.062)		(0.036)
$\ln Vol^T$	0.011***	0.065***	0.011***	0.096***
	(0.000)	(0.006)	(0.000)	(0.011)
$D_i \times D_t$	-0.001	0.021	-0.001	-0.004
	(0.000)	(0.014)	(0.000)	(0.010)
Constant	-0.158***	-1.323***	-0.173***	-1.323***
	(0.005)	(0.193)	(0.006)	(0.193)
Observations	20872	20872	21021	20872
R^2	0.294	0.118	0.282	0.118

*Notes: a) Table 12 presents the regression results of the price efficiency indicators, RRD and OV, calculated based on the small and large market capitalization of stocks, respectively. b) These subsample results are generally consistent with the results based on the whole 340 stocks (see Table 8), and still, the coefficient of the interaction term remains statistically insignificant for both subsamples. c) *, **, and *** signify the statistical significance levels at 10%, 5%, and 1%, respectively.*

The stock-level cluster-robust standard error is in parentheses.

3.5 Further Regression Results on the Institutional Ownership

Conventional wisdom suggests that the institutional investors prefer to trade at closing call auctions. To investigate whether institutional and retail investors behave differently, we rank all 340 stocks based on the institutional investors' holding rate (IIHR)[3] in descending order and divide them equally into 3 subsamples. Then, we run regressions respectively with the small and large sub-samples. Tables 13 and 14 report the results of the regressions of the volume ratio dV and market volatility indicators Rv and Pv. The results are consistent with those that use the whole selected 340 stocks (see Tables 5 and 7) based on retail investors and small heterogeneity is found. Our exercise confirms the following. Through Tables 13 and 14 where the effect of IIHRs is characterised as a control variable, the data are not able to separate the different forces that may underpin the decreased trading volume. Hence, the change in volume following the adoption of closing auction may be unrelated to institutional investors. This leads us to believe that the decrease in trading volume during the closing session may be attributed to the behaviour of informed traders. Informed traders are more likely to move their trading forward as a result of the closing call auction reform.

Table 13: Results of the Regressions of Volume Ratio Calculated from Stocks with Small and Large Institutional Investors' Holding Rate

Variable	Small-IIHR Stock Sample		Large-IIHR Stock Sample	
	dV^{C}	dV^{15}	dV^{C}	dV^{15}

[3] Data are from CNRDS. We take the average of the IIHRs at the end of 2017 and 2018 as the IIHR of the stock. Considering that the policy adjustment may have a greater impact on funds and securities companies, we also run regressions based on different holding rate of funds and securities companies, with similar results being obtained.

$Return$		0.007***		0.006***
		(0.002)		(0.002)
$Return^C$	0.010***		0.012***	
	(0.002)		(0.003)	
Rv	0.004***	0.054***	0.002	0.050***
	(0.001)	(0.003)	(0.001)	(0.006)
$\ln Vol^T$	-0.003***	-0.019***	-0.003***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.002)
$\ln FSize$	0.022***	0.030***	0.007	0.021**
	(0.005)	(0.010)	(0.005)	(0.008)
$D_i \times D_t$	-0.017***	0.003	-0.011***	0.003
	(0.001)	(0.002)	(0.001)	(0.002)
Constant	-0.418***	-0.301	-0.091	-0.145
	(0.111)	(0.215)	(0.119)	(0.178)
Observations	13983	13983	14125	14125
R^2	0.176	0.268	0.139	0.227

*Notes: a) Table 13 reports the results of the regressions of the volume ratio dV, calculated based on the small and large institutional investors' holding rates (IIHRs) of stocks. b) These subsample results are consistent with those that use the whole 340 stocks, and small heterogeneity is found in terms of the impact on stocks under the closing call auction system with a different IIHR. c) * , ** , and *** signify the statistical significance levels at 10%, 5% and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

Table 14: Results of the Regressions of Market Volatility Indicators Calculated from Stocks with Small and Large Institutional Investors' Holding Rates

Variable	Small-IIHR Stock Sample		Large-IIHR Stock Sample	
	Rv	Pv	Rv	Pv
Rv		-0.035***		-0.031**
		(0.013)		(0.015)
$\ln Vol$	0.115***		0.127***	
	(0.014)		(0.012)	
$\ln FSize$	-0.148		-0.291***	
	(0.108)		(0.071)	
$\ln NT$	0.142***		0.117***	
	(0.017)		(0.014)	
$\lvert Return^C \rvert$		0.813***		0.803***
		(0.014)		(0.015)
$\ln Vol^C$		0.001		0.000
		(0.002)		(0.002)
$D_i \times D_t$	0.022	-0.020***	0.005	-0.010**
	(0.021)	(0.005)	(0.016)	(0.005)

Constant	1.504	0.032	4.889***	0.041*
	(2.402)	(0.022)	(1.608)	(0.022)
Observations	13983	13983	14125	14125
R^2	0.293	0.856	0.268	0.859

*Notes: a) Table 14 reports the results of the regressions of the market volatility indicators Rv and Pv calculated based on the small and large institutional investors' holding rates (IIHRs) of stocks. b) These subsample results are consistent with those that use the whole 340 stocks, and small heterogeneity is found in terms of the impact on stocks under the closing call auction system with a different IIHR. c) * , ** , and *** signify the statistical significance levels at 10%, 5% and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

3.6 Robustness Check for the Matching Method

The previous matching algorithm selects 170 pairs of stocks (340 stocks) in Shanghai and Shenzhen, which may be quite different from the original sample of 910 stocks (738 Shanghai stocks and 172 Shenzhen stocks). Therefore, we re-perform the regression analysis on the entire sample in order to check the consistency of the two sets of results, thus the robustness of the matching method. We also attempt to use an alternative matching method that is to match each Shanghai with a Shenzhen stock (multiple Shanghai stocks may be matched with one Shenzhen stock) and this results in 636 pairs of stocks.[4]

Table 15 reports the regression results of liquidity indicators using the alternative matching method. The results are generally consistent with the previous results based on the selected 170 pairs of stocks - the coefficients on the interaction terms remain the same signs while their statistical significances have some changes. The results validate that moving to the closing call auction regime may have a negative impact on market depth. Table 16 reports the regression results of relative volume. The results also confirm that moving to the closing call auction regime resulted in a shift of trading volume from closing to pre-closing. Table 17

[4] The final stock pair is less than 738 because we strictly require that the matched stocks belong to the same industry.

reports the regression results of volatility indicators which shows moving to the closing call auction increased the continuity of closing price and volatility at pre-closing.

Table 15: Results of the Regressions of Market Liquidity Indicators Calculated from Different Matching Methods

Variable	Sample without matching			Sample with alternative matching		
	RSP	$\ln Vol$	$\ln Depth$	RSP	$\ln Vol$	$\ln Depth$
Rv	0.085***	0.700***	-0.405***	0.077***	0.745***	-0.428***
	(0.004)	(0.017)	(0.015)	(0.003)	(0.014)	(0.012)
$\ln P$	-0.107***			-0.113***		
	(0.006)			(0.005)		
$\ln Vol$	-0.018***		0.352***	-0.016***		0.352***
	(0.001)		(0.006)	(0.001)		(0.005)
$\ln FSize$		1.423***	-0.023		1.441***	-0.007
		(0.147)	(0.044)		(0.101)	(0.033)
$Return$		0.030***			0.028***	
		(0.006)			(0.005)	
$D_i \times D_t$	-0.001	0.024	-0.040***	-0.000	0.057***	-0.032***
	(0.001)	(0.032)	(0.013)	(0.001)	(0.020)	(0.009)
Constant	0.579***	-19.467***	8.748***	0.568***	-19.744***	8.419***
	(0.012)	(3.314)	(0.981)	(0.009)	(2.272)	(0.745)
Observations	112241	112241	112241	156661	156661	156661
R^2	0.425	0.293	0.354	0.431	0.313	0.367

*Notes: a) Table 15 reports the results of the regressions of the liquidity indicators calculated based on the full sample (910 stocks) and the sample (636 pairs of stocks) constructed by an alternative matching method. b) These results are generally consistent with those that use the 170 pairs of stocks, and suggest a negative impact on market depth under the closing call auction system. c) * , ** , and *** signify the statistical significance levels at 10%, 5% and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

Table 16: Results of the Regressions of Volume Ratio Calculated from Different Matching Methods

Variable	Sample without matching		Sample with alternative matching	
	dV^C	dV^{15}	dV^C	dV^{15}
$Return$		0.007***		0.007***
		(0.001)		(0.001)
$Return^C$	0.012***		0.011***	

	(0.001)		(0.001)	
Rv	0.003***	0.049***	0.003***	0.054***
	(0.000)	(0.001)	(0.000)	(0.001)
$\ln Vol^T$	-0.004***	-0.017***	-0.003***	-0.019***
	(0.000)	(0.000)	(0.000)	(0.000)
$\ln FSize$	0.011***	0.017***	0.011***	0.020***
	(0.002)	(0.003)	(0.002)	(0.003)
$D_i \times D_t$	-0.014***	0.003***	-0.013***	0.005***
	(0.000)	(0.001)	(0.000)	(0.001)
Constant	-0.179***	-0.054	-0.171***	-0.103*
	(0.040)	(0.076)	(0.033)	(0.056)
Observations	112241	112241	156661	156661
R^2	0.188	0.230	0.147	0.252

*Notes: a) Table 16 reports the results of the regressions of relative volume calculated based on the full sample (910 stocks) and the sample (636 pairs of stocks) constructed by an alternative matching method. b) These results are consistent with those that use the 170 pairs of stocks, and confirm that there exists a shift of trading volume from closing to pre-closing. c) * , ** , and *** signify the statistical significance levels at 10%, 5% and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

Table 17: Results of the Regressions of Market Volatility Indicators Calculated from Different Matching Methods

Variable	Sample without matching		Sample with alternative matching	
	Rv	Pv	Rv	Pv
Rv		-0.034***		-0.028***
		(0.007)		(0.005)
$\ln Vol$	0.110***		0.115***	
	(0.005)		(0.004)	
$\ln FSize$	-0.197***		-0.277***	
	(0.034)		(0.026)	
$\ln NT$	0.124***		0.135***	
	(0.006)		(0.005)	
$\lvert Return^C \rvert$		0.843***		0.823***
		(0.008)		(0.006)
$\ln Vol^C$		0.000		0.002***
		(0.001)		(0.001)
$D_i \times D_t$	0.016*	-0.013***	-0.008	-0.011***
	(0.009)	(0.002)	(0.006)	(0.001)
Constant	2.796***	0.033***	4.452***	0.016**
	(0.754)	(0.008)	(0.593)	(0.006)
Observations	112241	112241	156661	156661

R^2	0.259	0.869	0.281	0.869

*Notes: a) Table 17 reports the results of the regressions of market volatility indicators calculated based on the full sample (910 stocks) and the sample (636 pairs of stocks) constructed by an alternative matching method. b) These results are generally consistent with those that use the 170 pairs of stocks, and suggest the volatility increases 15 minutes before closing but decreases during the closing of trade and closing price continuity increases. c) * , ** , and *** signify the statistical significance levels at 10%, 5% and 1%, respectively. The stock-level cluster-robust standard error is in parentheses.*

4 Conclusions

We analyze and explain changes in market quality before and after the Shanghai closing call auction is implemented using the difference-in-difference method that characterizes a treatment group (Shanghai A shares) and a control group (Shenzhen A shares). Our empirical results show that with the implementation of the Shanghai closing call auction: 1) market liquidity during the last 15 minutes before the market formally closes has not changed significantly; 2) percentage of closing volume in the overall daily volume has decreased significantly; 3) percentage of trading volume in the last 3 minutes pre-closing in the overall daily volume has increased significantly; 4) volatility during the final 15 minutes of trading has increased significantly; 5) closing price volatility appears significantly lower than pre-closing price volatility, and 6) continuity of closing price has improved. Also, we find that the pricing efficiency has not changed significantly, meaning that market efficiency has not improved in a significant manner. Overall, our empirical results suggest that the regulatory reform brought by the Shanghai Stock Exchange has achieved its objectives.

It should be noted that, although every attempt has been made to identify the causal relationship among policy measures using robust econometrics method, we are limited by the shortage of investors' trading data. Also, there is no real change in the effectiveness of closing price, which may be related to the current regulatory design of the closing auction mechanism.

A horizontal comparison across similar international markets suggests that there may be room for further optimization of such a mechanism.

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