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Limited Attention and Post-Earnings Announcement Drift: Evidence from China's Stock Market

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ABSTRACT

This paper utilizes Chinese stock data to provide further evidence on the power of limited attention theory in explaining post-earnings announcement drift. As retail investors prevail in China and they are easily distracted by market swings, we should expect severe attention problems, resulting in larger underreaction to firm information and higher sensitivity to market movement, i.e., the so-called "market movement effect". After accounting for special arrangements such as preannouncements and earnings previews, we confirm a strong presence of this effect in Chinese stock market, given the "Friday effect" and "announcement concentration effect" being controlled for. Moreover, the effect is asymmetric in market up and down, and becomes more pronounced for small-cap and value stocks.

Keywords: Limited Attention, Earnings Announcement, Market Movement, China's Stock Market, Abnormal Returns
JEL Classifications: C58, G14, G41

1. INTRODUCTION

Post-earnings announcement drift (PEAD) refers to the phenomenon that stocks with higher earnings surprises have higher abnormal returns lasting for a relatively long time (say more than 6 months) after the underlying companies' earnings announcement. In other words, investors underreact to the news. Among all financial market anomalies, PEAD poses a great threat to the holding of the efficient market hypothesis (EMH), which predicts that asset price will react to public information quickly and accurately. As a result, it is important to provide a good explanation in bringing this anomalous phenomenon compatible with the EMH. Such efforts have been made by many scholars since the 1990s (e.g., Bernard and Thomas, 1990; Jegadeesh and Livnat, 2006; Hung et al., 2014). In recent years, the limited attention theory draws academic attention and is proved to be useful in explaining the existence of PEAD. What is more, Kottimukkalur (2019) finds a "market movement effect"---PEAD is stronger in firms that release earnings on days when market returns are higher in magnitude---which is consistent with attention-constrained investors being distracted by market swings and missing firm-specific information announced.

China is an ideal laboratory for investigating the power of limited attention theory in explaining PEAD, given that investors in China's A-share market are highly constrained regarding attention. According to the official survey conducted by the Shenzhen Stock Exchange (SZSE) in 2016, less than 30% of the investors make their investment decisions according to earnings announcements of publicly listed companies. Moreover, over 40% of investors buy and sell their stocks based on media news and market swings (Dong and Gil-Bazo, 2020). As a result, Chinese A-share stock market participants focus more on the market movement and pay less attention to changes in individual firm earnings. Thus, they are in turn inclined to underreact to new earnings information and to be over-distracted by the market movement.

Following the perspective of Kottimukkalur (2019), we attempt to attribute PEAD in China to China's large market movement

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events, hence providing further evidence of the explanatory power of limited attention. Specifically, we examine the relationship between this so-called "market movement effect" explanation and other alternative explanations for PEAD based on non-market event effects, such as the "Friday effect" (DellaVigna and Pollet, 2009), "announcement concentration effect" (Hirshleifer et al., 2009), and "ostrich effect" (Hou et al., 2009). Besides, we contribute to the PEAD measurement literature by proposing a more accurate and detailed methodology to capture the impact of firm earnings information, since Chinese public firms stick to more complicated announcement rules.

As there exist just a few papers linking PEAD to investors' attention issue and, to our knowledge, as there are scarce studies testing such linkage in an environment of large market movement event, our article adds to the research body about the impact of limited attention in China as well as that about the cause of Chinese financial market anomalies. Practically speaking, the presence of the PEAD financial market anomaly in China indicates that investors can continuously beat the market using trading rules developed on the basis of historical prices and current public information. Therefore, at the end of this paper, we propose a novel investment strategy for A-share investors to beat the market. The idea at the core of our strategy is that investors should pay great attention to the earnings information of individual stocks; hence it will be profitable to hold stocks with high earnings surprises over a long investment horizon.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature and develops hypotheses. Section 3 describes our data and variables. Section 4 specifies the empirical models. Section 5 presents the results and section 6 validates them with an array of robustness checks, followed by Section 7 that concludes.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

In this section, we first introduce the strand of literature on limited attention and that on earnings announcement anomaly, separately. Then, we compare our paper with research on the connections among investor attention, information processing, and financial market anomalies. At last, our hypotheses are developed, clarifying what is new and how the new finding fits in all of the previous works reviewed.

2.1. Limited Attention Theory

Investors nowadays have access to a huge amount of market information in the modern financial market environment. So, attention becomes a limited resource, and researchers begin to investigate how investors make decisions facing distractions. For example, De Bondt and Thaler (1985) find that investors distracted by past stock performance might undervalue losers and overvalue winners. Corwin and Coughenour (2008) use a limited attention story to explain market makers' efforts of excessively pricing actively-traded stocks. The attention of retail investors can be attracted by stocks paying large dividends and having more frequent earnings surprises (Aboody et al., 2010), stocks with high open prices (Berkman et al., 2012), stocks hitting their upper price limits (Seasholes and Wu, 2007), and stocks whose underlying firms are releasing news report currently (Barber and Odean, 2008). What is more, there exists evidence that investors' attention is affected by events ranging from M&A (Louis and Sun, 2010) to news coverage and corporate governance actions (Da et al., 2011).

Concerning the consequences of limited attention, Karlsson et al. (2005) discover an "ostrich effect" that describes the phenomenon of investors paying more attention to their portfolios in up markets. Peng and Xiong (2006) document that investors favor market-level information much more than firm earnings information. Analysts are affected as well. They exhibit a lack of attention when writing reports (Choi and Gupta-Mukherjee, 2016) and a feature of less timeliness if many stocks are publicizing their earnings on the same day (Driskill et al., 2020). By realizing the existence of limited attention, firms may strategically schedule their announcements. Commonly, the good news is deliberately released during trading hours; but the bad news is out only in non-trading times (Patell and Wolfson, 1982) or on Fridays (Damodaran, 1989). Some firms tend to cover their miserable earnings by taking advantage of limited attention (Doyle and Magilke, 2009; DeHaan et al., 2015). Our paper adds to this literature by considering limited attention as the main driver of PEAD in China's stock market.

2.2. Earnings Announcement Anomaly

Earnings announcement anomaly arises from PEAD found by Ball and Brown (1968). PEAD means that stocks with higher earnings surprises will produce higher abnormal returns for quite a while after the earnings announcement day. Such high returns may last for over 6 months. Thus, this phenomenon is sometimes referred to as earnings momentum. Bernard and Thomas (1989) propose a trading strategy, which longs positive surprise stocks and shorts negative surprise stocks, and consistently gains abnormal returns. Livnat and Mendenhall (2006) and Francis et al. (2007) show that PEAD-induced high abnormal returns are still present after controlling for the size and value factor and using an alternative FF3 model to calculate the abnormal return. Besides the U.S. market, the earnings announcement anomaly is a worldwide pattern, as documented in the U.K. market (Hew et al., 1996; Liu et al., 2003), German market (Dische, 2002), Japanese market (Mande and Kwak, 1996), New Zealand market (Truong, 2010), etc. Our paper is valuable by confirming PEAD in China with special earnings preannouncement policies. Most importantly, we add value by exploring the mechanism of a behavioral perspective in explaining PEAD, since traditional explanations such as risk factors and trading costs (Bernard and Thomas, 1989; Fama, 1998; Bhushan, 1994) fail to fully absorb this market inefficiency.

2.3. The Limited Attention Explanation for Earnings Announcement Anomaly Compared with Alternative Explanations

In precedent studies, scholars try to justify the earnings announcement anomaly from the perspective of traditional financial theories in the rational investor setup. More recent explanations rely on findings in the field of behavioral finance. The initial behavioral explanation is heterogeneous investor opinions, which cause the price to decrease for overvalued stocks during earnings announcement periods (Garfinkel and Sokobin, 2006; Anderson et al., 2007). But this explanation is problematic in that opinion divergence will disappear too soon post announcement. The "disposition effect" is another explanation for the earnings announcement anomaly in the viewpoint of behavioral finance. In other words, investors are risk-averse towards profits, and risk-seeking towards loss (Shefrin and Statman, 1985; Odean, 1998). The "disposition effect" has been proven to be an effective (if not sufficient) explanation for PEAD (Grinblatt and Han, 2005; Frazzini, 2006) in the U.S. market.

The limited attention theory provides an even more powerful explanation for the earnings announcement anomaly. Media coverage is frequently used as a proxy for investors' attention. For example, Peress (2008) use the number of articles on the *Wall Street Journal* that mention the underlying stock. Drake et al. (2012) uses the volume of searching on Google to proxy for attention. These studies find a significant negative correlation between media coverage and PEAD. This implies more attention leads to longer drifts. In addition to media exposure, Hou et al. (2009) employ the turnover rate to measure investor attention. They arrive at similar conclusions.

It merits a note that the "timing" of making earnings announcements is an important factor for the limited attention theory to explain PEAD. The literature emphasizes three types of "timing". First, DellaVigna and Pollet (2009) demonstrate that investors underreact to earnings on Fridays, leading to a stronger PEAD. This is also known as the "Friday effect," which is evident in the Chinese stock market as well. Second, there exists an "announcement concentration effect" (Hirshleifer et al., 2009), in which a stronger PEAD happens on a few announcement days when many companies simultaneously release their earnings. Since investors are distracted by all these reports, we should observe underreaction. However, investors in China often overreact on concentrated announcement days. This is probably because more than 70% of investors in China only hold 2-5 stocks. Hence, Chinese investors are less likely to get distracted by irrelevant earnings information.

The third type relates to the "market movement effect" proposed by Kottimukkalur (2019). His idea is that PEAD would be stronger for firms releasing earnings on a day when the market return is relatively higher in magnitude. As a result, due to limited attention, investors tend to allocate more of their time studying the market and hence distracted by the large market movement. The advantage of the "market movement effect" in explaining the earnings announcement anomaly lies in the observation that this effect can last for over 120 days in the U.S. market. However, studies on how it affects the PEAD in China is void as far as we know. Therefore, the present paper attempts to explore the role played by the "market movement effect" in China, given China's special disclosure procedures like preannouncement and earnings previews.

2.4. Hypothesis Development

Given the extensive review of the literature above, we rely on periods of large market movements to investigate the relationship between investor's limited attention and PEAD. The basic logic behind this "market movement effect" is that investors are distracted by market swings that coincide with earnings release days of individual firms, especially so for less sophisticated investors facing highly volatile markets. For this reason, investors collectively underreact to earnings information, and the PEAD phenomenon will stay stronger thereafter. First of all, we formally test the existence of the "market movement effect" in China.

Hypothesis 1: The "market movement effect" is evident in China's stock market, i.e., PEAD is stronger in Chinese firms that happen to release their earnings announcements on days of large market movements.

Secondly, since market rise or fall is an independent distracting event, it differs from other attention-grabbing events, such as the "Friday effect" and "announcement concentration effect". All these events may coexist in the Chinese financial market. Thus, we put forward our second hypothesis.

Hypothesis 2: The evidence for the existence of "market movement effect" is not compromised by the "Friday effect" and "announcement concentration effect". These effects may coexist at the same time in the Chinese financial market.

Further, when the direction of market movements is under consideration, as both positive and negative large market movements will distract investors and lead them to underreact to firm news, we expect divergent investors' responses to the up-trending market and down-trending market. According to the "ostrich effect", investors will pay more attention to their portfolio during good market times, and they will choose to neglect the earnings information during bad market times. PEAD should be stronger if firms release their earnings information in market downturns. Consequently, the third hypothesis is proposed as below.

Hypothesis 3: The "market movement effect" exists in both the up-trending market and down-trending market in China, and the effect will be more pronounced during down market times.

Last but not least, we investigate the relationship between the "market movement effect" and firm-level characteristics. Ali et al. (2003) demonstrate that few arbitrage activities are observed around small-cap stocks and value stocks. Therefore, any financial market anomaly could be stronger for these stocks in China as well. This leads to the following fourth hypothesis.

Hypothesis 4: The "market movement effect" varies according to the firm-level characteristics of Chinese publicly listed companies, and this effect will be more pronounced for small-cap stocks and value stocks in China.

3. DATA SOURCES

This section first describes how we select firms into our base sample, and then constructs an array of variables used in our empirical setup.

3.1. Sample Selection

Our study utilizes annual earnings data, book-to-market ratio, annual average turnover rate, and proportion of institutional investors for all Chinese companies listed on the A-share market sourced from the Wind database. Data on daily stock price and free-float market capitalization is obtained from the CSMAR database. The sample period for annual earnings announcement dates spans from the fiscal year 2006-2017.

It is important for us to correctly determine the date of occurrence for earnings announcement events. We consider only annual earnings information for two reasons. On the one hand, in China, the disclosure time of the first quarter report starts from April 1st to April 30th, largely overlapping with that of the annual report. As investors tend to pay much more attention to the earnings figure from the annual report, the first quarter report usually has a lesser effect in terms of information disclosure. On the other hand, according to China Securities Regulatory Commission requirements, while annual reports are always audited, the quarterly and semi-annual reports are not necessarily reviewed by a third-party auditor. For this reason, the information presented in the annual report is of higher quality and is more trustworthy.

To capture the consequences of earnings announcements promptly, this study also considers earnings preannouncements and previews. In 2017, more than 70% of A-share companies have had some form of earnings preannouncement, and over 50% of them have released earnings preview before publishing the annual report since qualified public firms are required to do so to stay in compliance with Shanghai Stock Exchange and SZSE policies. Given these special types of announcements, investors may immediately react to the information publicized there, rather than waiting until the release of the formal annual report. Thus, we set a firm's event date as the announcement date of its earliest reports (irrespective of whether the report is preannouncement, preview. or annual statement). In specific, whenever earnings preview or annual report comes out first, the net income figure from either of the two documents can be directly used in subsequent analysis.

However, when earnings preannouncement is the earliest, additional calculations are needed. The reason is that, in earnings preannouncement files, firms usually disclose an expected range of earnings, or the expected percentage change of earnings from last year, or merely the expected changing direction. Based on different contents of disclosure, the value of net profit can be computed accordingly as follows.

1. When the expected range is disclosed

Let us denote the upper limit of the net income as *NI_UP* and the down limit as *NI_DOWN*. The expected net income is computed as the midpoint within the range:

$$NI_{it} = \frac{(NI\_UP_{it} - NI\_DOWN_{it})}{2}$$

2. When expected percentage change is disclosed

Let us denote the expected percentage change as *Chg*. Then, the expected net income used is calculated by using the net income data from the annual report of last year:

$$NI_{it} = \begin{cases} NI_{it-1} \times (1+Chg), if\ NI_{it-1} > 0 \\ NI_{it-1} \times (1-Chg), if\ NI_{it-1} < 0 \end{cases} \tag{2}$$

3. When expected changing direction is disclosed

Due to the missing of the exact number, such data will be removed from our sample.

Next, our data is filtered by removing observations which have overlapping announcement dates or time windows for annual reports and quarterly reports. ST (Special Treatment for companies with abnormal financial positions) stocks, *ST (ST with significant market withdrawn risk) stocks, and the stocks that have been publicly listed for less than 1 year are also removed. Finally, to ensure data accuracy, we match our data obtained from the Wind database with that sourced from the CSMAR database and delete those with no match.

3.2. Variable Construction

As for the dependent variable, the abnormal return (*AR*) is defined as the difference between a stock's actual return and its expected return. We utilize it to study the effect of earnings announcement events on stock prices, and how this effect changes when these announcements are made during volatile market times. In line with Ritter (1991) and DellaVigna and Pollet (2009), the following three *AR* calculation methods are adopted.

1. Buy and hold abnormal return (*BHAR*)

$$BHAR_i[t_1,t_2] = \prod_{t=t_1}^{t_2}(1+R_{it}) - \prod_{t=t_1}^{t_2}(1+R_{mt}) \tag{3}$$

where t_1, t_2 is the number of trading days elapsed after the announcement date. R_{it} is the return of stock *i* on trading date *t*, R_{mt} is the return of all A-share stocks weighted by free-float market capitalization on trading date *t*. *BHAR* hence measures the abnormal return obtained if an investor buys a stock at t_1 and sells it at t_2.

2. Cumulative abnormal return (*CAR*)

$$CAR_i[t_1,t_2] = \sum_{t=t_1}^{t_2}(R_{it} - R_{mt}) \tag{4}$$

The cumulative abnormal return sums up the part of the individual stock return beyond the market return from t_1 to t_2. Like *BHAR*, this method is also widely used. It has the advantage of computation simplicity, but it does not account for the compound effect on the stock return. We continue to introduce the next indicator.

3. Beta-adjusted buy and hold return (*BABHAR*)

$$BABHAR_i[t_1,t_2]=\prod_{t=t_1}^{t_2}(1+R_{it})-1-\hat{\beta}_i\left[\prod_{t=t_1}^{t_2}(1+R_{mt})-1\right] \quad (5)$$

where $\widehat{\beta_i}$ is the estimate from regressing daily stock returns on market returns over the period of 200 trading days to 20 trading days before the announcement. Comparing to the *BHAR* proxy, this method incorporates the impact of the beta factor on the stock price. Hence, we consider *BHAR* a better illustration of the investors' yield, and we use it as our main dependent variable. Nevertheless, *CAR* and *BABHAR* are used as alternative dependent variables for robustness tests. Furthermore, to remove the biased effects from possible outliers, our BHAR proxy is winsorized at the 1% level.

Turning to independent variables, we define a list of proxies below.

1. Standard earnings surprise groups (*S_RANK*)

We define earnings surprise as the difference between a firm's actual earnings and the expected earnings formed by all market participants. This paper uses a random-walk model to measure earnings surprise as this model can mitigate the problem of incomprehension and untimeliness common in analyst forecasts on China's market. To compare the earnings surprises of different stocks on the same basis, each stock's theoretical earnings surprise outcome will be standardized following the standardization method proposed by Kottimukkalur (2019).

$$SUE_{it}=\frac{NI_{it}-NI_{it-1}}{Mktcap_{it}} \quad (6)$$

In the equation, SUE_{it} is the standard earning surprise for stock *i* at reporting period *t*. $Mktcap_{it}$ is the total market value of the stock under concern on the day before the announcement event at *t*. Kothari (2001) finds that the relationship between earnings surprise and abnormal returns is non-linear. To address the nonlinearity problem, we resort to DellaVigna and Pollet (2009) and sort all sample stocks into 10 standard earnings surprise groups (*S_RANK*) based on the level of *SUE*. For example, *S_RANK* = 10 if the stock's *SUE* ranks in the top 10% among others in the same period; similarly, *S_RANK* = 1 if the stock's *SUE* falls into the bottom 10% among others in the same period. A larger number equates to a higher ranking.

2. Market movement groups (*MM_RANK*)

To examine the return effect of market movement when earnings are released, we sort Chinese firms into 10 groups based on the relative magnitude of absolute market returns $|R_{mt}|$ computed on the firms' announcement days. The market movement groups (*MM_RANK*) are obtained by comparing the absolute market return on the announcement date to a collection of corresponding returns in the past. Consider 2 time windows to choose these past returns from. Window 1 utilizes trading days in the latest 3 months, backward counting from the announcement date. For example, the absolute market returns on 2019-04-18 will be compared with daily returns taken from 2019 January, 17 to 2019 April, 17. Figure 1a shows graphically the relation between the reference time range and the announcement day of this method. Window 2 relies on trading days in the last quarter. This second method is used in Kottimukkalur (2019). For example, the absolute market returns on 2019 April, 18 will be compared with a sequence of values over the period from 2019 January, 01 to 2019 March, 31. Figure 1b illustrates the idea of this method.

For either of the 2 time windows within the reference range, *MM_RANK* = 10 if the absolute value of market return on the announcement date is classified to be top 10% of all daily returns within a chosen time window. *MM_RANK* = 1 if the absolute value of market return on the announcement date is classified to be bottom 10%.It is agreed upon that both retail and institutional investors in China conduct short-sighted trading acts and that herding is even more severe among Chinese institutional investors. Therefore, in China, the first method is more suitable to calculate *MM_RANK*; whereas, the second method is a good choice for running robustness tests.

3. Friday dummy variable (*FRIDAY*)

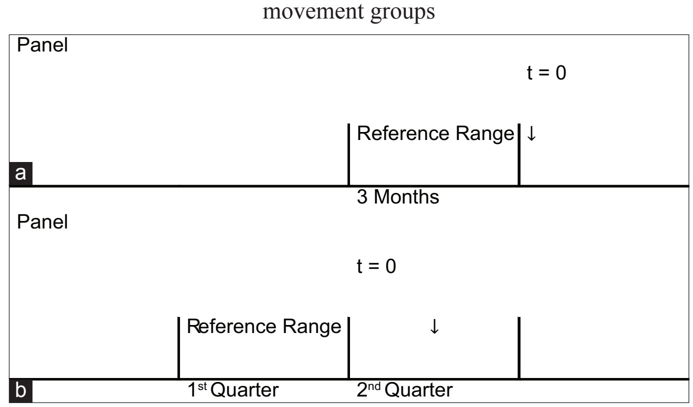
To control for the "Friday effect" described in DellaVigna and Pollet (2009), we construct a dummy variable (*FRIDAY*) as follows:

$$FRIDAY=\begin{cases}1, & \textit{if announcement date is Friday;}\\ 0, & \textit{if announcement date is not Friday.}\end{cases} \quad (7)$$

4. Number of announcements groups (*N_RANK*)

Another important issue to deal with is the "announcement concentration effect." Chinese scholars find that this effect in China displays different characteristics from those of the original effect in Hirshleifer et al. (2009). Consistent with the grouping method used in previous studies, we first document that the number of firms that release earnings information on the same day, i.e. the concentration of announcement. Then, we sort their stocks into 4 groups based on the concentration intensity, so that we can obtain our last rank variable, *N_RANK*. A firm will have

Figure 1: (a and b) Time windows for computing ranks of market movement groups



a *N_RANK* = 4 if its earnings report is released on a date with the highest concentration; and a *N_RANK* = 1 if the announcement date delivers the smallest concentration. Note that only the maximum and minimum concentration levels are used. No finer grouping like the previous distributional categorization is feasible, because A-share listed Chinese companies usually release announcements on the same day.

At the end of this subsection, we tabulate the above main dependent variable and several explanatory variables, along with control variables, in Table 1. The seven controls are selected as the prior research has established their effects on the PEAD.

3.3. Summary Statistics

The sample includes annual earnings of 2003 A-share listed firms from 2006 to 2017. There are 897 different earnings announcement days and 8239 earnings announcement observations. To save space, a comprehensive summary statistics of variables are presented in Table A1 in the Appendix. Besides, the sample distribution for each year is shown in Appendix Table A2.

Table 2 reports the average *SUE* in different *S_RANK* groups. It can be seen from the table that the average *SUE* of groups1-5 is always negative, which means the earnings announced on average are bad news, i.e. lower than what the analysts have expected. In contrast, the average *SUE* of groups 6-10 are positive, which represents good news. The number of good news equals approximately that of bad news.

Figure 2 plots the average $|R_{mt}|$ in different groups according to *MM_RANK* in all times. Further, Table 3 summarizes the average returns and the number of positive earnings announcements in the up-trending market and down-trending market, respectively, for each market movement group. Interestingly, for the two groups with very small market movement (e.g., Group 1 and 2) and the two groups with the largest market movement (e.g., Group 8 and 10), more positive earnings announcements have occurred in down-trending market than those occurred in up-trending market.

Figure 3 depicts the announcement concentration phenomenon in China. Most of the Chinese companies' earnings are released at the end of January and March to April. In our sample, the highest concentrated date is 2018 January, 31 when 285 A-share listed companies released their annual earnings announcement simultaneously.

Table 4 summarizes what firm characteristics are associated with earnings surprises. We can easily tell that small stocks have experienced more frequent bad news. Meanwhile, the relationship between standard earnings surprise groups and the book-to-market ratio is nonlinear. Firms underlying value stocks produce more extreme news, either good or bad. Low book-to-market ratio stocks in most cases meet the expectation agreed upon by analysts.

Figure 2: Market movements of all times on earnings announcement days

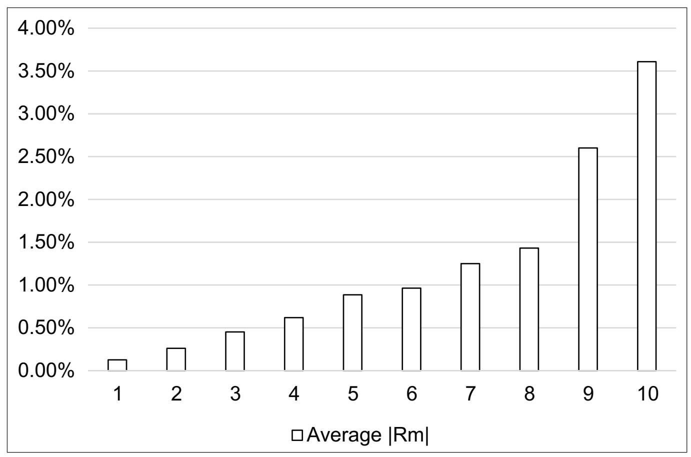


Table 1: Variable description

Variables	Definition	Source
Dependent variable		
BHAR $[t_1, t_2]$	The buy and hold abnormal return from t_1 to t_2	Ritter (1991)
Independent variables		
S_RANK	The decile rank is calculated by the standard earnings surprise of stocks in the same fiscal year	DellaVigna and Pollet (2009)
MM_RANK	The decile rank is calculated by the absolute market returns on the announcement dates	Kottimukkalur (2019)
FRIDAY	This dummy variable equals 1 if the announcement is on Friday	DellaVigna and Pollet (2009)
N_RANK	The decile rank calculated by the number of announcements on the same day	Hirshleifer et al. (2009)
Control variables		
SIZE	Free-float market capitalization on last announcement date	Bernard and Thomas (1989)
BM	The book-to-market ratio calculated from the last announcement	Chambers and Penman (1984)
LAG_DAY	Number of days between the fiscal year-end and earning announcement date	Chambers and Penman (1984)
TURNOVER	Average 12-month turnover rate before the announcement date	Hou et al. (2009)
IO	Institutional investors ownership from the last announcement	Piotroski and Roulstone (2004)
YEAR	Dummy variables on fiscal years	Authors' Calculation
INDUSTRY	Dummy variables on the classification system of 28 industries, excluding bank and non-bank financial companies	Authors' Calculation

Table 2: The distribution of earnings surprise by groups

S_RANK	1	2	3	4	5
Average *SUE*	–6.55%	–2.01%	–0.99%	–0.45%	–0.11%
N	833	827	821	814	819
S_RANK	6	7	8	9	10
Average *SUE*	0.14%	0.38%	0.72%	1.37%	5.21%
N	808	819	835	844	819

Table 3: Comparison of market movement on earnings announcement days in up versus down market

MM_RANK	1	2	3	4	5
R_m<0					
Average R_m	–0.12%	–0.27%	–0.47%	–0.58%	–0.80%
N	516	502	223	328	292
R_m>0					
Average R_m	0.14%	0.25%	0.45%	0.64%	0.94%
N	355	394	515	526	465
MM_RANK	6	7	8	9	10
R_m<0					
Average R_m	–0.99%	–1.28%	–1.23%	–2.18%	–3.94%
N	527	313	558	234	520
R_m>0					
Average R_m	0.94%	1.22%	1.76%	2.87%	3.03%
N	605	361	343	364	298

Table 4: Description of firm characteristics

S_RANK	1	2	3	4	5
Average *SIZE*	5.00	4.47	4.28	4.32	4.64
Average *BM*	0.45	0.39	0.35	0.33	0.31
N	833	827	821	814	819
S_RANK	6	7	8	9	10
Average *SIZE*	5.07	5.32	6.59	7.54	6.26
Average *BM*	0.31	0.32	0.36	0.39	0.42
N	808	819	835	844	819

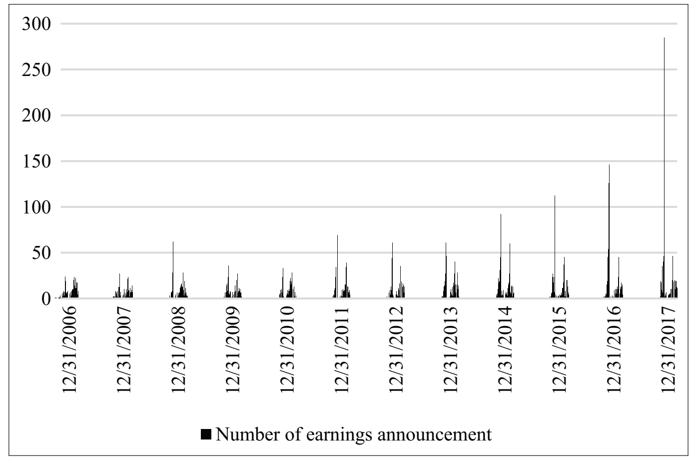
4. EMPIRICAL SPECIFICATIONS

In this section, we construct proper econometric models to test the hypotheses that have been discussed in Section 2.4. First of all, we propose Model 1:

$$BHAR[2,20] = \alpha_0 + \alpha_1 S\_RANK + \alpha_2 MM\_RANK + \alpha_3 (S\_RANK \times MM\_RANK) + \sum_{i=1}^{n} c_i X_i + \sum_{i=1}^{n} b_i (S\_RANK \times X_i) + YEAR + INDUSTRY + \varepsilon \quad (8)$$

where X_i is a vector of control variables. We expect that the PEAD will be stronger for stocks whose issuers release earnings announcements on days when market returns are higher in magnitude. Therefore, the "market movement effect" can be verified in China if the estimated α_3 coefficient is statistically significant and positive. By comparing the estimate with its U.S. counterparty, after standardization, we also expect to see that this effect in China where retail investors prevail to be much larger. This provides further evidence for the holding of our hypothesis 1.

Figure 3: The announcement concentration phenomenon in China



For hypothesis 2, which investigates the validity of the "market movement effect" with other attention-distracting effects being controlled for, Model 2 is specified as:

$$BHAR[2,20] = \alpha_0 + \alpha_1 S\_RANK + \alpha_2 MM\_RANK + \alpha_3 (S\_RANK \times MM\_RANK) + \alpha_4 FRIDAY + \alpha_5 (S\_RANK \times FRIDAY) + \alpha_6 N\_RANK + \alpha_7 (S\_RANK \times N\_RANK) + \sum_{i=1}^{n} c_i X_i + \sum_{i=1}^{n} b_i (S\_RANK \times X_i) + YEAR + INDUSTRY + \varepsilon \quad (9)$$

In this model, we expect that, besides responding to large market movement, investors also underreact to earnings released on Fridays. So, the "Friday effect" will be present if α_5>0. Similarly, the "announcement concentration effect" will be verified with a significant estimate of α_7. As the "market movement effect" is argued to be an independent attention diversion event, α_3>0 will still hold after we incorporate the "Friday effect" and "announcement concentration effect" in model 2.

Recall that hypothesis 3 discusses the relationship between "market movement effect" and market direction on the announcement date. To test this hypothesis, we divide our sample into two groups according to market direction, and then we re-examine Model 1 in each of these two subsamples, respectively. As both large market rise and fall will distract investors, we should observe α_3>0 in both subsamples. The "ostrich effect" suggests that investors are more attentive to stock earnings when the market rises, hence the PEAD will be weaker. When the market goes down, investors are likely to underreact to earnings surprise, and the PEAD will be stronger (Hou et al., 2009). Thus, it is also our expectation that the value of α_3 estimated from the upside-market subsample is larger than that estimated from the downside-market subsample.

Lastly, hypothesis 4 is about linking the "market movement effect" to firm characteristics. In the first step, the sample is divided into small- versus large-size group, and Model 1 is evaluated for each subgroup. In the second step, the original sample is divided into the low and high book-to-market ratio group, and again Model 1 is run repeatedly in two subgroups. We use the median value of either size or book-to-market ratio across all stocks each year as the group dividing line. In line with Ali et al. (2003), the "market movement effect" should become more severe for small and value stocks. As a result, the magnitude of estimatedin the small-size subgroup and the high book-to-market ratio subgroup is expected to be larger than that in the big-size subgroup and that in the low book-to-market ratio subgroup, respectively.

5. EMPIRICAL RESULTS

Table 5 reports the results of regressing Model 1 which concerns hypothesis 1. Looking at column (1), *S_RANK*'s coefficient is significantly positive at the 5% significance level, which implies that stocks with larger standard earnings surprises continue to have higher abnormal returns after the earnings release dates. This finding confirms the existence of the PEAD in China. From columns (2)-(4), the coefficients of *MM_RANK* are significantly negative at the significance level of at least 5%. These negative estimates support the intuition that stocks continue to have lower returns after large market movements. Our focus lies on the coefficient of the interaction term *S_RANK* × *MM_RANK*.

In columns (2)-(4), they are significantly positive at least at the 5% significance level. Thus, the existence of the "market movement effect" is confirmed in China. In other words, the PEAD becomes stronger during volatile market times because Chinese investors are very likely to be distracted by large market movements, and underreact to earnings announcement released on market-moving days. Hypothesis 1 is therefore a true statement in China.

Given the above being said, the results in Table 5 concerning the control variable are all consistent with the findings in the literature, except for the coefficient of *S_RANK* × *IO*. Though the sign of this exception is negative and consistent with the finding of Piotroski and Roulstone (2004), it is statistically insignificant.

Table 6 contains the estimation results of Model 2. From columns (1)-(2), the coefficients of *S_RANK* × *FRIDAY* are significantly positive at the level of 5%, which confirms the "Friday effect". The coefficients of *S_RANK* × *N_RANK* are negative but not significant, thus the "announcement concentration effect" is attenuated. The main interest lies in the coefficients of *S_RANK* × *MM_RANK*, which remain significant at the 5% significance level and positive. Thus, the "market movement effect" is a different distracting event than Fridays and the number of simultaneous announcements. The results of control variables remain largely unchanged comparing to the results presented in Table 5.

Table 7 demonstrates the estimation results for testing hypothesis 3. Columns (1)-(2) contain results for the subgroup that the market

Table 5: Evidence for the existence of the "Market Movement Effect" in China

Variables	*BHAR*[2,20]			
	(1)	(2)	(3)	(4)
S_RANK	0.0711*	–0.0852	0.0688	0.0798
	(1.84)	(–1.00)	(0.31)	(0.36)
MM_RANK		–0.190**	–0.226***	–0.209**
		(–2.20)	(–2.67)	(–2.48)
S_RANK × *MM_RANK*		0.0288**	0.0324**	0.0305**
		(2.11)	(2.41)	(2.28)
SIZE			–0.0497	–0.0321
			(–1.50)	(–0.94)
S_RANK × *SIZE*			0.00209	0.000426
			(0.51)	(0.10)
BM			2.448***	3.174***
			(2.81)	(3.46)
S_RANK × *BM*			–0.124	–0.117
			(–0.88)	(–0.83)
LAG_DAY			–0.0547***	–0.0591***
			(–7.52)	(–8.10)
S_RANK × *LAG_DAY*			0.00429***	0.00453***
			(3.56)	(3.73)
TURNOVER			0.939***	0.958***
			(5.80)	(5.50)
S_RANK × *TURNOVER*			–0.0675*	–0.0656*
			(–1.91)	(–1.84)
IO			–0.00464	0.00302
			(–0.33)	(0.21)
S_RANK × *IO*			–0.00241	–0.00276
			(–1.08)	(–1.25)
YEAR & INDUSTRY CONTROL	NO	NO	NO	YES
_CONS	1.165***	2.188***	1.786	2.830*
	(4.87)	(4.03)	(1.45)	(1.82)
N	8239	8239	8239	8239
Adj. R^2	0.000	0.001	0.040	0.055

***, **, and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error

Table 6: Evidence for the validity of the "Market Movement Effect" in China

Variables	*BHAR*[2,20]	
	(1)	(2)
S_RANK	0.0849 (0.30)	0.0896 (0.31)
MM_RANK	–0.226*** (–2.68)	–0.205** (–2.44)
S_RANK × *MM_RANK*	0.0324** (2.41)	0.0302** (2.26)
FRIDAY	–1.412** (–2.46)	–1.470** (–2.57)
S_RANK × *FRIDAY*	0.158* (1.74)	0.154* (1.71)
N_RANK	0.343 (1.18)	0.436 (1.50)
S_RANK × *N_RANK*	–0.00726 (–0.15)	–0.00530 (–0.11)
SIZE	–0.0470 (–1.41)	–0.0288 (–0.84)
S_RANK × *SIZE*	0.00185 (0.45)	0.000199 (0.05)
BM	2.465*** (2.82)	3.185*** (3.45)
S_RANK × *BM*	–0.127 (–0.89)	–0.114 (–0.81)
LAG_DAY	–0.0528*** (–7.14)	–0.0573*** (–7.75)
S_RANK × *LAG_DAY*	0.00407*** (3.35)	0.00430*** (3.51)
TURNOVER	0.966*** (5.89)	0.977*** (5.54)
S_RANK × *TURNOVER*	–0.0710** (–2.00)	–0.0687* (–1.92)
IO	–0.00449 (–0.32)	0.00367 (0.26)
S_RANK × *IO*	–0.00241 (–1.09)	–0.00279 (–1.26)
YEAR & INDUSTRY CONTROL	NO	YES
_CONS	0.677 (0.41)	1.479 (0.78)
N	8239	8239
Adj. R^2	0.041	0.057

***, **, and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error

goes down on the announcement day, and columns (3)-(4) for the market goes up on the announcement day.

The coefficients of *S_RANK* × *MM_RANK* are positive and significant at the level of 5%, while those are positive but not significant in columns (3)-(4). The result suggests that it is mainly the negative large market movements that distract investors and lead to the underreaction towards the earnings announcements. Investors are relatively more attentive to earnings when in an upside market. This is consistent with the "ostrich effect". Thus, our hypothesis 3 is effectively tested. It is interesting that other information proxy variables, like BM, also become not so significant in the upside market. This result further illustrates that investors are less likely to underreact to stock earnings information when the market is good.

Table 8 displays the results concerning hypothesis 4. Columns (1)-(2) contain results for the small size and large size stocks, respectively; and columns (3)-(4) contain results for the low book-to-market ratio and high book-to-market ratio stocks, respectively. The variable of our interest is the interaction term *S_RANK* × *MM_RANK*. The coefficient of *S_RANK* × *MM_RANK* is positive and significant at the 1% significance level in column (1). While it is still positive, it becomes insignificant in column (2). This observation confirms that the "market movement effect" is larger for small-cap stocks. The coefficient before *S_RANK* × *MM_RANK* is positive but insignificant in column (3). However, this estimated coefficient is both positive and significant at the 1% level in column (4). The results combined suggest that the "market movement effect" is larger for value stocks in China. Our hypothesis 4 is hence confirmed.

Table 7: Linking the "Market Movement Effect" with market directions

Variables	*BHAR*[2,20]			
	R_m<0		R_m>0	
	(1)	(2)	(3)	(4)
S_RANK	0.0467 (0.18)	0.114 (0.43)	–0.0486 (–0.17)	–0.0838 (–0.29)
MM_RANK	–0.363*** (–2.88)	–0.248** (–1.97)	–0.162 (–1.38)	–0.253** (–2.15)
S_RANK × *MM_RANK*	0.0509*** (2.59)	0.0409** (2.09)	0.0255 (1.35)	0.0282 (1.50)
SIZE	–0.0565 (–1.24)	–0.0346 (–0.76)	–0.0292 (–0.62)	–0.00201 (–0.04)
S_RANK × *SIZE*	0.00114 (0.20)	–0.000859 (–0.15)	0.00103 (0.18)	–0.00147 (–0.25)
BM	3.282** (2.57)	3.553*** (2.65)	1.646 (1.42)	2.659** (2.14)
S_RANK × *BM*	–0.0761 (–0.39)	–0.0106 (–0.05)	–0.164 (–0.88)	–0.201 (–1.06)
LAG_DAY	–0.0572*** (–5.57)	–0.0604*** (–5.92)	–0.0557*** (–5.28)	–0.0586*** (–5.54)
S_RANK × *LAG_DAY*	0.00496*** (2.94)	0.00497*** (2.95)	0.00441** (2.53)	0.00489***
TURNOVER	1.239*** (5.92)	1.296*** (5.79)	0.663*** (3.11)	0.665*** (2.59)
S_RANK × *TURNOVER*	–0.120*** (–3.05)	–0.124*** (–3.13)	0.000244 (0.01)	0.0114 (0.33)
IO	–0.0153 (–0.75)	–0.00491 (–0.24)	0.00605 (0.31)	0.0118 (0.60)
S_RANK × *IO*	–0.00101 (–0.32)	–0.00144 (–0.46)	–0.00385 (–1.23)	–0.00405 (–1.30)
YEAR & INDUSTRY CONTROL	NO	YES	NO	YES
_CONS	1.584 (0.96)	1.222 (0.59)	2.393 (1.36)	5.655** (2.37)
N	4013	4013	4226	4226
Adj. R^2	0.041	0.062	0.043	0.064

***, **, and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error

Table 8: Linking the "Market Movement Effect" to firm-level characteristics

Variables	*BHAR*[2,20]			
	SIZE		*BM*	
	Small	Large	Low	High
	(1)	(2)	(3)	(4)
S_RANK	–0.138 (–0.39)	0.0716 (0.30)	0.0734 (0.25)	0.0365 (0.12)
MM_RANK	–0.371*** (–2.95)	–0.0504 (–0.45)	–0.0489 (–0.35)	–0.302*** (–2.86)
S_RANK × *MM_RANK*	0.0534*** (2.59)	0.00819 (0.47)	0.0103 (0.48)	0.0433*** (2.59)
SIZE	–0.968** (–2.09)	0.0223 (0.68)	–0.0417 (–0.84)	–0.0240 (–0.52)
S_RANK × *SIZE*	0.0709 (1.02)	–0.00401 (–1.00)	0.00394 (0.66)	–0.00219 (–0.40)
BM	2.697* (1.82)	3.338*** (2.96)	10.51** (2.51)	1.885 (1.39)
S_RANK × *BM*	–0.0514 (–0.23)	–0.109 (–0.64)	–0.746 (–1.13)	–0.0260 (–0.13)
LAG_DAY	–0.0522*** (–4.72)	–0.0593*** (–6.12)	–0.0797*** (–6.24)	–0.0473**** (–5.31)
S_RANK × *LAG_DAY*	0.00333* (1.72)	0.00550*** (3.58)	0.00689*** (3.21)	0.00359** (2.45)
TURNOVER	0.800*** (3.55)	0.885*** (3.38)	0.869*** (4.13)	0.889*** (3.06)
S_RANK × *TURNOVER*	–0.0674* (–1.81)	–0.0200 (–0.54)	–0.0270 (–0.85)	–0.0694 (–1.61)
IO	–0.00367 (–0.17)	0.00739 (0.39)	0.00632 (0.28)	0.00469 (0.26)
S_RANK × *IO*	–0.00272 (–0.77)	–0.00291 (–1.02)	–0.00311 (–0.86)	–0.00272 (–0.97)
YEAR & INDUSTRY CONTROL	YES	YES	YES	YES
_CONS	7.172*** (2.83)	0.123 (0.06)	1.309 (0.52)	4.843** (2.07)
N	4088	4151	4046	4193
Adj. R^2	0.074	0.036	0.051	0.069

***, **, and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error

6. ROBUSTNESS CHECKS

Robustness tests are conducted in the section to address the potential bias of estimation or failure of the model caused by (i) omitted variables; (ii) measurement errors in calculating abnormal returns; (iii) identification of market movements; (iv) appropriateness of the grouping method; as well as (v) outliers.

Firstly, to address bias caused by omitted firm-level control variables, we include firm-year fixed effects in the model and compare it to the industry-year fixed-effect model in the above analysis. The corresponding results are tabulated in Table B1 in the Appendix. It is shown that the coefficient of *S_RANK* × *MM_RANK* remains significantly positive at the 5% significance level. Thus, the "Market movement effect" still exists after we consider firm-level time-invariant variables. Our empirical model stays robust to possibly omitted control variables related to firm additional characteristics.

Secondly, to ensure that the empirical results of our model are not affected by the calculation method for abnormal return, alternative proxies such as *CAR* and *BABHAR* defined in equations (4) and (5) are used as the dependent variable in Model 1 and Model 2. Detailed results are included in Tables B2 and B3 for Model 1 and Model 2, respectively. The coefficients of *S_RANK* and those of *S_RANK* × *MM_RANK* are still significant with signs consistent with baseline results presented in Section 5. Therefore, we are confident to say that our analysis is robust to other commonly used measurements of abnormal return.

Thirdly, to ensure that the estimation of the models is not affected by the calculation method for market movement groups, the method in Kottimukkalur (2019) is employed to construct *MM2_RANK*. The corresponding regression results are presented in Appendix B Table B4 and B5, the coefficients of *S_RANK* × *MM2_RANK* are significantly positive at the level of 5% in each case. Again, the estimation is robust to alternative calculation methodology for determining groups and rankings of financial market movement.

Also, to test whether the estimation is robust to the grouping procedures, we re-calculate the standard earnings surprise groups and market movement groups by dividing the data into 5 groups to construct new independent variables: *S_RANK5* and *MM_RANK5*. The regression results are attached in Tables B6 and B7 in Appendix B, the coefficients of main interest remain significant and the same signs are obtained once again as in the previous analysis. Thus, our results are robust to different grouping procedures.

Last but not least, previously, to account for possible influential outliers, the dependent variable *BHAR* is winsorized at the 1% level. To verify that the results are not affected by the outliers in the return distribution, regression results using the raw *BHAR* data and winsorized data at 1%, 2%, and 5% levels are compared. The estimation results of Model 1 is summarized in Table B8 in Appendix B. The coefficients of *S_RANK* × *MM_RANK* remain positively significant at least at the 5% significant level. Plus, the significance of other control variables is also very close to that presented in the benchmark results from Section 5. It is straightforward for us to find out that, our previous estimation of models is robust to a more careful treatment imposed on extreme values.

7. CONCLUSION

This paper studies the distraction effect of market movement and its relationship with PEAD and extends the main findings of Kottimukkalur (2019). Investors usually use "category thinking" when making investment decisions, that is they are more attentive to market-level information, specifically the large market movement, and underreact to firm-specific earnings, which leads to a stronger PEAD. Because most investors in China's A-share stock market are individual investors, their access to investment information is very limited, it may further aggravate the impact of limited attention on earnings announcement anomaly. In this paper, we use the annual announcement data between 2006 and 2017 to investigate the relationship between announcement day market movement and the PEAD. To capture in time the investors' response to the key information in the earnings announcement, we use three disclosure forms of annual announcements and set the release date of the earliest report as our event date.

Specifically speaking, the conclusions are fourfold. One, the "market movement effect" is also in presence for China. Investors underreact to earnings information when the magnitude of the market return is high on the announcement day. PEAD is stronger for stocks whose earnings are released on market-moving days. Two, the existence of the "market movement effect" is not affected by other distracting events such as the "Friday effect" and "announcement concentration effect." Three, it is in the downside market when we observe the occurrence of investor underreaction to the firm's earnings announcements. Four, the "market movement effect" varies with firm characteristics, in particular, the effect is more pronounced in samples of small-cap stocks and value stocks.

Future works can be performed in the following aspects. Firstly, more distracting information factors may be taken into account. Savor and Wilson (2013) find evidence that the average payoff and Sharpe ratio of the stock market are both significantly higher during inflation, unemployment, interest rates, and other macroeconomic data announcements. Chen et al. (2018) also notice that scheduled macroeconomic data release will affect PEAD. In addition, industry-level information can also affect investors' attention. Hirshleifer et al. (2009) further prove that announcements from the same industry will reduce PEAD, while unrelated earnings announcements from different industries will increase PEAD. Hence, macro and industry level information can be taken into consideration in our future work. Secondly, Basu (1997) finds that investors have a greater reaction to good news comparing to bad news. DeGeorge et al. (1999) find that a marginal unexpected loss causes a greater reaction comparing to a marginal unexpected profit. Therefore, future work can study the "market movement effect" for stocks with different earnings surprise values.

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APPENDIXES

Appendix A: Table of sample distribution and summary statistics

Table A1: Summary statistics

Variables	Obs.	Unit	Mean	S.D.	Min	25%	Median	75%	Max
BHAR[2,20]	8239	%	1.68	11.2840	–84.13	–4.54	0.34	6.27	216.50
S_RANK	8239	-	5.50	2.8805	1	3	6	8	10
MM_RANK	8239	-	5.38	2.8422	1	3	6	8	10
FRIDAY	8239	-	0.23	0.4197	0	0	0	0	1
N_RANK	8239	-	3.49	0.8395	1	3	4	4	4
SIZE	8239	Billion	5.36	9.9180	0.05	1.60	2.81	5.36	343.75
BM	8239	-	0.36	0.2292	–0.11	0.20	0.31	0.47	2.04
LAG_DAY	8239	Day	54.54	35.4897	–61	25	36	88	120
IO	8239	%	56.10	16.0172	0.12	44.73	56.55	67.51	92.50
TURNOVER	8239	%	3.44	2.6272	0.27	1.75	2.82	4.56	18.17
SUE	8239	%	–0.23	4.0542	–86.47	–0.91	0.06	0.72	63.83
$\|R_m\|$	8239	%	1.17	1.2581	0.00	0.34	0.80	1.34	9.09

Shenzhen Inovance Technology Co., Ltd (300124.SZ) released the 2016 earnings preannouncement on 2016 October, 31, 61 days before the fiscal year-end. This table reports the raw data distribution, we winsorize *BHAR*[2,20] at the 1% level

Table A2: Sample distribution of firms and announcements from 2006 to 2017

Fiscal year	2006	2007	2008	2009	2010	2011
Number of firms	479	471	538	485	511	584
Number of announcement days	81	78	70	74	74	69
Fiscal year	2012	2013	2014	2015	2016	2017
Number of firms	572	672	802	846	1077	1202
Number of announcement days	68	68	75	82	80	78

Appendix B: Robustness test results

Table B1: Results of firm-year fixed-effect model

Variables	*BHAR*[2,20]	
	Benchmark model	Firm-year fixed effect model
	(1)	(2)
S_RANK	0.0798 (0.36)	0.0739 (0.30)
MM_RANK	–0.209** (–2.48)	–0.198** (–2.00)
S_RANK × *MM_RANK*	0.0305** (2.28)	0.0316** (2.08)
SIZE	–0.0321 (–0.94)	–0.0223 (–0.45)
S_RANK × *SIZE*	0.000426 (0.10)	0.00240 (0.51)
BM	3.174*** (3.46)	7.487*** (5.72)
S_RANK × *BM*	–0.117 (–0.83)	–0.00651 (–0.04)
LAG_DAY	–0.0591*** (–8.10)	–0.0564*** (–6.48)
S_RANK × *LAG_DAY*	0.00453*** (3.73)	0.00413*** (3.01)
TURNOVER	0.958*** (5.50)	1.075*** (4.96)
S_RANK × *TURNOVER*	–0.0656* (–1.84)	–0.0661 (–1.60)
IO	0.00302 (0.21)	–0.0230 (–1.05)
S_RANK × *IO*	–0.00276 (–1.25)	–0.00309 (–1.25)
YEAR CONTROL	YES	YES
INDUSTRY CONTROL	YES	NO
FIRM CONTROL	NO	YES
_CONS	2.830* (1.82)	3.005 (1.50)
N	8239	8239
Adj. R^2	0.055	0.058

***, **, and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error

Table B2: Model 1: Changing the calculation method of abnormal return

Variables	*CAR*[2,20]			*BABHAR*[2,20]		
	(1)	(2)	(3)	(4)	(5)	(6)
S_RANK	0.0775** (2.15)	0.0886 (0.43)	0.0964 (0.46)	0.0656* (1.73)	0.116 (0.54)	0.108 (0.50)
MM_RANK		–0.183** (–2.32)	–0.175** (–2.22)		–0.179** (–2.14)	–0.223*** (–2.66)
S_RANK × MM_RANK		0.0283** (2.26)	0.0271** (2.17)		0.0226* (1.70)	0.0259* (1.96)
SIZE		–0.0463 (–1.44)	–0.0302 (–0.92)		–0.0575* (–1.79)	–0.0449 (–1.33)
S_RANK × SIZE		0.00194 (0.49)	0.000384 (0.10)		0.00325 (0.81)	0.00127 (0.31)
BM		2.178*** (2.69)	2.907*** (3.40)		1.370 (1.60)	2.121** (2.35)
S_RANK × BM		–0.127 (–0.96)	–0.120 (–0.91)		–0.0479 (–0.35)	–0.0730 (–0.53)
LAG_DAY		–0.054*** (–8.02)	–0.058*** (–8.53)		–0.052*** (–7.29)	–0.054*** (–7.52)
S_RANK × LAG_DAY		0.0042*** (3.77)	0.0044*** (3.91)		0.0043*** (3.59)	0.0046*** (3.80)
TURNOVER		0.866*** (5.90)	0.886*** (5.63)		0.850*** (5.38)	0.893*** (5.24)
S_RANK × TURNOVER		–0.0603* (–1.85)	–0.0585* (–1.77)		–0.0610* (–1.85)	–0.0599* (–1.75)
IO		–0.00179 (–0.14)	0.00544 (0.41)		0.00344 (0.25)	0.00675 (0.48)
S_RANK × IO		–0.00261 (–1.26)	–0.00291 (–1.41)		–0.00340 (–1.54)	–0.00357 (–1.62)
YEAR & INDUSTRY CONTROL	NO	NO	YES	NO	NO	YES
_CONS	1.164*** (5.19)	1.698 (1.48)	2.440* (1.72)	1.164*** (4.93)	1.687 (1.39)	1.719 (1.12)
N	8239	8239	8239	8239	8239	8239
Adj. R^2	0.000	0.042	0.057	0.000	0.035	0.052

***, **, and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error

Table B3: Model 2: Changing the calculation method of abnormal return

Variables	*CAR*[2,20]		*BABHAR*[2,20]	
	(1)	(2)	(3)	(4)
S_RANK	0.0861 (0.32)	0.0935 (0.35)	0.0420 (0.15)	0.0593 (0.21)
MM_RANK	–0.183** (–2.32)	–0.172** (–2.18)	–0.181** (–2.16)	–0.222*** (–2.65)
S_RANK × MM_RANK	0.0283** (2.27)	0.0268** (2.15)	0.0228* (1.72)	0.0258* (1.95)s
FRIDAY	–1.254* * (–2.34)	–1.317** (–2.46)	–1.557*** (–2.73)	–1.513*** (–2.66)
S_RANK × FRIDAY	0.141* (1.67)	0.139* (1.65)	0.161* (1.78)	0.152* (1.68)
N_RANK	0.297 (1.08)	0.391 (1.42)	0.126 (0.44)	0.229 (0.79)
S_RANK × N_RANK	–0.00178 (–0.04)	–0.00150 (–0.03)	0.0170 (0.36)	0.0101 (0.22)
SIZE	–0.0440 (–1.36)	–0.0272 (–0.82)	–0.0553* (–1.70)	–0.0424 (–1.25)
S_RANK × SIZE	0.00174 (0.43)	0.000187 (0.05)	0.00307 (0.75)	0.00111 (0.27)
BM	2.195*** (2.70)	2.916*** (3.40)	1.413* (1.65)	2.152**(2.38)
S_RANK × BM	–0.130 (–0.98)	–0.117 (–0.89)	–0.0533 (–0.38)	–0.0724 (–0.52)
LAG_DAY	–0.0523*** (–7.64)	–0.0562*** (–8.18)	–0.0508*** (–6.98)	–0.0530*** (–7.23)
S_RANK × LAG_DAY	0.00401*** (3.57)	0.00420*** (3.70)	0.00414*** (3.44)	0.00443*** (3.63)
TURNOVER	0.889*** (5.99)	0.903*** (5.67)	0.878*** (5.48)	0.913*** (5.28)
S_RANK × TURNOVER	–0.0634* (–1.94)	–0.0612* (–1.85)	–0.0645* (–1.94)	–0.0629* (–1.84)
IO	–0.00169 (–0.13)	0.00602 (0.46)	0.00356 (0.25)	0.00728 (0.52)
S_RANK × IO	–0.00260 (–1.25)	–0.00294 (–1.42)	–0.00340 (–1.54)	–0.00360 (–1.63)
YR & IND CONTROLS	NO	YES	NO	YES
_CONS	0.742 (0.48)	1.238 (0.70)	1.402 (0.85)	1.126 (0.60)
N	8239	8239	8239	8239
Adj. R^2	0.043	0.058	0.036	0.053

***, **, and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error

Table B4: Model 1: Changing market movement grouping methods

Variables	*BHAR*[2,20]			
	(1)	(2)	(3)	(4)
S_RANK	0.0711* (1.84)	–0.0913 (–1.06)	0.0637 (0.29)	0.0740 (0.33)
MM2_RANK		–0.192** (–2.24)	–0.238*** (–2.83)	–0.221*** (–2.63)
S_RANK × MM2_RANK		0.0290** (2.13)	0.0332** (2.49)	0.0313** (2.36)
SIZE			–0.0488 (–1.48)	–0.0315 (–0.92)
S_RANK × SIZE			0.00198 (0.48)	0.000327 (0.08)
BM			2.409*** (2.77)	3.154*** (3.43)
S_RANK × BM			–0.119 (–0.84)	–0.113 (–0.80)
LAG_DAY			–0.0547*** (–7.51)	–0.0591*** (–8.09)
S_RANK × LAG_DAY			0.00427*** (3.54)	0.00452*** (3.72)
TURNOVER			0.945*** (5.83)	0.962*** (5.52)
S_RANK × TURNOVER			–0.0683* (–1.94)	–0.0663* (––1.86)
IO			–0.00410 (–0.29)	0.00340 (0.24)
S_RANK × IO			–0.00247 (–1.11)	–0.00282 (–1.27)
YEAR & INDUSTRY CONTROLS	NO	NO	NO	YES
_CONS	1.165*** (4.87)	2.240*** (4.07)	1.854 (1.51)	s
N	8239	8239	8239	8239
Adj. R^2	0.000	0.001	0.041	0.055

***, **, and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error

Table B5: Model 2: Changing market movement grouping methods

Variables	*BHAR*[2,20]	
	(1)	(2)
S_RANK	0.0870 (0.31)	0.0902 (0.32)
MM2_RANK	–0.238*** (–2.84)	–0.217*** (–2.59)
S_RANK × MM2_RANK	0.0331** (2.48)	0.0309** (2.33)
FRIDAY	–1.401** (–2.44)	–1.459** (–2.55)
S_RANK × FRIDAY	0.156* (1.72)	0.152* (1.69)
N_RANK	0.355 (1.22)	0.446 (1.53)
S_RANK × N_RANK	–0.00889 (–0.19)	–0.00675 (–0.14)
SIZE	–0.0461 (–1.38)	–0.0281 (–0.82)
S_RANK × SIZE	0.00174 (0.42)	0.0000995 (0.02)
BM	2.425*** (2.78)	3.164*** (3.43)
S_RANK × BM	–0.122 (–0.86)	–0.110 (–0.78)
LAG_DAY	–0.0527*** (–7.12)	–0.0573*** (–7.74)
S_RANK × LAG_DAY	0.00405*** (3.33)	0.00429*** (3.50)
TURNOVER	0.972*** (5.92)	0.982*** (5.56)
S_RANK × TURNOVER	–0.0718** (–2.03)	–0.0693* (–1.94)
IO	–0.00395 (–0.28)	0.00405 (0.29)
S_RANK × IO	–0.00248 (–1.12)	–0.00285 (–1.29)
YEAR & INDUSTRY CONTROLS	NO	YES
_CONS	0.701 (0.42)	1.557 (0.81)
N	8239	8239
Adj. R^2	0.042	0.057

***, **, and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error

Table B6: Model 1: Changing grouping number in constructing *BHAR*

Variables	***BHAR*[2,20]**			
	(1)	**(2)**	**(3)**	**(4)**
S_RANK5	0.157** (2.00)	–0.0934 (–0.50)	0.201 (0.44)	0.225 (0.49)
MM_RANK5		–0.300 (–1.58)	–0.367** (–1.98)	–0.344* (–1.85)
S_RANK5 × MM_RANK5		0.0858* (1.66)	0.101* (1.82)	0.0926* (1.67)
SIZE			–0.0566 (–1.56)	–0.0397 (–1.06)
S_RANK5 × SIZE			0.00569 (0.67)	0.00271 (0.31)
BM			2.714*** (2.87)	3.445*** (3.48)
S_RANK5 × BM			–0.329 (–1.14)	–0.318 (–1.11)
LAG_DAY			–0.0572*** (–7.29)	–0.0619*** (–7.88)
S_RANK5 × LAG_DAY			0.00873*** (3.60)	0.00924*** (3.79)
TURNOVER			0.914*** (5.21)	0.920*** (4.88)
S_RANK5 × TURNOVER			–0.120* (–1.67)	–0.114 (–1.59)
IO			–0.00145 (–0.10)	0.00671 (0.44)
S_RANK5 × IO			–0.00545 (–1.21)	–0.00624 (–1.39)
YEAR & INDUSTRY CONTROLS	NO	NO	NO	YES
_CONS	1.085*** (4.18)	1.957*** (3.13)	1.537 (1.14)	2.674 (1.61)
N	8239	8239	8239	8239
Adj. R^2	0.000	0.000	0.040	0.054

***, **, and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error

Table B7: Model 2: Changing grouping number in constructing *BHAR*

Variables	***BHAR*[2,20]**	
	(1)	**(2)**
S_RANK5	0.105 (0.18)	0.115 (0.20)
MM_RANK5	–0.361* (–1.95)	–0.330* (–1.78)
S_RANK5 × MM_RANK5	0.101* (1.81)	0.0902* (1.67)
FRIDAY	–1.307** (–2.11)	–1.383** (–2.24)
S_RANK5 × FRIDAY	0.258 (1.40)	0.256 (1.40)
N_RANK	0.231 (0.74)	0.324 (1.03)
S_RANK5 × N_RANK	0.0233 (0.24)	0.0277 (0.29)
SIZE	–0.0545 (–1.49)	–0.0371 (–0.98)
S_RANK5 × SIZE	0.00541 (0.63)	0.00249 (0.28)
BM	2.748*** (2.90)	3.469*** (3.48)
S_RANK5 × BM	–0.340 (–1.18)	–0.317 (–1.11)
LAG_DAY	–0.0554*** (–6.98)	–0.0602*** (–7.58)
S_RANK5 × LAG_DAY	0.00837*** (3.43)	0.00885*** (3.60)
TURNOVER	0.939*** (5.28)	0.938*** (4.90)
S_RANK5 × TURNOVER	–0.126* (–1.74)	–0.119* (–1.66)
IO	–0.00147 (–0.10)	0.00724 (0.48)
S_RANK5 × IO	–0.00540 (–1.20)	–0.00626 (–1.39)
YEAR & INDUSTRY CONTROLS	NO	YES
_CONS	0.811 (0.45)	1.720 (0.84)
N	8239	8239
Adj. R^2	0.040	0.056

***, **, and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error

Table B8: Robustness test results under different winsorizing levels

Variables	*BHAR*[2,20]			
	No winsorizing	Winsorizing at 1% level	Winsorizing at 2% level	Winsorizing at 5% level
	(1)	(2)	(3)	(4)
S_RANK	0.0205 (0.07)	0.0798 (0.36)	0.0888 (0.43)	0.110 (0.60)
MM_RANK	–0.219** (–2.30)	–0.209** (–2.48)	–0.183** (–2.30)	–0.135* (–1.91)
S_RANK × MM_RANK	0.0299* (1.91)	0.0305** (2.28)	0.0275** (2.18)	0.0215* (1.91)
SIZE	–0.0305 (–0.85)	–0.0321 (–0.94)	–0.0329 (–0.99)	–0.0299 (–0.96)
S_RANK × SIZE	0.000467 (0.11)	0.000426 (0.10)	0.000491 (0.12)	0.000286 (0.07)
BM	3.737*** (3.76)	3.174*** (3.46)	2.901*** (3.35)	2.372*** (3.08)
S_RANK × BM	–0.177 (–1.15)	–0.117 (–0.83)	–0.0918 (–0.69)	–0.0611 (–0.51)
LAG_DAY	–0.0607*** (–7.28)	–0.0591*** (–8.10)	–0.0574*** (–8.34)	–0.0527*** (–8.81)
S_RANK × LAG_DAY	0.00489*** (3.45)	0.00453*** (3.73)	0.00431*** (3.76)	0.00383*** (3.81)
TURNOVER	1.129*** (4.89)	0.958*** (5.50)	0.858*** (5.42)	0.701*** (5.19)
S_RANK × TURNOVER	–0.0683 (–1.41)	–0.0656* (–1.84)	–0.0583* (–1.80)	–0.0475* (–1.75)
IO	–0.00597 (–0.39)	0.00302 (0.21)	0.00490 (0.37)	0.00734 (0.61)
S_RANK × IO	–0.00116 (–0.48)	–0.00276 (–1.25)	–0.00301 (–1.42)	–0.00315* (–1.66)
YR & IND CONTROLS	YES	YES	YES	YES
_CONS	2.587 (1.44)	2.830* (1.82)	2.798* (1.93)	2.607** (2.04)
N	8239	8239	8239	8239
Adj. R^2	0.053	0.055	0.055	0.054

***, ** and * represent significant levels at 1%, 5% and 10%, respectively. T-statistics are adjusted by the heteroskedasticity-robust standard error