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Component ACD Model and Its Application in Studying the Price-Related Feedback Effect in Investor Trading Behaviors in Chinese Stock Market*

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Abstract This paper explores the investors' feedback to the price change by modelling the price-related dynamics of trading intensity. A component decomposition duration modeling approach, called the component autoregressive conditional duration (CACD) model, is proposed to capture the variation of trading intensity across time intervals between price change events. Based on the CACD model, an empirical analysis is carried out on the Chinese stock market that covers different market statuses. The empirical results suggest that the CACD model can capture the price-related dynamics of trading intensity, which supports the existence of the feedback effect and is robust across different market statuses. The authors also study how the investors react to the price change by examining the driven factors of the price-related dynamics of trading intensity. The authors find that the trading can be triggered by the fast rise in the price level and the high trading volume. Besides, investors are more sensitive to the price change direction in the sideways market than in the upward or downward markets.

Keywords Component ACD model, feedback effect, investor behavior, market status, trading intensity.

1 Introduction

The availability of intraday high-frequency data provides a foundation to develop analytical tools to directly capture the intraday dynamics of trading intensity and study the investor

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behaviors. A central theme of investor behavior study is that the investors may not be rational agents in the financial market. Shiller, et al.[1] firstly linked the investor behavior to the social-psychological factors and argues that there exists "ordinary investors" who make decision according to historical price and the market trend instead of the rational expectation of the future cash flow. Shiller[2] provided a simple feedback model that builds the relationship between the price change and the investor behavior. At the same time, De Long, et al.[3–5] also argued that the noise traders may follow the positive feedback strategy, i.e., buy when price rises and sell when price falls. Their models suggest that, given the existence of the feedback investors, even the rational investors tend to follow the market trend to arbitrage, which strengthens the feedback trading and enhances the impact of price change on trading intensity. Moreover, Mendel and Shleifer[6] further suggested that even a small part of irrational noise investors could drive the market as the uninformed rational investors tend to chase the noise generated by the irrational noise investors.

As to the empirical studies, some scholars study the feedback effect by examining the stock returns' autocorrelation function. For example, in Sentana and Wadhwani[7], Koutmos[8] and Watanabe[9], they suggested that the feedback effect exists in various financial markets based on the autocorrelations of stock returns. On the other hand, some works investigate the feedback effect by directly measuring investor behaviors based on the transaction data. Hasbrouck[10] captured the interaction of trades and quote changes via a VAR model and verifies the positive feedback effect on NYSE stock market. In addition, Cohen and Shin[11] used a similar method and they show the feedback effect on the US Treasury market.

In this paper we study the feedback effect by modelling the price-related dynamics of trading intensity based on the trade duration data. Modelling the trade duration and studying dynamics of trading intensity have been one of the central themes in high frequency finance and a large number of specific econometric methods have been developed over last two decades. Engle and Russell[12] proposed the autoregressive conditional duration (ACD) model as the seminal work of the duration modeling and following this spirit many other econometric models on this issue have been proposed subsequently, for example, the logarithmic ACD model[13] and several non-linear ACD models (for example, [14, 15]). These methods have been widely used to study the trading intensity dynamics and its economic implication. Spierdijk[16] modeled the trade durations and some economic variables for five actively traded NYSE stocks and shows that large trades, large order imbalance and small absolute return increase the trading intensity. Taylor[17] studies the trading intensity in the future market and finds that large bid-ask spread, high trading volume and large pricing error induce high trading intensity. Manganelli[18] jointly modeled the trade duration, expected volume and price volatility and finds that high trading intensity is associated with high level of information asymmetric for the frequently traded stocks. Liu and Maheu[19] examined the information content of trading intensity in the Chinese stock market and Ryu[20] studied a similar issue in the South Korean stock market.

This paper extends the component multiplicative error model (CMEM) proposed by Brownlees, et al.[21] to capture the price-related dynamics of trading intensity. Our model, called the "component autoregressive conditional duration" (CACD) model, decomposes the trade durations into two different components: The dynamic component that measures the high-frequency dynamics of the trade duration process at the transaction level and the intercept component that captures the variation of the duration mean across the time intervals between price change events. Both components are autoregressive and we also allow the exogenous factors impact on the intercept component.

In the econometrical perspective, the CACD model provides an alternative way to generate the long term dependence in the trade duration series. The long term dependence in the duration series is critical and widely-documented in the literature. Granger and Hyung[22] provided several data generating process for the long term dependence, including the structural break, specific trend and low frequency component, and the fractionally integrated duration models (Jasiak[23]; Chen and Deo[24]; Deo, et al.[25]) and the Mixed ACD model (Brownlees and Vannucci[26]) are developed to capture this stylized effect. In our model, the intercept component that varies at a low frequency leads a long persistence feature of the duration series. Moreover, the variation of the intercept component is related to the price change event and therefore our model provides a link between the price series and the long term dependence in trade duration series.

In the economical perspective, via the CACD model, we study the feedback effect and examine whether and how the investor trading behaviors react to the price change by modelling the price-related dynamics of trading intensity. Our empirical study focuses on the Chinese stock market, which is the largest emerging financial market, for its specific market structure. Only domestic investors can trade in this market and most of them are individual investors. Compared with institutional investors, the individual investors are less informative and more irrational, therefore they are more likely to have the feedback effect in their trading decisions. Since rare literature on this issue focuses on Chinese stock market, it is necessary to fill this gap and study the feedback effect issue in the trading behavior of Chinese investors.

The empirical studies in this paper apply the CACD model to 5 sample stocks listed on Shenzhen stock exchange (SZSE) and three time periods that related to the downward market, upward market and sideways market, respectively. The empirical study suggests that, firstly, there is a strong evidence of the existence of the feedback effect verified by the extra trading intensity dynamics associated with the price changes. Specifically, the CACD model captures extra variation of trading intensity across different time interval of price change events and the statistic tests show that the trade duration data is better fitted after capturing this price-related dynamics. Moreover, our result is robust across all cases taken into account, i.e., all the sample stocks and market statuses pairs. In addition, we also uncover the determination of the investor's reaction to the price change by examining the driven factors of price-related trading intensity dynamics. We find that trading can be triggered by the fast rise in the price level and the large trading volume and investors are more sensitive to the price change direction in the sideways market than in the upward or downward market.

The contributions of this paper are both empirical and methodological. Firstly, we capture the price-related dynamics of trading intensity and provide evidence of the existence of the feedback effect in Chinese stock market, which has not been extensively studied yet. Secondly, the CACD model introduced in this paper provides an alternative way to model the trade duration data and capture the long term dependence in the trade duration series. In our model, the long term dependence is generated by an autoregressive component that linked to the price series, which sheds a light on modeling trading intensity.

The remainder of this paper is organized as follows. Section 2 introduces the intraday periodicity adjustment and the CACD model. Section 3 describes our sample data. An empirical experiment that employs the CACD model to analyze the price-related dynamics of trading intensity and the feedback effect in Chinese stock market is presented in Section 4. Section 5 concludes this paper.

2 Model Specification

We employ a two-step procedure to model the trade duration process. In the first step the trade duration process is corrected for the intraday periodicity. In the second step the adjusted trade duration data is fitted by the CACD model to capture the price-related dynamics of trading intensity.

It is well known that the financial duration process is related to the intraday periodicity. Engle and Russell[12] proposed an intraday periodicity adjustment method that standardizes the duration data by a cubic-spline-type seasonal factor. Recently, however, Wu[27] documented that this adjustment may generate systematic bias and therefore a so-called "time change" approach is developed to address this issue. In this paper, we frame our modelling approach based upon the time change approach to conduct the intraday periodicity adjustment for the trade durations.

The time change approach is based on the assumption that the transactions would be evenly observed through the day without the disturbance of periodicity. Correspondingly, one can adjust the calendar time of a trade arrival to a uniformly distributed adjusted time according to the empirical distribution of the time of transaction arrivals to remove the intraday periodicity. Specifically, let $N(t)$ be the counting function and denote the number of transactions up to time t, then the daily counting function can be defined as:

$$N_\tau^d = N((d-1)p + \tau) - N((d-1)p), \quad d = 1, 2, \cdots, k, \tag{1}$$

where d and τ indicate the τth second in a trading window of the dth trading day, p is the total seconds of the trading window in one trading day and k is the total number of trading days in the sample. The daily counting function computes the cumulated transaction number in one trading day and then the intraday cumulated transaction number across several trading days can be computed as $\sum_d N_\tau^d$. The calendar time is adjusted according to the proportion of trade numbers up to time t and the adjusted time is expressed as:

$$T(\tau) = \frac{p}{N(kp)} \sum_{d=1}^{k} N_\tau^d. \tag{2}$$

It can be shown that $T(0) = 0$, $T(p) = p$ and $\forall \tau_1 \leq \tau_2, T(\tau_1) \leq T(\tau_2)$, which means that the calendar time in the trading window is orderly mapped to the adjusted time. Hence, the adjusted trade duration can be directly defined as $T(t_{i+1}) - T(t_i)$.

Now, following the similar spirit of the component MEM (CMEM)[21], we introduce the component autoregressive conditional duration (CACD) model. In the CACD model, the trade duration process is decomposed into two components: The intercept component that captures the variation of the conditional expectation of trade durations mean across the time intervals between price change events, and the dynamic component that measures the high-frequency dynamics of durations at the transaction level.

Let $\tau_{i,t}$ denote the series of arrival times for the ith trade in the price interval t, where the price interval is defined as the time interval between the tth and the $(t+1)$th price changes. The corresponding durations $x_{i,t} = \tau_{i,t} - \tau_{i-1,t}$ for $i \neq 1$ or $x_{i,t} = \tau_{i,t} - \tau_{n_{t-1},t-1}$ for $i = 1$ where n_t is the transaction number in price interval t. The CACD model is defined as follows:

$$\begin{cases} x_{i,t} = \phi_{i,t}\mu_t\varepsilon_{i,t}, \\ \mu_t = \omega^\mu + \beta^\mu\mu_{t-1} + \alpha^\mu x^\mu_{t-1}, \\ \phi_{i,t} = \omega^\phi + \beta^\phi\phi_{i-1,t} + \alpha^\phi x^\phi_{i-1,t}, \end{cases} \tag{3}$$

where the standardized trade durations $x^\phi_{i,t} = \frac{x_{i,t}}{\Gamma(1+1/\gamma)\mu_t}$ and $x^\mu_t = \frac{1}{n_t}\sum_i \frac{x_{i,t}}{\Gamma(1+1/\gamma)\phi_{i,t}}$ and the error term $\varepsilon_{i,t} \sim$ i.i.d. Weibull distribution $W(1,\gamma)$ with scale parameter 1 and shape parameter γ. The dynamics of intercept component μ_t and dynamic component $\phi_{i,t}$ are both specified as standard autoregressive processes that controlled by the standardized observations x^μ_t and $x^\phi_{i,t}$, respectively. A distinct feature of our CACD model from the CMEM in Brownlees, et al.[21] is that the intercept component will be updated based on the new information contained in the price changes and therefore the intercept component follows a stair-step shape in terms the price changes.

We restrict the unconditional expectation of dynamic component to be 1 by the parameter restriction $\omega^\phi = 1 - \alpha^\phi - \beta^\phi$. Under this setting, the time span of the trade duration series is divided into several price event intervals by the occurrence of the price change event. The mean of the trade durations is determined by two parts, i.e., the intercept component at each price event interval and the dynamic component at high-frequency transaction level. As the trading intensity is measured by the reciprocal of the trade duration mean, the time-varying intercept component captures extra dynamics of trading intensity across different price event intervals in addition to the transaction level dynamics captured by the dynamics component. This price-related extra dynamics of trading intensity can be generated by the investors reaction for the price change event and therefore it is associated with the price-related feedback effect in investor trading behaviors. Note that the intercept component shall be time-invariant when both α^μ and β^μ are equal to 0. In this case the trading intensity is homogeneous during different price event intervals and therefore, as discussed above, the price-related feedback effect in investor trading behaviors can be examined by the significance of α^μ and β^μ.

Since both two components are autoregressive, the coefficients α^ϕ and β^ϕ in the dynamic component and α^μ and β^μ in the intercept component all capture the persistence in the duration mean series, i.e., the effect of historical trade durations on the current duration expectation. However, each coefficient acts in different scale. Specifically, in the dynamic component, the coefficient α^{ϕ} measures the direct impact of the last occurred trade on the current duration mean and the coefficient β^{ϕ} captures the long-term persistence in the transaction level trading intensity dynamics. In the intercept component, the coefficients α^{μ} measures the direct impact of the average level of trade duration during last price event interval on the duration mean in the current price event interval, while β^{μ} captures the long-term persistence in the price-related dynamics. Compared to the standard ACD model, the CACD model contains the intercept component that provides an alternative way to capture the long-term persistence.

The exogenous variables can be introduced into the intercept component to investigate the driven factors of price-related dynamics of trading intensity. Specifically, the dynamic function of the intercept component can be replaced by following equation:

$$\mu_t = \omega^{\mu} + \beta^{\mu}\mu_{t-1} + \alpha^{\mu}x^{\mu}_{t-1} + cz_{t-1}, \tag{4}$$

where z_{t-1} is the vector of lagged exogenous variables associated with the $(t-1)$th price interval and c is the vector of coefficients.

In this paper, we only consider the CACD model with the first order lag specification. However, one can also consider the multi-lag CACD model and specify either the intercept component or the dynamic component impacted by the high-order lagged historical values directly. This extended model can be obtained similarly and thus is not provided in details.

Then the log likelihood function of the CACD model follows:

$$\ln\mathcal{L} = \sum_{i,t}\left\{\ln\left(\frac{\gamma}{x_{i,t}}\right) + \gamma\ln\left(\frac{\Gamma(1+\frac{1}{\gamma})x_{i,t}}{\phi_{i,t}\mu_t}\right) - \left(\frac{\Gamma(1+\frac{1}{\gamma})x_{i,t}}{\phi_{i,t}\mu_t}\right)^{\gamma}\right\}, \tag{5}$$

and the model parameters could be estimated via the maximum likelihood estimation as for the standard ACD model.

Next, we discuss how to examine the price-related dynamics of trading intensity by the model diagnostics. The robust t-test can be conducted to the model. As discussed above, the significant coefficients α^{μ} and β^{μ} in the intercept component verify the price-related dynamics of trading intensity and which is associated with the price-related feedback effect in the investor trading behavior. We can also perform the likelihood ratio test to examine the existence of the price-related dynamics of trading intensity and we expect a significant likelihood gain of the model with time-varying intercept component over that model with constant intercept component. Another test of interest is whether the unrestricted CACD model can better capture the autocorrelation in the trade duration process than the model with constant intercept component, which can be accomplished by the Ljung-Box test for the model residuals. Both of the likelihood ratio test and the Ljung-Box test examine whether the data is well fitted by the model that captures the extra price-related dynamics. Besides, since the restricted CACD model, i.e., the model with time-invariant intercept component, is equivalent to the standard ACD model, the tests mentioned above also suggest whether the proposed CACD model performs better than the ACD model.

3 Data Description

We select 5 sample stocks listed on Shenzhen stock exchange (SZSE) in China to examine the price-related dynamics of trading intensity and the feedback effect. All the sample stocks belong to CSI 300 companies, where CSI 300 is a market index that contains the largest and most liquid stocks on Chinese stock market. The five sample stocks come from five different main sectors, i.e., finance, business support, IT, manufacturing and Mining. Table 1 presents the information about the selected sample stocks. In terms of sample span, the data covers three different periods and each periods contains two months. Period 1 is a downward market that from November 2011 to December 2011; Period 2 is an upward market that from December 2012 to January 2013; Period 3 is a sideways market that from May 2014 to June 2014. We study each sample stocks during Periods 1–3, respectively, to ensure the empirical result does not depend on the market status. The summarized statistics of the sample periods are given in Table 2. It shows that the average daily market return is around 0.014% during Period 3, while it reaches a remarkably high level (0.502%) during Period 1, and decreases to a low level (−0.358%) during Period 2. These different market trends suggest the downward, upward and sideways market statuses during Periods 1–3, respectively. Figure 1 plots the SZSE Composite Index during 2011 to 2014 and marks the selected sample periods, which illustrates different market trends of each period suggested above.

Table 1 The stock codes and company names of the 5 Chinese sample stocks together with their industries

Stock code	Company name	Industry
000001	Ping An Bank	Finance
000061	Shenzhen Agricultural Products Co Ltd	Business support
000503	Searainbow Holding Corp	IT
000651	Gree Electric Appliances Inc of Zhuhai	Manufacturing
000983	Shanxi Xishan Coal and Electricity Power Co Ltd	Mining

Table 2 Sample periods and summary of market trends

Period	1	2	3
Dates	Nov 2011–Dec 2011	Dec 2012–Jan 2013	May 2014–Jun 2014
Number of trading days	44	41	40
Status	Downward	Upward	Sideways
Begin and end market index	10480.9–8918.8	7903.3–9667.7	7312.9–7343.3
Mean of daily market returns	−0.358%	0.502%	0.014%
Standard deviation of daily market returns	1.318%	1.403%	0.885%

Notes: The market return is based on the market index SZSE composite index.

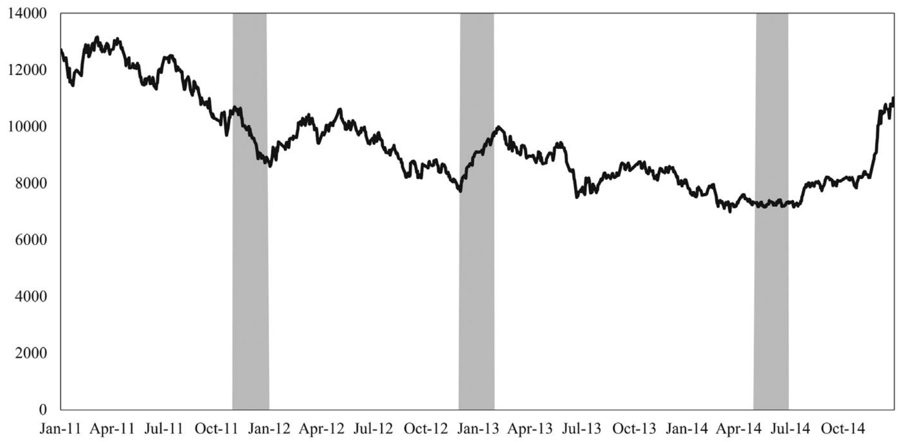


Figure 1 SZSE composite index during 2011–2014 and the selected sample periods in the shadow

The empirical analysis is carried out over 15 stock-period pairs that covers the 5 sample stocks during Periods 1–3. We collect the intraday high-frequency data over the 15 stock-period pairs from the CSMAR TAQ database. In order to exclude the impact of trading mechanism, we eliminate the observations from the opening call auction period and the off market period. Since SZSE implements the 10%-price limit rule, for each sample stocks we eliminate the trading days which the price limits have been reached.

In this paper, we compute the trade duration as follows. Firstly, we estimate the occurrence time of each trades. Limited by the precision of the timestamp, several trades may share the same timestamp and we do not know the durations among these trades exactly. Most of previous studies omit these incomputable trade durations by treating the overlapped trades as one trade. This method, however, may generate bias for the fact that the duration calculated by this method is in fact the aggregation of all durations among the overlapped trades. For this reason, we equally divide the time interval between timestamps for the overlapping trades and estimate the occurrence time of these trades by the fractiles. Then we calculate the durations based on this estimation. We adopt the definition of trade duration similarly with Brownlees and Vannucci[26] that the waiting time of 100 consecutive transactions, instead that of each consecutive transactions. This definition avoids the consecutive equal trade durations generated by the treatment for the overlapping trades mentioned above and reduce the computational burden.

Then we extra the price change event from the high-frequency price series, where the price change event is defined as that the price rises or falls exceeding a given threshold. We extract the price change event based on the mid-point price, i.e., the mean of best bid and ask prices listed on the limit order book. To unify price change threshold for all sample stocks with different price level, we take the logarithm to the price and set the threshold as 0.2%.

The descriptive statistics of the trade durations and price change events is reported in Table 3. During the 15 stock-period pairs, the number of trade durations is range from 1126 to 7224 and the mean of trade durations is range from 76.92 seconds to 518.82 seconds. The autocorrelation is remarkably high and decaying slowly in all cases, indicating the high persistence of the trade duration series. Besides, we also notice that the mean of trade durations exceeds their standard deviations, which suggests that the trade duration defined in this paper follows the under-dispersion distribution. The number of price change event is range from 566 to 1943 and there is a trend that the price changes rapidly in the upward market than in the downward and sideways markets.

Table 3 Descriptive statistics of the trade duration and the price change

Stock code	$\#TD$	$M(TD)$	$sd(TD)$	$\rho_1(TD)$	$\rho_{25}(TD)$	$\rho_{50}(TD)$	$\#PU$	$\#PD$
Period 1: Downward market								
000001	3153	192.32	133.51	0.61	0.24	0.14	348	395
000061	1126	518.82	335.07	0.55	0.15	0.14	315	375
000503	2608	221.01	178.91	0.73	0.39	0.35	665	680
000651	3124	198.34	131.55	0.55	0.11	0.06	494	585
000983	4809	129.84	93.18	0.68	0.28	0.25	615	761
Period 2: Upward market								
000001	7224	76.92	64.69	0.77	0.44	0.35	946	807
000061	4679	106.20	96.62	0.71	0.33	0.24	786	806
000503	2455	234.02	178.54	0.70	0.24	0.18	730	692
000651	5439	107.40	65.97	0.65	0.21	0.16	806	739
000983	6360	91.71	72.55	0.72	0.31	0.15	971	972
Period 3: Sideways market								
000001	6080	93.61	63.91	0.72	0.29	0.21	483	443
000061	1770	306.76	219.11	0.70	0.26	0.32	442	522
000503	1685	331.63	188.94	0.64	0.21	0.12	452	458
000651	4230	134.45	70.39	0.64	0.19	0.13	317	335
000983	1938	281.43	209.19	0.67	0.28	0.23	271	295

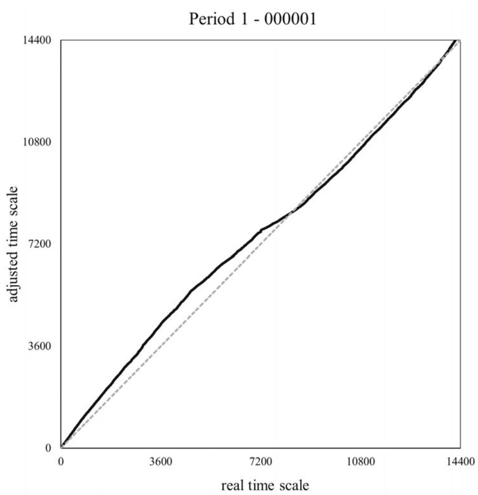
Notes: The trade duration in this paper is defined as the waiting time of the 100 consecutive transactions. $\#TD$ is the number of trade durations in the sample period. $M(TD)$ and $sd(TD)$ are the mean and standard deviation of the trade durations, respectively. $\rho_1(TD)$, $\rho_{25}(TD)$ and $\rho_{50}(TD)$ are the autocorrelation of the trade durations at lags 1, 25 and 50, respectively. $\#PU$ and $\#PD$ are the numbers of occurred price upward events and price downward events of the corresponding sample stock during the sample period.

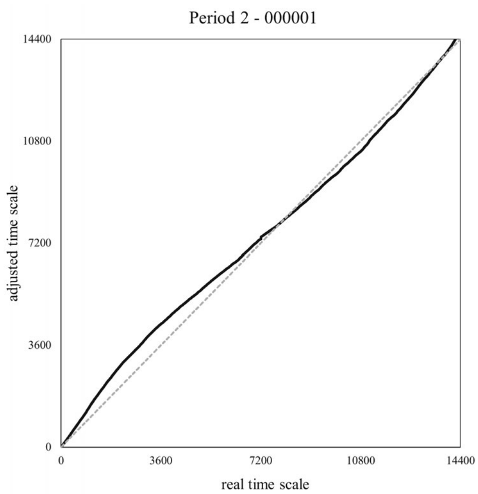
4 Empirical Analysis

4.1 Price-Related Dynamics of Trading Intensity

We firstly adjust the trade durations to remove intraday periodicity according to the time change approach introduced in Section 2. The transaction time of continuous auction period at each trading days in SZSE is from 9:30 to 11:30 in the morning and from 13:00 to 15:00 in the afternoon. The time change approach maps the real time scale to the adjusted time scale during the four-hour trading window in a non-parametric manner and the adjusted duration is calculated as the difference of the adjusted trading times Figure 2 exhibits the mapping relation from the real time to the adjusted time for the sample stock 000001 in Periods 1–3, respectively, and the transform functions of other sample stocks are similar. The x-axis is the real time and the y-axis is the adjusted time in a single trading day and both the real time and the adjusted time are measured in second. As shown in Figure 2, the transform function (the solid line) does not follow the 45 degree line (the dash line), which suggests the existence of intraday periodicity. Specifically, since more trades arrive at the beginning and end of the transaction hours, the slope of the transform function is greater than 1, which leads the expansion of the time scale and therefore the adjusted trade durations are larger than the real durations at these points. Figure 2 plots the total trade numbers of each minutes across the whole sample period under the real and adjusted time scale for sample stock 000001 in Period 1. The trade arrival has significant "U" shape intraday periodicity and it is removed after the adjustment.

Then we fit the adjusted duration data by the CACD model for 5 sample stocks during Periods 1–3, respectively. Figure 4 plots the trade duration series, the intercept component, dynamic component and the residuals estimated by the CACD model for the sample stock 000001 during Period 1, while similar results hold for other cases. Both the intercept component and the dynamic component capture the dynamic trend of the duration series while the intercept component is related to the price change event and in the lower frequency.





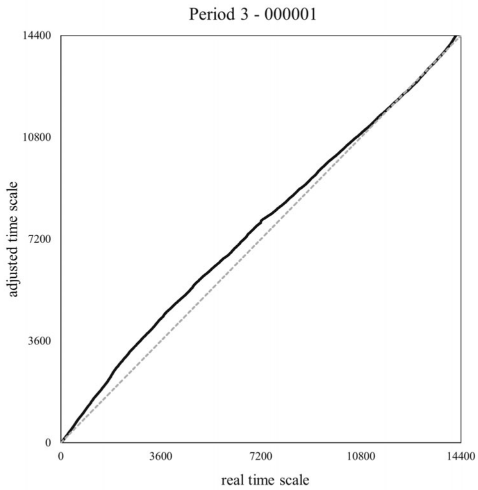


Figure 2 The time adjusted by the time change approach versus the real time for sample stock 000001 in Periods 1–3 (from left to right)

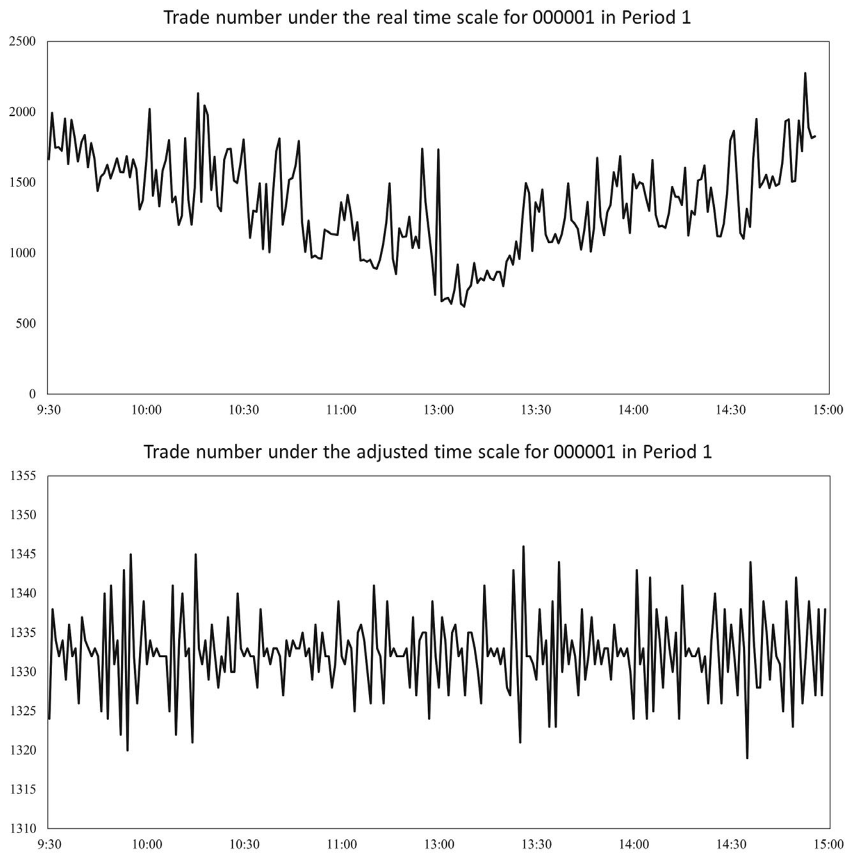


Figure 3 The number of trades during each minutes under the real time scale (top) and under the adjusted time scale (bottom) for sample stock 000001 during Period 1

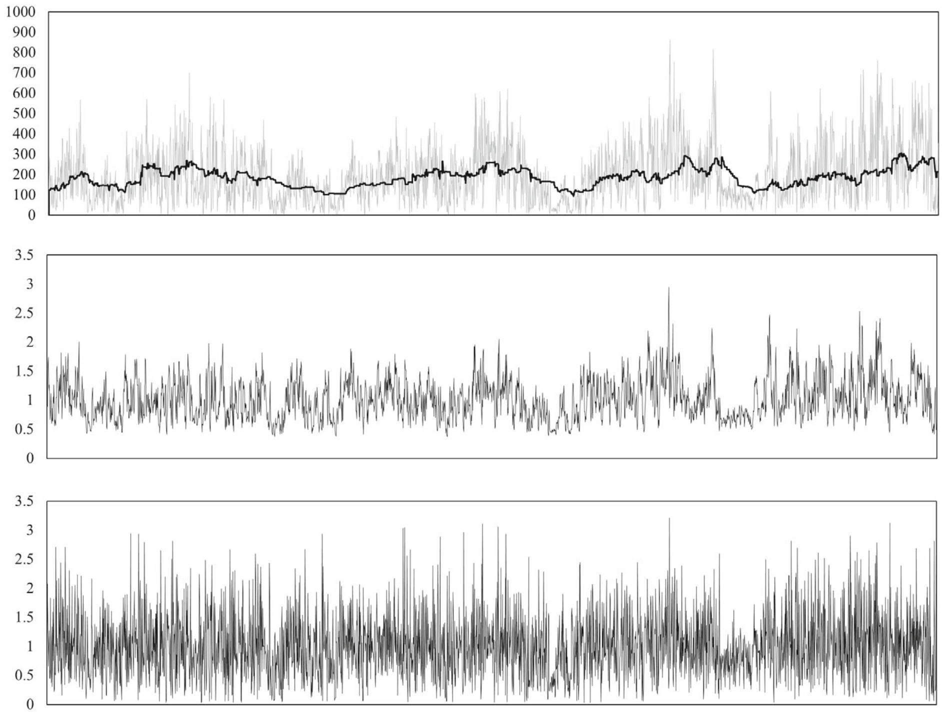


Figure 4 The trade duration data (the gray line in the top figure), the intercept component (the black line in the top figure), the dynamic component (the central figure) and the residual (the bottom figure) for sample stock 000001 during Period 1

The parameter estimation results are reported in Table 4. We firstly focus on the intercept component in the model. Specifically, the coefficient β^{μ} is significantly positive in all 15 cases and α^{μ} is significantly positive in 13 cases at the 0.9 significant level. Recall the specification of the intercept component, the significant β^{μ} and α^{μ} suggests that the intercept component is time-varying and therefore the duration mean varies at different price event intervals. As the trading intensity is measured by the reciprocal of trade duration mean, the time-varying intercept component captures the price-related extra dynamics of trading intensity in addition to the transaction level dynamics captured by the dynamics component. Investors make trading decision according to the price dynamics, which leads the variation of the trading intensity when the price changes. It provides the evidence of the this price-related feedback effect in the investor trading behaviors and is consistent with findings in previous empirical literature, e.g., Hasbrouck[10] and Cohen and Shin[11].

The positive estimates of β^{μ} and α^{μ} in the intercept component indicate that the trading intensity after price change is positively correlated with the historical trading intensity before price change, which suggests the persistence of trading intensity. Besides, the estimated coefficients β^{ϕ} and α^{ϕ} in the dynamic component are all significantly positive, which suggests the persistence in the high-frequency dynamics of trading intensity and is consistent with previous studies on the trade duration modelling and trading intensity.

Table 4 Parameter estimation of the CACD model

Stock code	Intercept component			Dynamic component		Residual
	ω^μ	α^μ	β^μ	α^ϕ	β^ϕ	γ
Period 1: Downward market						
000001	6.163^{***}	0.134^{***}	0.816^{***}	0.400^{***}	0.382^{***}	1.884^{***}
	(1.230)	(0.032)	(0.033)	(0.033)	(0.097)	(0.028)
000061	4.445	0.049^{*}	0.937^{***}	0.292^{***}	0.549^{***}	2.078^{***}
	(3.911)	(0.028)	(0.038)	(0.033)	(0.058)	(0.056)
000503	0.821^{***}	0.206^{***}	0.770^{***}	0.443^{***}	0.288^{***}	2.153^{***}
	(0.282)	(0.025)	(0.027)	(0.025)	(0.065)	(0.035)
000651	5.980^{***}	0.135^{***}	0.820^{***}	0.346^{***}	0.472^{***}	1.922^{***}
	(1.335)	(0.038)	(0.038)	(0.027)	(0.088)	(0.032)
000983	0.169^{*}	0.026^{*}	0.970^{***}	0.422^{***}	0.474^{***}	2.085^{***}
	(0.088)	(0.015)	(0.018)	(0.024)	(0.036)	(0.030)
Period 2: Upward market						
000001	0.197^{***}	0.094^{***}	0.891^{***}	0.400^{***}	0.513^{***}	2.159^{***}
	(0.060)	(0.030)	(0.034)	(0.022)	(0.038)	(0.028)
000061	1.241^{***}	0.097	0.878^{***}	0.422^{***}	0.484^{***}	2.131^{***}
	(0.409)	(0.071)	(0.082)	(0.022)	(0.060)	(0.036)
000503	3.997^{***}	0.163^{***}	0.801^{***}	0.571^{***}	0.188^{*}	2.082^{***}
	(1.212)	(0.050)	(0.058)	(0.044)	(0.107)	(0.040)
000651	2.043^{***}	0.083^{**}	0.887^{***}	0.367^{***}	0.528^{***}	2.314^{***}
	(0.419)	(0.041)	(0.046)	(0.021)	(0.046)	(0.032)
000983	2.865^{*}	0.073	0.890^{***}	0.479^{***}	0.480^{***}	2.065^{***}
	(1.549)	(0.045)	(0.050)	(0.020)	(0.030)	(0.028)
Period 3: Sideways market						
000001	2.773^{***}	0.334^{***}	0.594^{***}	0.422^{***}	0.431^{***}	2.221^{***}
	(0.672)	(0.052)	(0.062)	(0.020)	(0.038)	(0.028)
000061	1.389	0.142^{**}	0.840^{***}	0.442^{***}	0.184^{*}	2.332^{***}
	(1.451)	(0.060)	(0.071)	(0.040)	(0.106)	(0.049)
000503	5.096^{***}	0.148^{***}	0.822^{***}	0.409^{***}	0.305^{***}	2.501^{***}
	(1.504)	(0.033)	(0.036)	(0.038)	(0.089)	(0.057)
000651	1.888^{**}	0.098^{***}	0.876^{***}	0.369^{***}	0.490^{***}	2.721^{***}
	(0.774)	(0.021)	(0.023)	(0.021)	(0.037)	(0.041)
000983	2.402^{***}	0.264^{***}	0.704^{***}	0.454^{***}	0.323^{***}	1.932^{***}
	(0.736)	(0.034)	(0.035)	(0.043)	(0.089)	(0.045)

Notes: The standard error are in the bracket and the symbols *, ** and *** indicate statistical significance at the 10%, 5% and 1%, respectively.

Table 5 Model diagnostics

Stock code	Likelihood ratio test			Ljung-Box test		
	LLF_0	$Stat^{LRT}$	$CVal^{LRT}$	LB_0	LB_1	$CVal^{LBT}$
Period 1: Downward market						
000001	−18620.91	28.77	9.21	133.22	127.77	25.00
000061	−7695.57	24.98	9.21	9.76	13.49	25.00
000503	−15179.68	120.64	9.21	44.39	166.44	25.00
000651	−18548.47	18.04	9.21	54.54	71.89	25.00
000983	−26006.15	163.48	9.21	146.16	214.76	25.00
Period 2: Upward market						
000001	−34402.14	127.59	9.21	65.23	238.14	25.00
000061	−24014.48	46.41	9.21	33.97	78.16	25.00
000503	−14620.46	42.37	9.21	54.37	84.75	25.00
000651	−28146.22	202.45	9.21	130.78	133.70	25.00
000983	−31774.69	23.54	9.21	184.65	195.99	25.00
Period 3: Sideways market						
000001	−30462.71	247.54	9.21	150.15	198.89	25.00
000061	−10913.56	160.18	9.21	36.66	117.52	25.00
000503	−10522.60	141.34	9.21	38.82	54.95	25.00
000651	−22417.19	614.85	9.21	123.35	101.53	25.00
000983	−11912.16	21.95	9.21	51.23	127.32	25.00

Notes: The likelihood ratio test and the Ljung-Box test are conducted for the unrestricted and restricted CACD models, where the restricted CACD model is with time-invariant intercept component and is equivalent to the standard ACD model. LLF_0 is the log-likelihood value for the estimation of unrestricted CACD model, $Stat^{LRT}$ is the likelihood ratio statistics and $CVal^{LRT}$ is the critical value of the likelihood ratio test at the 0.99 level. LB_0 and LB_1 are the Ljung-Box statistics for the residuals of the unrestricted and restricted CACD model, respectively, and $CVal^{LBT}$ is the critical value of the Ljung-Box test at the 0.99 level.

Then we diagnose the model efficiency by comparing the fitness of the unrestricted and restricted CACD models via the likelihood ratio test and the residual Ljung-Box test, where the restricted model contains a time-invariant intercept component and is equivalent to the standard ACD model. The results are presented in Table 5. The likelihood ratio test shows that the likelihood of the unrestricted model is significantly greater than that of the restricted model in all cases, indicating that the data is better fitted after incorporating the time varying intercept component. Besides, the residual Ljung-Box statistics shows that the unrestricted model performs better than the restricted model in terms of capturing the self-dependence in the trade duration series. Specifically, in 13 of 15 cases the statistics of the unrestricted model is low than that of restricted model, indicating that in general the residuals of CACD model are more close to the i.i.d. series as more information is captured. However, neither the Ljung-Box test for restricted model nor for the unrestricted model can reject the self-dependence in the residual series in almost all cases, indicating the residuals in two models are not i.i.d. random variables and the data has not been perfectly fit. In sum, both two tests suggest that incorporating the intercept component in the CACD model leads efficiency gains. It may attribute to the gain in capturing the extra dynamics of trading intensity, which also provides evidence of the existence of the price-related feedback effect in the investor trading behaviors.

4.2 Driven Factors of the Price-Related Dynamics of Trading Intensity

In this subsection we study how the investors react to the price change events. Several economic factors associated with price change events are introduced into the CACD model as the exogenous explanatory variables of the intercept component and therefore we can examine the driven factors of the price-related dynamics of trading intensity.

We develop the exogenous explanatory variables as follows and further economic interpretations are given in the analysis of estimation results. Firstly we consider the price change direction and it is the most salient feature investors can get from a price change event. The price change direction dummy, $PDir_t = I(r_t > 0)$, where r_t is the return on price interval t, is incorporated into model to examine the asymmetric effect. Then we turn to the price duration, $Pdur_t$, which is calculated as the time length from the last to current price change events that measured in second. The price duration is associated with the reciprocal of price volatility as shown by Engle and Russell[12], Andersen, et al.[28] and Tse and Yang[29], as the short price duration indicates a quickly moved price and high price volatility. Investors can realize volatility from the price duration and therefore we examine its impact on trading intensity. Besides, we also consider the trading volume flow. As suggested by Easley and O'hara[30, 31] and Lee, et al.[32], informed traders tend to maximize their trading volume when the private information arrives and uninformed investors can realize this information from the high trading volume. We standardize the trading volume by the time horizon for different length of price interval and the trading volume per second for time interval t is

$$VpS_t = \frac{1}{PDur_t}\sum_i V_i, t,$$

where $PDur_t$ is the price duration defined above and $V_{i,t}$ is the trading volume for the transaction occurs at $\tau_{i,t}$. These three economic variables can be viewed as the market indicators that provides information to investors and we would like to study how investors react to these indicators.

The parameter estimation of the CACD model with exogenous variables is presented in Table 6. Firstly, the coefficient of $PDir_{t-1}$ suggests that, in general, the trading intensity is positive correlated with the price. Specifically, the negative coefficient of $PDir_{t-1}$ in most of cases suggests the trading intensity after price rises is higher than that after price falls. It is consistent with the disposition effect that investors tend to ride loser stocks too long and sell the winner stock too early (Shefrin and Statman[33]). Considering the different market statuses, this asymmetric effect is significant on all 5 sample stocks in the sideways market Period 3 but is only significant on 3 and 2 sample stocks in the upward market Period 2 and in the downward market Period 1. It suggests that investors are more sensitive to the price change direction and the disposition effect is more significant in the sideways market than in the upward or downward markets. Besides, the high price duration generally increase the reciprocal of trading intensity, which suggests a positive relationship between volatility and trading intensity. However this relationship is not robust and only significant in 6 of 15 cases. The high trading volume is associated with increased trading intensity and it is significant in most of cases in the downward and upward market. However, in the sideways market the coefficient of the trading volume is not so significant, indicating investors are less sensitive to the trading volume in this period.

Table 6 Parameter estimation of the CACD model with exogenous variables

Stock code	Intercept component						Dynamic component		Residual
	ω^μ	α^μ	β^μ	$PDir_{i-1}$	$PDur_{i-1}$	VpS_{t-1}	α^ϕ	β^ϕ	γ
Period 1: Downward market									
000001	11.397***	0.055	0.890***	13.506***	1.777**	−2.743***	0.395***	0.419***	1.889***
	(3.596)	(0.039)	(0.042)	(3.788)	(0.744)	(0.708)	(0.033)	(0.080)	(0.028)
000061	8.841	0.067*	0.912***	−15.781	0.079	0.907	0.279***	0.538***	2.082***
	(7.724)	(0.034)	(0.045)	(10.470)	(0.128)	(0.854)	(0.034)	(0.063)	(0.054)
000503	13.489***	0.110***	0.845***	−10.612***	1.887***	−1.630***	0.454***	0.305***	2.202***
	(4.565)	(0.025)	(0.028)	(2.670)	(0.530)	(0.556)	(0.026)	(0.055)	(0.036)
000651	247.050***	0.000	0.121	9.885**	18.176***	−27.928***	0.318***	0.529***	2.016***
	(28.805)	(0.000)	(0.119)	(4.820)	(1.700)	(1.831)	(0.039)	(0.090)	(0.037)
000983	0.625	0.066**	0.924***	−2.511***	0.022	−0.071**	0.423***	0.451***	2.087***
	(0.471)	(0.032)	(0.036)	(0.919)	(0.058)	(0.032)	(0.023)	(0.046)	(0.031)
Period 2: Upward market									
000001	8.820	0.028	0.936***	−2.044	0.413	−0.939**	0.408***	0.506***	2.181***
	(6.065)	(0.086)	(0.102)	(1.305)	(0.322)	(0.448)	(0.020)	(0.044)	(0.027)
000061	16.368**	0.000	0.978***	−2.492*	−0.520	−1.313***	0.436***	0.486***	2.158***
	(6.428)	(0.000)	(0.004)	(1.464)	(0.606)	(0.407)	(0.022)	(0.029)	(0.034)
000503	146.724***	0.000*	0.793***	−2.988	6.539***	−18.159***	0.584***	0.129**	2.235***
	(38.339)	(0.000)	(0.069)	(3.161)	(2.158)	(3.418)	(0.030)	(0.050)	(0.043)
000651	9.505***	0.015	0.954***	−4.257***	0.197	−0.739***	0.379***	0.522***	2.332***
	(2.881)	(0.032)	(0.039)	(1.037)	(0.188)	(0.217)	(0.021)	(0.035)	(0.032)
000983	32.439***	0.060	0.848***	−6.034***	−0.545	−2.573***	0.488***	0.414***	2.103***
	(5.508)	(0.046)	(0.059)	(1.118)	(0.453)	(0.481)	(0.019)	(0.036)	(0.029)

Table 6 (Continued) Parameter estimation of the CACD model with exogenous variables

Stock code	Intercept component						Dynamic component		Residual
	ω^μ	α^μ	β^μ	$PDir_{i-1}$	$PDur_{i-1}$	VpS_{t-1}	α^ϕ	β^ϕ	γ
Period 3: Sideways market									
000001	8.568***	0.229***	0.680***	−8.437***	0.627	−0.317	0.418***	0.426***	2.244***
	(3.013)	(0.049)	(0.060)	(1.535)	(0.378)	(0.321)	(0.018)	(0.035)	(0.028)
000061	8.065*	0.103***	0.835***	−9.184**	4.997***	−2.423***	0.467***	0.155**	2.365***
	(3.957)	(0.026)	(0.030)	(3.676)	(1.158)	(0.824)	(0.031)	(0.066)	(0.046)
000503	11.306*	0.091*	0.881***	−19.164***	0.299	0.373	0.429***	0.329***	2.519***
	(6.744)	(0.052)	(0.061)	(4.779)	(0.441)	(0.531)	(0.039)	(0.104)	(0.055)
000651	1.125***	0.005	0.0.983***	−9.911***	0.772***	0.095	0.371***	0.493***	2.741***
	(0.258)	(0.006)	(0.008)	(1.135)	(0.122)	(0.067)	(0.021)	(0.033)	(0.040)
000983	104.225***	0.000	0.905***	−17.224***	−1.922	−9.239***	0.491***	0.346***	2.022***
	(22.432)	(0.000)	(0.023)	(3.246)	(2.033)	(1.655)	(0.037)	(0.053)	(0.043)

Notes: $PDir_t = I(r_t > 0)$ is the dummy for the price change direction; $PDur_t$ is the logarithmic price change duration measured in seconds; VpS_t is the logarithmic average trading volume per second measured in shares. The standard error are in the bracket and the symbols *, ** and *** indicate statistical significance at the 10%, 5% and 1%, respectively.

Compared with the basic CACD model without exogenous variables shown in Table 5, α^μ decreases in all 15 cases and is insignificant in over half cases after incorporating three exogenous variables in the intercept component. As α^μ measures the lag effect in the intercept component, this result indicates that the self-dependence in the price-related trading intensity dynamics can be partly explained by the impact on investor trading behaviors of the price change direction, price duration and trading volume.

In sum, the trading intensity is driven by some market indicators and which partly explains the persistence in the trading intensity dynamics. The trades can be triggered by the fast rise in the price level and the high trading volume. Investors are more sensitive to the price change direction in the sideways market while more sensitive to the trading volume in the upward and downward markets. It also suggests that the trading volume is more informative in the upward and downward market while the price series is more informative in the sideways market.

5 Conclusion

This paper proposes a CACD model to examine the feedback effect in the trading behavior by modelling the price-related dynamics of trading intensity. A main feature of the CACD model lies in that it allows the conditional mean of the trade duration process varies with the price changes, by which we can capture the extra dynamics of trading intensity corresponding to the price change. A set of intraday transaction data from the Chinese stock market covered 5 sample stocks and different market statuses is conducted for the empirical studies. We find that the CACD model captures extra dynamics of trading intensity when the price changes, which verifies the existence of the price-related feedback effect in investor trading behaviors in Chinese stock market.

We also study how the investors react to the price change by examining the driven factors of the price-related extra dynamics of trading intensity. We find that the fast rise in the price level and the high trading volume can trigger more trades. Moreover, Investors are more sensitive to the price change direction in the sideways market than in the upward or downward markets, which suggests the price series contain more information in the sideways market.

The contributions of this paper are twofold. We examine the feedback effect and study whether and how the investors react to the price change, which has not yet been extensively studied in Chinese stock market. Besides, the CACD model introduced in this paper provides an alternative way to model the trade durations and capture the long term dependence in the trade duration series. In our model, the long-term dependence is generated by an autoregressive component that related to the price series, which sheds lights on the modeling of the trading intensity.

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