Order flow dynamics around extreme price changes on an emerging stock market

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Abstract. We study the dynamics of order flows around large intraday price changes using ultra-high-frequency data from the Shenzhen Stock Exchange. We find a significant reversal of price for both intraday price decreases and increases with a permanent price impact. The volatility, the volume of different types of orders, the bid–ask spread and the volume imbalance increase before the extreme events and decay slowly as a power law, which forms a well-established peak. The volume of buy market orders increases faster and the corresponding peak appears earlier than for sell market orders around positive events, while the volume peak of sell market orders leads buy market orders in the magnitude and time around negative events. When orders are divided into four groups according to their aggressiveness, we find that the behaviors of order volume and order number are similar, except for buy limit orders and canceled orders that the peak of order number postpones 2 min later after the peak of order volume, implying

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that investors placing large orders are more informed and play a central role in large price fluctuations. We also study the relative rates of different types of orders and find differences in the dynamics of relative rates between buy orders and sell orders and between individual investors and institutional investors. There is evidence that institutions behave very differently from individuals and that they have more aggressive strategies. Combining these findings, we conclude that institutional investors are better informed and play a more influential role in driving large price fluctuations.

1. Introduction

The current financial tsunami, which is regarded as the biggest one since the Great Depression, has attracted much interest, not only in industry but also in the academic community. The direct trigger of the financial breakdown was the subprime mortgage crisis in the United States of America, and there are numerous efforts aiming to explain its causes and paths. From a complex systems point of view, the financial tsunami has nothing special since ‘the accumulation of several bubbles and their interplay and mutual reinforcement has led to an illusion of a ‘perpetual money machine’, allowing financial institutions to extract wealth from an unsustainable artificial process’ [1]. In this framework, unfolding the crisis is related at least to the speculative bubble of foreign capital inflow to the USA [2], the ‘new economy’ ICT
bubble [3], the slaving of the USA Federal Reserve to the stock market [4], the real-estate bubble [5] and the commodity bubble [6]. These phenomena are identified as bubbles and crashes [7].

More generally, one of the focal issues of economics is understanding the price formation mechanism. By now, much is known about the stylized facts related to the price fluctuations (see e.g. [8, 9]), but we are far from having a clear picture about the origins. As illustrated by the events mentioned in the previous paragraph, this is a question of general public interest. It is natural to assume, especially from the physics point of view, that the behavior around major changes will tell us important related details. As we would like to take a statistical approach, we have to restrict ourselves to ‘large changes on small scales’, i.e. to the question: What happens in the neighborhood of a relatively large change if high-resolution data are considered?

Early work about aftershock market behavior was done by Lillo and Mantegna, who studied the relaxation dynamics of the occurrence of large volatility after volatility shocks, as an analogue of Omori’s law after earthquakes [10, 11]. They investigated 1 min logarithmic changes of the Standard and Poor’s 500 (S&P 500) index during 100 trading days after Black Monday and found that the occurrence of events larger than some threshold exhibits power-law relaxation for different thresholds [10, 11]. Selçuk investigated daily index data from ten emerging stock markets (Argentina, Brazil, Hong Kong, Indonesia, Korea, Mexico, Philippines, Singapore, Taiwan and Turkey) and observed Omori’s law after the two largest crashes in each market [12]. Selçuk and Gençay utilized the 5 min Dow Jones Industrial Average 30 index (DJI) and identified Omori’s law after 8 October 1998 and 3 January 2001 [13]. In addition, the power-law relaxation could happen after intermediate shocks, which was confirmed in the USA markets [14] and in the Chinese markets [15, 16].

Another related topic is to study the relaxation dynamics of financial measures after large price changes. Sornette et al [17] found that the implied variance of the S&P 500 index after the infamous Black Monday (19 October 1987) decays as a power law decorated with log-periodic oscillations. Zawadowski et al [18] examined the evolution of price, volatility and bid–ask spread after extreme 15 min intraday price changes on the New York Stock Exchange (NYSE) and the NASDAQ. They found a well-established price reversal, and the volatility, which increases sharply at the event, decays according to a power law with an exponent of about 0.4. Zawadowski et al [19] further showed that the volume and, in the case of the NYSE, the bid–ask spread, which increase sharply at the event, stay significantly high over days afterwards and the decay of the volatility follows a power law [19]. Tóth et al [20] found similar power-law relaxations after large intraday price changes in the volatility, the bid–ask spread, the bid–ask imbalance, the number of queuing limit orders, and the activity (number and volume) of limit orders placed and canceled in the stocks traded on the London Stock Exchange (LSE) [20]. Very recently, Ponzi et al [21] performed an analysis studying possible market strategies around large events, and they found empirically that the bid–ask spread and the mid-price decay very slowly to their normal values when conditioned to a sudden variation in the spread. These findings show that the resiliency is slower than the assumed exponential form [22, 23].

So far only mature markets have been studied with the technique of the statistical analysis of large changes in high-resolution data. The aim of this paper is to study an emergent market, namely the Chinese stock market, from this point of view. We investigate the dynamics of several financial quantities around large price changes, with special emphasis on the order volume, using a database of the order book data of 23 stocks from the Shenzhen Stock Exchange (SZSE). More interestingly, the ultra-high-frequency data allow us to investigate the effect of
order directions (buy and sell), order aggressiveness (partially filled orders, filled orders, limit orders and canceled orders, as explained in section 2) and investor types (individual versus institution) on the volume dynamics around extreme events and the behavior of relative rates of orders around large price changes. We note that there are other econophysics studies where the investors’ classification has been performed or taken into account [24]–[27].

This paper is organized as follows. Section 2 presents a brief description of the database that we investigated. In section 3, we explain the definition of large price changes and show that there is a price reversal after price jumps. Section 4 studies the dynamics of the absolute return, the volume, the bid–ask spread and the volume imbalance around large price changes. Sections 5–7 investigate, respectively, the effect of order directions, order aggressiveness and investor types on the volume dynamics around extreme events and the behavior of relative rates of orders around large price changes. Section 8 summarizes our findings.

2. Data sets

We use a database that records all orders of submission and cancelation of 23 liquid stocks traded on the SZSE in the whole year of 2003. The market consists of three time periods on each trading day, namely, the opening call auction (9:15 to 9:25 AM), the cooling period (9:25 to 9:30 AM) and the continuous double auction (9:30 to 11:30 AM and 1:00 to 3:00 PM). In this paper, we consider only transactions occurring in the continuous double auction. The time, price and size of each order are recorded in the data set. In the Chinese stock market, the size of a buy order is limited to a board lot of 100 shares or an integer multiple thereof, while a seller can place a sell order with any size. The recorded trade size is in units of shares rather than board lots. The data set also contains the investor type for each order, indicating whether the investor is an individual or an institution.

Note that only limit orders were allowed to submit in 2003. There are situations where a limit order is only partially executed since the total outstanding volume of orders waiting in the opposite order book with the prices no more aggressive than the submitted order is less than the size of the submitted order. Hence, only a part of the shares are executed and the remaining shares are stored in the limit order book. This order is treated as two orders, one as a partially filled order and the other as an effective limit order. If the price of a buy (resp. sell) order is higher (resp. lower) than the best ask (resp. bid) price, the limit order is called an effective market order or a marketable order. The remaining limit orders are called effective limit orders. Without loss of clarity, in this work we term these two types of orders as market orders and limit orders. A market order is either a filled order or a partially filled order.

The tickers of the 23 stocks investigated are the following: 000001 (Shenzhen Development Bank Co Ltd), 000002 (China Vanke Co Ltd), 000009 (China Baoan Group Co Ltd), 000012 (CSG Holding Co Ltd), 000016 (Konka Group Co Ltd), 000021 (Shenzhen Kaifa Technology Co Ltd), 000024 (China Merchants Property Development Co Ltd), 000027 (Shenzhen Energy Investment Co Ltd), 000063 (ZTE Corporation), 000066 (Great Wall Technology Co Ltd), 000088 (Shenzhen Yan Tian Port Holdings Co Ltd), 000089 (Shenzhen Airport Co Ltd), 000406 (Sinopec Shengli Oil Field Dynamic Group Co Ltd), 000429 (Jiangxi Ganyue Expressway Co Ltd), 000488 (Shandong Chemning Paper Group Co Ltd), 000539 (Guangdong Electric Power Development Co Ltd), 000541 (Foshan Electrical and Lighting Co Ltd), 000550 (Jiangling Motors Co Ltd), 000581 (Weifu High-Technology Co Ltd), 000625 (Chongqing Changan
Automobile Co Ltd), 000709 (Tangshan Iron and Steel Co Ltd), 000720 (Shandong Luneng Taishan Cable Co Ltd) and 000778 (Xinxing Ductile Iron Pipes Co Ltd).

The 23 stocks investigated in this work cover a variety of industry sectors, including financials, real estate, conglomerates, metals & nonmetals, electronics, utilities, IT, transportation, petrochemicals, paper & printing, and manufacturing. Our sample stocks were part of the 40 constituent stocks included in the SZSE Component Index in 2003 [28]. More information about the database and the market can be found in other relevant works [29]–[31].

3. Defining large intraday price changes

To study the limit order book dynamics around extreme events, we first have to give an exact definition of extreme events. We generated a minute-to-minute data set using the mid-price of the last best bid and ask prices in every minute. In this paper, we continue to use a combined trigger to find intraday events, as done in [18]–[20].

3.1. Absolute filter

This is used to find out the cumulative intraday price changes exceeding a given threshold value within a certain interval. In this paper, we choose 4% and \( \Delta t = 60 \) min as the threshold value and the length of time windows, respectively. Since the cumulative return \( R_{\Delta t}(t) = [p(t) - p(t - \Delta t)] / p(t - \Delta t) \approx \ln[p(t)/p(t - \Delta t)] = r(t) \), for small \( \Delta t \) we use the logarithmic return as an alternative quantity to the price change. However, some events located in this way are just usual trades rather than extreme events because of the existence of an intraday pattern in volatility. Moreover, a 4% change may be an everyday event for a volatile stock, though this can be a signal of an extreme event for a less volatile stock.

3.2. Relative filter

We measure the average intraday volatility as another contrast. This means that the filter searches for intraday cumulative return exceeding 6 times the average volatility during the same time windows. Here, we utilize the sum of squared returns to define the volatility of a certain time window [32]–[34]:

\[
v(t, \Delta t) = \sqrt{\sum_{\tau=t-\Delta t}^{t} r^{2}(\tau)},
\]

where \( \Delta t \) is the length of the time windows and \( t \) is the end time of the time windows. This filter also has a weakness, because the method maybe only finds out the events that happened in the period of low average volatility, but actual price changes are very small so that they are not true extreme events.

To be able to find out real intraday large events, we combine the two filters together and consider an event to be extreme if it passes both of them. Furthermore, we omit the first 5 min of the trading day to get rid of opening effects. In order to investigate the intraday dynamics after events, we also have to omit the last 60 min of each trading day. Having found an event for the window size \( \Delta t = 60 \) min, we shrink the window as long as the event still passes both filters. The time of the event, considered as \( t = 0 \), is identified with the end of the window for the smallest \( \Delta t \) satisfying these criteria.
With the method above, we find 5450 events in 2003. In order to avoid computing a major event repeatedly, we only include the first events during a given day for a given stock in the average for convenience. Then 163 events are eligible, of which 131 events are positive events; the others are negative events. Figure 1 gives the average cumulative return for positive and negative events. After averaging, the two curves are shifted respectively downwards and upwards so that the cumulative returns at $t = 0$ are zero. An overreaction of around $1\%$ is found during the first 10 min for both, which is consistent with the results in [18], but in our case the peak is sharper. After overreaction, in the case of positive events, the price relaxes to a rather stable value. This is not so for negative events, although it should be mentioned that the much smaller number of negative events causes stronger fluctuations.

In the following, we will give some empirical results around the extreme events. Because eligible negative events are rare, we will place emphasis on the positive events in the following analysis. When we filter events, we only use intraday data. However, when we investigate the dynamics over the events, the evolution is not restricted within one day. Note that all events will have equal weight in the averaging procedure.

Before aggregating all the positive events, we removed the usual dynamics from all investigated quantities. For each quantity $X(d, t')$, the intraday pattern $P(t')$ is determined as the reference, where $d$ identifies trading days and $t' = 1, 2, \ldots, 240$ is the intraday time. The intraday pattern is removed from $X(d, t')$,

$$x(d, t') = X(d, t')/P(t'),$$

for each trading day $d$. For each event $k$, the evolutionary trajectory $\{x_k(t) : t = -100, -99, \ldots, -1, 0, 1, \ldots, 200\}$ is extracted from $x(d, t')$, which contains 100 min before event $k$ and 200 min after event $k$. If the time distance of the event to the closing time is less than 200 min, we simply extend the time series to the next trading day, which is rational since the intraday pattern has been removed [18]. We then obtain the average of quantity $X$ for a group of events $\mathcal{K}$:

$$x_{\mathcal{K}}(t) = \frac{1}{||\mathcal{K}||} \sum_{k \in \mathcal{K}} x_k(t), \quad t = -100, \ldots, 200,$$

\textbf{Figure 1.} Cumulative return averaged over 131 price increases ((a) positive events) and 32 price decreases ((b) negative events), respectively. Minute 0 corresponds to the time when the price change exceeds both absolute and relative filters. Peak value happens at minute 0. Overreaction is obvious.
where $\|K\|$ is the number of events in group $K$. Note that $t = 0$ corresponds to the time when the extreme event happens.

4. Dynamics of four basic quantities: absolute return, trading volume, spread and imbalance

In this section, we investigate the dynamics of four important quantities around positive and negative events. The first quantity is the 1 min absolute return. The second quantity is the total volume of market orders in 1 min. Note that the volume has been adjusted for stock splitting. The third quantity is the bid–ask spread defined as the difference of best ask and best bid at the end of each minute. The fourth quantity is the buy imbalance for positive events defined as the ratio of total volume $V_b$ of buy market orders to the total volume $V_b + V_a$ of market orders in each minute [35]:

$$I = \frac{V_b}{V_b + V_a}.$$  \hfill (4)

The sell imbalance for negative events can be defined in an analogous way. All the events are partitioned into two groups, that is, 131 positive events and 32 negative events. We stress that we define the imbalance here for market orders [35], which is different from that in [20], where both market orders and limit orders are included.

4.1. Positive events

Figure 2 gives the average evolution of the four quantities around 131 positive events. All four plots share the same pattern with a sharp peak and an accumulation before the peak and a decrease after that. The faster decay and very slow accumulation of the imbalance of volume is very different from the LSE case [20]. For absolute return, volume and imbalance, the pre-event accumulation is slower than the relaxation. In contrast, the post-event relaxation of the bid–ask spread is slower than its accumulation. The dynamics of the bid–ask spread in figure 2(c) is very similar to the cases of NYSE and LSE but different from the NASDAQ case [19, 20]. An intriguing feature is that the imbalance of volume reaches its maximum at $t_{\text{max}} = -2$, while the peaks of the other three quantities happen at $t_{\text{max}} = 0$ for absolute return and volume, and at $t_{\text{max}} = 1$ for bid-ask spread. This phenomenon in the imbalance dynamics is different from the LSE case in which $t_{\text{max}} > 0$ [20], which might be due to the fact that we have a different definition of the imbalance.

Another intriguing feature of the buy imbalance dynamics around positive events is that the maximum of the relative buy imbalance is about 1.70. We found empirically that the unconditional average of the buy imbalance is 0.47, which is reminiscent of the fact that the Chinese stock market was ‘bear’ from mid-2001 to 2005 [36]. On average, about 79.9% of the total volume of executed orders was placed on the buy side in the preceding minute before extreme positive events. It is natural to assume that there is a monotonic relationship between the imbalance and the price difference. Accordingly, we observe the same kind of asymmetry in the shape of the pre- and post-event graphs of these quantities. Note that the difference from figure 3(a) of [20] comes from the different definitions of the imbalance.
Figure 2. Dynamics of four variables around 131 positive events: (a) absolute return, (b) trading volume, (c) bid–ask spread and (d) buy imbalance. The maximal values of bid–ask spread and buy imbalance locate at $t_{\text{max}} = 1$ and $t_{\text{max}} = -2$, respectively, whereas the other two quantities have $t_{\text{max}} = 0$. The vertical lines correspond to $t = 0$.

4.2. Negative events

Figure 3 gives the average evolution of the four quantities around 32 negative events. We find that the four temporal evolutions around negative events are qualitatively the same as those around positive events. It is not surprising that the curves for negative events have larger fluctuations than the curves for positive events, since there are many more positive events recognized from the data. All four trajectories share the same pattern, with a sharp peak, an accumulation before the peak and a decrease after that. For absolute return, volume and imbalance, the accumulation is slower than the relaxation. Again, the dynamics of the bid–ask spread in figure 2(c) is similar to the cases of NYSE and LSE but different from the NASDAQ case [19, 20]. We observe that the peaks of absolute return, volume and bid–ask spread happen at $t_{\text{max}} = 0$. Although the imbalance curve is very noisy, we are still able to identify the peak at $t_{\text{max}} = -7$, which is also different from the LSE case, where $t_{\text{max}} > 0$ [20].

From figure 3(d), the maximum sell imbalance around negative events is about 1.4. In addition, the unconditional average sell imbalance is $I_0 = 0.53$. It follows that, on average, about 74% of the total volume of executed orders was placed on the sell side in the preceding minute before extreme negative events.
Figure 3. Dynamics of four variables around 32 negative events: (a) absolute return, (b) trading volume, (c) bid–ask spread and (d) sell imbalance. The maxima of the quantities are $t_{\text{max}} = 0$, except for the imbalance, where the data are too noisy to enable the identification of a proper maximum. The vertical lines correspond to $t = 0$.

4.3. Power-law relaxation of the four financial variables

To study relaxations of the normal value, we plot the excess variables defined as the difference between the actual value and the value in normal periods,

$$x_{\text{ex}}(t) = x(t) - x_0 = x(t) - 1,$$

where the value in normal periods $x_0$ is 1 by definition. Figure 4 illustrates the relaxation of the excess variables around positive events on log–log scales. All the curves exhibit power-law behaviors

$$x_{\text{ex}}(t) \sim t^{-\alpha},$$

which have the same form as those for western mature stock markets [18]–[21]. The power-law relaxation is more significant with less fluctuation and longer scaling ranges for absolute return and volume than for bid–ask spread and volume imbalance.

The estimates of the $\alpha$ values can be obtained through the linear least-squares regression of $\ln x$ against $\ln t$, and we have $\alpha_{\text{AR}} = 0.50 \pm 0.03$ for absolute return, $\alpha_{V} = 0.47 \pm 0.02$ for volume, $\alpha_{\text{BAS}} = 0.60 \pm 0.09$ for bid–ask spread and $\alpha_{\text{Imb}} = 0.23 \pm 0.06$ for volume imbalance.
Figure 4. Power-law relaxation of excess variables for the absolute mid-price return, the trading volume, the bid–ask spread and the buy imbalance after positive extreme events on log–log scales with power-law fits. The relaxation exponents $\alpha$ are $0.50 \pm 0.03$, $0.47 \pm 0.02$, $0.60 \pm 0.09$ and $0.23 \pm 0.06$, respectively.

Table 1. Relaxation exponents of different variables.

| Variable          | Positive events | Negative events |
|-------------------|-----------------|-----------------|
| Absolute return   | $0.50 \pm 0.03$ | $0.53 \pm 0.02$ |
| Volume            | $0.47 \pm 0.02$ | $0.64 \pm 0.08$ |
| Bid–ask spread    | $0.60 \pm 0.09$ | $0.54 \pm 0.11$ |
| Volume imbalance  | $0.23 \pm 0.06$ | –               |

Similarly, there are also power-law decays for negative events, and we find that $\alpha_{AR} = 0.53 \pm 0.02$ for absolute return, $\alpha_V = 0.64 \pm 0.08$ for volume and $\alpha_{BAS} = 0.54 \pm 0.11$ for bid–ask spread, while for volume imbalance the fit is too vague. In both cases of positive and negative events, the fitting was performed on the range $[1, 300]$ for absolute return, volume, bid–ask spread and imbalance. All the resulting power-law relaxation exponents are listed in table 1.

The relaxation of absolute return for SZSE stocks is faster than that for western stocks, in which the exponent $\alpha_{AR} = 0.39 \pm 0.01$ (negative) and $\alpha_{AR} = 0.34 \pm 0.01$ (positive events) for
Table 2. Relaxation exponents of absolute return for different stock markets.

| Stock markets | Positive events | Negative events |
|---------------|-----------------|-----------------|
| SZSE          | 0.50 ± 0.03     | 0.53 ± 0.02     |
| NYSE [18]     | 0.34 ± 0.01     | 0.39 ± 0.01     |
| NASDAQ [18]   | 0.44 ± 0.01     | 0.43 ± 0.01     |
| NYSE [19]     | 0.25–0.40       | 0.25–0.38       |
| NASDAQ [19]   | 0.35–0.41       | 0.32–0.40       |
| LSE [20]      | –               | 0.37 ± 0.01     |

NYSE stocks, and $\alpha_{AR} = 0.43 \pm 0.01$ (negative) and $\alpha = 0.44 \pm 0.01$ (positive) for NASDAQ stocks [18], $\alpha = 0.25–0.40$ for NYSE stocks and $\alpha = 0.32–0.41$ for NASDAQ stocks [19], and $\alpha = 0.38 \pm 0.01$ (all events) for LSE stocks [20]. In addition, the relaxation exponents of the bid–ask spread of SZSE stocks are also different from the LSE stocks, where $\alpha = 0.38 \pm 0.03$ [20, 21]. A comparison of the resulting exponents is illustrated in table 2. It is interesting to note that, when a large price change is simply defined as the 1 min absolute return larger than several times of its average normal level, the absolute returns of NYSE and NASDAQ stocks also exhibit a power-law relaxation after the events with the exponent equal to 0.5 [37].

5. Volume dynamics of buy and sell market orders

In this section we investigate the flow dynamics of buy and sell market orders around extreme events. The intraday pattern is determined for each quantity, which has been removed according to equation (2). The events are divided into two groups, one containing all the 131 positive events and the other including all the 32 negative events. In this section we consider only the positive events. The behavior around negative ones is similar (with exchanged roles of buyer and seller initiated orders), although the fluctuations are considerably larger due to the much smaller number of negative events.

5.1. Pre-event and post-event dynamics

Figure 5 shows the dynamics of the two quantities. Roughly speaking, the shapes of the dynamics are similar to those for volume shown in figures 2(b) and figure 3(b). Also, the two trajectories around negative events are noisier than positive events. The buy volume around positive events reaches its maximum at $t_{\text{max}} = -1$, which is about 20 times its average value in regular moments. The sell volume around negative events reaches its maximum at $t_{\text{max}} = 1$, which is about 12 times its average value in regular moments. The buy volume around negative events reaches its maximum at $t_{\text{max}} = 0$, which is about 8 times its average value in regular moments. The sell volume around negative events reaches its maximum at $t_{\text{max}} = -1$, which is about 13 times its average value in regular moments. Around positive events, the volumes of buy market orders are larger than those of sell market orders, which implies a persistent positive buy imbalance of volumes driving the price up. This observation is consistent with the positivity of buy imbalance in figure 2(d) and sell imbalance in figure 3(d), and in agreement with figure 1.
Figure 5. Dynamics of the relative volume of buy market orders and sell market orders around 131 positive events. The moment that the volume reaches its maximum is (a) $t_{\text{max}} = -1$ for buys around positive events and (b) $t_{\text{max}} = 1$ for sells around positive events.

Another very interesting feature is the significant difference in the structure of the peaks for buy orders and sell orders. This can be intuitively explained by a propagation chain of order flows. Due to an endogenous or exogenous process, the price starts to rise. The hope that the process will lead to a new, higher average value of the stock drives the buyers to place an increasing number of orders. With a little delay, the number of sell market orders also increases, indicating the intention to realize the profit due to the price change. The correlation between order size and liquidity was verified empirically [38]. Before the peak at $t = -1$, the aggregate price impact of buy market orders is greater than that of sell market orders and the price increases continually. This trend reverses at time $t = 0$ when the price impact of buy executed orders is identical to that of sell executed orders. After $t = 0$, the price impact of sell executed orders dominates and the price drops. The situation around negative events is very similar.

5.2. Power-law relaxation of the excess volume of buy and sell orders

Figure 6 illustrates the post-event relaxation of the excess volume of buy market orders and sell market orders around positive events on log–log scales. All the curves exhibit power-law behaviors. The scaling ranges span more than two orders of magnitude. The relaxation exponent is $\alpha_{\text{buy}} = 0.55 \pm 0.03$ for buy market orders and $\alpha_{\text{sell}} = 0.41 \pm 0.02$ for sell market orders around positive events. The fitting was performed on the range $[1, 300]$.

6. Volume dynamics of four types of orders with different aggressiveness

We have shown that order direction (buy or sell) can be used to classify the dynamics of relative volume of the incoming market orders. In this section, we investigate further the dynamics of different types of orders around extreme events by taking into account order aggressiveness. Orders can be classified into different types according to their aggressiveness [39]. Here, we consider four types of orders on each side of the order flow, that is, partially filled market orders, filled market orders, limit orders and canceled orders. More rigorously, ‘market orders’ and ‘limit orders’ should be termed ‘effective market orders’ and ‘effective limit orders’ [40], since...
there were no market orders permitted to submit in the SZSE in 2003 [29]. The differentiation of partially filled orders and filled orders is validated due to the fact that they have very different behaviors of price impact [28].

We study the volume dynamics of four types of buy orders and sell orders around the extreme events. Therefore, there are eight quantities. The intraday pattern is determined for each quantity, which has been removed according to equation (2). Again, the events are divided into two groups, one containing all the 131 positive events and the other including 32 negative events. We also study the dynamics of numbers of buy orders and sell orders around the extreme event. We find that the results are quite similar, with minor differences.

Figure 7 illustrates the dynamics of volumes around 131 positive events for the four types of buy orders and sell orders. Figure 7(a) shows the results for partially filled market orders. The volume of buy orders that are partially filled starts to increase about 40–50 min before the extreme event and reaches about 22.4 times the normal value at $t_{\text{max}} = 0$. In contrast, the volume of sell orders that are partially filled market orders increases relatively more slowly and reaches its maximum of 10.3 at $t_{\text{max}} = 1$. Figure 7(b) shows the results for filled market orders. The volume of filled buy orders starts to increase about 50 min before the extreme event and reaches about 19.4 times the normal value at $t_{\text{max}} = -1$. In contrast, the volume of filled sell market orders increases relatively more slowly and reaches its maximum of 11.3 at $t_{\text{max}} = 1$. It is clear that sell market orders lag behind buy market orders, and there are many more buy market orders before $t = 0$, which push the price up. Figure 7(c) shows the results for limit orders. The volume of limit buy orders starts to increase about 50 min before the extreme event and reaches about 16.4 times the normal value at $t_{\text{max}} = 0$. In contrast, the volume of sell limit orders increases relatively more slowly and reaches its maximum of 19.0 at $t_{\max} = 2$. Figure 7(d) shows the results for canceled orders. We observe that the evolution behaviors are very similar to market orders in figures 7(a) and (b). The maximum volume is 24.4 at $t_{\text{max}} = -1$ for canceled buy orders and 19.0 at $t_{\text{max}} = 4$ for canceled sell orders. This reflects the fact that buy traders are very eager to execute their orders, and more unfilled orders are canceled in order to submit new buy orders.
The characteristic values ($t_{\text{max}}$ and $V_{\text{max}}$) of the peaks in figure 7 are listed in table 3. The dynamics of the numbers of the four order types around 131 positive events is very similar to that of volumes. However, there are still differences. The characteristic peak values ($t'_{\text{max}}$ and $N_{\text{max}}$) are also listed in table 3. We find that $t_{\text{max}} < t'_{\text{max}}$ for filled buy orders and canceled orders, and $t_{\text{max}} = t'_{\text{max}}$ for the remaining six types of orders. After $t = -1$, the volume of filled buy orders decreases while the number of filled buy orders still increases. This implies that investors (especially individuals) with small orders still rush into the market while investors (more probably institutions) with large orders have left the market.

Figure 8 shows the relaxation of excess volume after positive events ($t = 0$) for the four types of buy and sell orders. All curves exhibit power-law behaviors. The power-law relaxation exponents are $0.47 \pm 0.05$ for partially filled buy orders in the scaling range $[1, 300]$, $0.47 \pm 0.04$ for partially filled sell orders in the scaling range $[1, 300]$, $0.57 \pm 0.04$ for filled buy orders in the scaling range $[1, 300]$, $0.41 \pm 0.02$ for filled sell orders in the scaling range $[1, 300]$, $0.43 \pm 0.03$ for buy limit orders in the scaling range $[1, 300]$, $0.63 \pm 0.02$ for sell limit orders in the scaling range $[2, 300]$, $0.85 \pm 0.09$ for canceled buy orders in the scaling range $[1, 300]$ and $0.58 \pm 0.05$ for canceled sell orders in the scaling range $[4, 300]$.

The excess order numbers after positive events ($t = 0$) for the four types of buy and sell orders decay as power laws. The power-law relaxation exponents are $0.43 \pm 0.02$ for partially filled buy orders in the scaling range $[1, 300]$, $0.46 \pm 0.02$ for partially filled sell orders in the
Table 3. Peak characteristic values of the aggregate evolution trajectory of relative volume and relative number around 131 positive events for four types of buy orders and sell orders classified by order aggressiveness. The types of PFO, FO, LO and CO correspond to partially filled orders, filled orders, limit orders and canceled orders, respectively.

| Type | \( t_{\text{max}} \) | \( V_{\text{max}} \) | \( t'_{\text{max}} \) | \( N_{\text{max}} \) |
|------|----------------|----------------|----------------|----------------|
| PFO  | 0              | 22.4           | 0              | 12.5           |
| FO   | \(-1\)         | 19.4           | 1              | 12.9           |
| LO   | 0              | 16.4           | 0              | 11.7           |
| CO   | \(-1\)         | 24.4           | 0              | 18.4           |

Figure 8. Power-law relaxation of excess volume around 131 positive events for four types of buy orders and sell orders classified by order aggressiveness: (a) partially filled orders, (b) filled orders, (c) limit orders and (d) canceled orders.

scaling range \([1, 300]\), \(0.52 \pm 0.01\) for filled buy orders in the scaling range \([1, 300]\), \(0.44 \pm 0.01\) for filled sell orders in the scaling range \([1, 300]\), \(0.30 \pm 0.01\) for buy limit orders in the scaling range \([1, 300]\), \(0.65 \pm 0.01\) for sell limit orders in the scaling range \([2, 300]\), \(0.53 \pm 0.03\) for canceled buy orders in the scaling range \([1, 300]\) and \(0.54 \pm 0.02\) for canceled sell orders in the scaling range \([4, 300]\).
7. Individual and institutional investors

7.1. Volume dynamics

We investigate here whether the type of investor (individuals and institutions) has any effect on the volume dynamics of market orders around extreme price changes. Our database contains identifiers distinguishing the two types of investor. Specifically, we consider buy market orders and sell market orders by individuals and institutions around positive events and negative events (see section 5). In addition, we also consider partially filled buy and sell orders, filled buy and sell orders, buy and sell limit orders, and canceled buy and sell orders (see section 6). Since the findings are very similar, we present only the results for market buy and sell orders submitted by individuals and institutions around positive events.

The results are shown in figure 9. Comparing the volume dynamics of buy (or sell) market orders from individuals and institutions, it seems that the type of investor has a negligible effect on the dynamics. The volume dynamics of buy (resp. sell) market orders from individuals and institutions is very similar to that shown in figure 5(a) (resp. figure 5(b)). We observe that $t_{\text{max}} = -2$ and $V_{\text{max}} = 19.4$ for buy market orders submitted by individuals, $t_{\text{max}} = -1$ and

**Figure 9.** Dynamics of the relative volume of market orders submitted by individual and institutional investors around positive events: (a) buy market orders submitted by individuals, (b) sell market orders submitted by individuals, (c) buy market orders submitted by institutions and (d) sell market orders submitted by institutions.
$V_{\text{max}} = 17.5$ for buy market orders submitted by institutions, $t_{\text{max}} = 1$ and $V_{\text{max}} = 10.4$ for sell market orders submitted by individuals, and $t_{\text{max}} = 1$ and $V_{\text{max}} = 11.9$ for buy market orders submitted by institutions. The values of $t_{\text{max}}$ for individuals and institutions are identical to those shown in figure 5(a) for buy market orders and in figure 5(b) for sell market orders, except for buy market orders from individuals.

**7.2. Dynamics of the relative rates of market orders, limit orders and cancelations**

Following [20], we study in this section the dynamics of the relative rates of different types of orders (market orders, limit orders and canceled orders) around extreme events. Furthermore, we distinguish each type of order by the type of investor. For each type of investor, the numbers of market orders, limit orders and cancelations submitted in the same minute are determined and the relative order rates are calculated as the proportions of order numbers. Figure 10 shows the results for positive events. We do not show the results for negative events since the conclusion is the same. We do not find very strong variations in the different rates around the large price changes. This finding is qualitatively the same as the LSE stocks [20]. However, it seems justified to say that the values of the relative rates are not identical between SZSE stocks and LSE stocks.

In figure 10, the relative rates around extreme events are compared with those in normal periods. For individuals, the average relative rates in normal periods for market orders, limit orders and canceled orders are 0.26, 0.60 and 0.14, respectively. Before the extreme events at $t = 0$, the relative rate of market orders is higher than the normal level, while the relative rates of limit orders and canceled orders are lower than the normal level. After the extreme events, the situation is different. The relative rate of limit orders jumps above the normal level right after the events and then decreases to its previous level before the events in about 15 min. In contrast, the relative rate of market orders drops under its normal level immediately after the events and then returns to its previous level before the events. The relative rate of canceled orders becomes identical to the normal level. For institutions, the average relative rates in normal periods for market orders, limit orders and canceled orders are 0.42, 0.49 and 0.09, respectively. On average,
the relative rate of market orders is higher than the normal level, while those for limit orders and canceled orders are lower than the corresponding normal levels. The abrupt change right after the events is visible but not significant since the data are very noisy.

There are differences between the behavior of the relative rates for SZSE stocks and LSE stocks. For 12 LSE stocks, there are no strong changes in the rates for true market orders, true limit orders and canceled orders around large price changes, and their rates fluctuate around \(-0.07\), \(-0.61\) and \(-0.32\) [20]. This result means that no strategy of the investors about how they place orders is identified [20]. After accounting for the effective orders, the relative rates of limit orders, market orders and cancelations for 14 LSE stocks are 0.16, 0.49 and 0.35 [38]. We see that the cancelation ratio of LSE stocks is much higher than that of the SZSE stocks, while the rate of market order is much lower than that of SZSE stocks. If we consider only the orders submitted, the ratios of the number of effective market orders to the total number of limit and market orders are 0.30 and 0.25 for SZSE stocks and LSE stocks, respectively. This observation can be attributed to the fact that the proportion of institutional investors is much higher in the LSE, and that the LSE is a mature market while the SZSE is an emerging market.

Comparing the results for individuals and institutions, we see significant differences. For individuals, the relative rate of limit orders is about 0.58, much larger than that of market orders (about 0.30). In contrast, for institutions, the relative rate of market orders (about 0.50) is larger than that of limit orders (about 0.45). In addition, institutions have a smaller rate of canceled orders than individuals. The difference between the behavior of individual and institutional investors is very interesting since it sheds light on the strategies of these groups. It may indicate that institutions are more aggressive than individuals; thus institutions play a more important role in causing large price changes. Concerning the relative rate of market orders after the positive event, careful scrutiny unveils an increasing trend for individuals and a noisy decreasing trend for institutions. This means that individuals are still aggressively submitting buy market orders after the peak when institutions are quitting gradually. Combining together the fact that the relative rate of market orders is much higher for institutional investors, we can conclude that institutions are better informed than individuals in Chinese stock markets. This is consistent with conventional wisdom and we can conjecture that individuals show worse performance than institutions [41].

7.3. Dynamics of the relative rates of buy and sell market orders, limit orders and cancelations

The difference between the behaviors of individuals and institutions is more evident when we further distinguish buy orders and sell orders. Figures 11(a) and (b) illustrate the results for individuals, while figures 11(c) and (d) show the results for institutions. We find a strong buy–sell asymmetry in both types of investors. According to figure 11(a), the relative rate of buy market orders submitted by individuals increases continuously before the extreme events and then drops sharply below its normal level with a fast recovery above its normal level, while the relative rate of sell market orders decreases continuously before the extreme events and recovers soon to its normal level smoothly without a sharp increase above its normal level. The relative rate of canceled buy orders also increases to reach a high level before the extreme events and then drops rapidly to its normal level, while the relative rate of canceled sell orders decreases before the extreme events and increases suddenly to a high value, which is followed by a slow relaxation to its normal level. According to Figure 11(b), the two curves of the relative rates of buy limit orders and sell limit orders are almost symmetric to the mean of their normal
Figure 11. Dynamics of the relative rates of market orders (circles ◦), limit orders (squares □) and cancelations (triangles △) around positive events. Solid symbols denote buy orders, while open symbols denote sell orders. (a) Relative rates of market orders and canceled orders submitted by individuals. The average relative rates in normal periods are 0.13 for buy market orders, 0.12 for sell market orders, 0.07 for canceled buy orders and 0.07 for canceled sell orders. (b) Relative rates of limit orders submitted by individuals. The average relative rates in normal periods are 0.28 and 0.32 for buy and sell limit orders. (c) Relative rates of market orders and canceled orders submitted by institutions. The average relative rates in normal periods are 0.25 for buy market orders, 0.17 for sell market orders, 0.06 for canceled buy orders and 0.03 for canceled sell orders. (d) Relative rates of limit orders submitted by institutions. The average relative rates in normal periods are 0.30 and 0.19 for buy and sell limit orders.

values. The rate of buy limit orders increases before the extreme events and decreases markedly, which is followed by a slow recovery to its normal level.

It turns out that for institutional investors the relative rates of the buy and sell orders behave in an opposite way, such that the difference roughly cancels. This can be observed for both market and limit orders. On the other hand, although the results are very noisy, the difference seems somewhat smaller for market orders and significantly smaller for limit orders. It seems that individual investors would simply follow the events, while institutional ones act according to some strategies. We also find that there are fewer buy limit orders canceled by institutions and there are no cancelations of buy orders after all in many minutes around positive events. All these point toward the stronger aggressiveness of institutional investors.
8. Conclusion

We studied the dynamics of order flows around large price changes in 23 Chinese stocks traded on the SZSE in 2003. Special emphasis was placed on the dynamics of order volume. We found sound evidence of price reversal after large price changes. In the case of positive events, the price soars about 5% in 100 min and then drops about 1% in 15 min to a constant level. This reversal pattern indicates that the price impact of orders around positive events is permanent. The situation around negative events is similar, except that the price after large negative events does not seem to relax to a constant level. It should be noted that, due to the much lower number of negative events, the results for them are always much more noisy than for positive ones.

For the dynamics of volatility (absolute return), volume, bid–ask spread and volume imbalance, we found a significant peak around the extreme price changes followed by a slow relaxation, which can be well fitted by a power law. In most cases, the relaxation exponents are larger for the SZSE stocks than for the LSE stocks.

We investigated the effect of order direction, order aggressiveness and investor type on the dynamics of order flows. In each case, we found an increase in order volume followed by a slow decrease, which forms a peak around the extreme events. The volume peak of buyer-initiated execution orders was found to appear earlier and higher than seller-initiated execution orders around positive events, while the volume peak of seller-initiated execution orders was found to lead buyer-initiated execution orders in the magnitude and time around negative events. When orders are divided into four groups according to their aggressiveness, the behaviors of partially filled market orders, filled market orders and canceled orders are qualitatively the same: the volume peak of buy (sell) orders of each type appears earlier and higher than sell (buy) orders around positive (negative) events. However, the volume peak of sell (buy) limit orders shows up earlier and higher than buy (sell) orders around positive (negative) events. No qualitative difference has been observed in the volume dynamics around extreme events between individuals and institutions.

We also studied the relative rates of different types of orders. We confirmed that the relative rates of market orders, limit orders and cancelations do not fluctuate much around extreme events, but there is still a significant difference between individuals and institutions. In addition, we witnessed differences in the dynamics around extreme events for buy orders and sell orders. Interestingly, the behaviors are different when the type of investor is taken into consideration. Clearly, there is a sharp difference between the strategies of individual and institutional investors, and institutions are more aggressive and better informed.

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