Local Information Advantage, Investor Attention and Stock Returns

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This version: December 2015

[a] We gratefully acknowledge helpful comments from anonymous referees, Rui Chen, Lauren Cohen, Stefanos Delikouras, Wenxuan Hou, Fuwei Jiang, Yan Luo, Ying Wang, Guofu Zhou, as well as the comments of conference participants at the 2015 FMA Annual Meeting, the 12th Chinese Finance Annual Meeting, the 4th Chinese Capital Markets Conference, seminar participants at Central University of Finance and Economics. Huang thanks innovation research team in Central University of Finance and Economics and National Natural Science Foundation of China (Project No. 71203246) for support.

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Abstract

We construct a measure of abnormal relative attention (*ARA*), reflecting unusual changes in attention paid to a stock by local relative to non-local investors, to measure local information advantages. An increase in this measure predicts higher returns in the short term. This predictive power is more prominent for local-name stocks and is robust to alternative implementations. Furthermore, long-short portfolios based on levels of ARA generate significant alphas in various risk-adjustment models. And double-sorted analysis suggests that ARA imposes a much stronger influence on firms with worse information environments.

Keywords: local information advantage; investor attention; stock message board; stock return

JEL Classification: D82 ;G12 ; G14

1. Introduction

Existing research shows the existence of local information advantage. Coval and Moskowitz (1999, 2001) attribute local bias puzzle to information asymmetry between local and non-local investors. Since information acquisition is not easily observable, most studies investigate local information advantage by examining the returns on investors' investment accounts.

In this paper, we propose to investigate this issue by focusing on investor attention revealed in internet stock message boards. The underlying assumption of this literature is that investors have limited attention, which means that stocks have to draw investors' attention to enter their portfolios. If locals pay more attention to local stocks, they may obtain more adequate and prompt information than non-local investors. Correspondingly, if locals possess advantageous information about particular stocks, local investors pay more attention to these stocks before the market fully reacts to the information. And also, they may take investing actions before non-local investors. So we argue that relative invesor attention could reflects the extent of local information advantages and predict future stock returns.

We use the number of postings on Internet stock message boards as a revealed measure for attention following Huang et al. (2013). Previous literature on stock message boards suggests that some messages may contain value-relevant information (Antweiler and Frank (2004)), some messages may reveal investor sentiment (Das and Chen (2007)), and that some messages may be noise. Regardless of the content of these messages, the considerable time and effort devoted to creating posts suggest that the posters are paying attention.

Our attention measure has several advantages. First of all, this is a better measure for individual investors' attention than search volume index. Comparing with searching specific stock information through search engine, individual investors more likely use professional stock discussion board to collect information, express opinions, and even disminate rumor. If an investor posts messages about a stock, he or she is certainly paying attention to this particular security. Second, a particular advantage of these data is that they allow us to distinguish posters using the non-confidential IP address. There are stock message boards in many countries such as Yahoo! Message Boards, but most posters in the US and Europe are identified by their username, while in China, unregistered posters are identified by their IP address[1]. This special feature makes it possible to examine the link between investor attention and local information advantages. Finally, we collect more than 300 million postings on 2,399 stocks in the Chinese A-share markets. To our knowledge, this is one of the most comprehensive message posting data covering most of the stocks in the Chinese A-share markets. Given that China has predominantly retail investors and the largest number of netizens in the world[2], our findings could help understand individual investors' attention.

The first issue we investigate is whether investor attention reveals information acquisition. We construct abnormal relative attention (*ARA*) to capture unusual patterns of attention allocated to a stock by local relative to non-local investors. As the information acquisition is not directly observable, we use China's market upper price limit events and news release events to represent the time of mass information release. Event studies show that the mean of *ARA* increases dramatically during 3 weeks before upper price limit events, indicating that local investors tend

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1 There has been a change in the identification policy in Guba Eastmoney after we collected our data. Currently, instead of the IP address, Guba Eastmoney reveals the name of the city which the poster's IP address is associated with.

2 According to the *China Securities Depository and Clearing Statistical Yearbook* published by China Securities Depository and Clearing Corporation Limited (CSDC), 99.62% of the investors in Chinese A-share market were individual investors by June 2013. According to the St*atistical Report on Internet Development in China* published by the China Internet Network Information Center (CNNIC), there were 591 million Internet users in China by June 2013.

to pay attention to stocks with good future performance earlier than non-locals. We also document a decrease following news release events, because news reports can reduce the information asymmetry between local and non-local investors and lead non-locals to allocate attention to stocks they ignored before. All together, these results suggest that ARA reflects local information advantages.

One thing to note is that the link between local information advantages and our attention measure does not necessarily mean that local investors will share their advantageous information with others on the Internet. Local investors could possibly post something totally unrelated to the advantageous information they have received, but the unconscious posting behavior could still represent the increasing attention from local investors and reveal the fact that they obtain more information than non-local investors.

Next, we explore the asset pricing implications of investors' relative attention. Due to short-sale constraints and investors' attention-allocation preferences, we hypothesize that an abnormal rise in relative attention tends to be related to a subsequent price increase rather than a price decrease. Consistent with this hypothesis, our results show that a one standard deviation increase in *ARA* is associated with an outperformance of 1.28% during the subsequent week when measured in the annualized characteristic-adjusted return as in Daniel et al. (1997) (DGTW return). This relationship is stronger for stocks with ticker symbols that indicate their localities. Our results are robust to a host of other checks.

Finally, we construct portfolios sorted by levels of *ARA* and find that the long-short portfolios generate significant alphas in various risk-adjustment models. Furthermore, the results of a double-sorted analysis suggest that *ARA* imposes a much stronger influence on firms with worse information environments, implying that *ARA* is closely related to local investors' information advantages.

Our paper's main contribution to the literature is at least threefold. First, this paper contributes to literature on the information advantage of local investors. We present supporting evidence for the existence of local information advantages from a novel angle—investor attention. Information acquisition is not easily observable, but attention reflected in stock message boards is. Using relative attention measure, we find that local individual investors possess advantageous information about stocks. Compared with previous research based on local investors' investment accounts, our study utilizes a unique dataset that is more readily available and thus our results are more meaningful for the sake of trading.

Second, this study relates to the growing literature on the role of attention in financial markets. Using China's unique data, we advance the rare attempts to link investor attention, geography and stock returns (Mondria and Wu (2013)). By establishing a positive relationship between the abnormal relative attention and short-term returns, we document the asset pricing implications of geographical differences in attention.

Finally, as the attempt to examine investor attention using stock message boards, this paper connects literature on message boards, attention and stock returns. Previous literature on message boards has focused on three principal features: message sentiment (e.g., bullishness), message volume and the level of disagreement among postings. We use attention measure extracted from message boards to study the relation between relative attention and stock returns.

The remainder of this paper is organized as follows. Section 2 discusses related research. Section 3 describes our data sample and data sources. Section 4 constructs the attention variables from stock message board postings. Section 5 tests whether local investors are better informed than non-locals. Section 6 explores the relationship between *ARA* and future stock returns. Section 7 investigates portfolio returns with some factor models. Section 8 concludes the study.

2. Literature Review

A number of studies have investigated local information advantage. Feng and Seasholes (2004) argue that locals may become better informed thanks to more personal contact with the firm. Also local investors can also gain information advantages from other nearby investors through social networks (Feng and Seasholes (2004); Hong et al. (2004)) and through information spread by word of mouth (Hong et al. (2005)). Moreover, information advantages may result from a behavioral bias. For example, Van Nieuwerburgh and Veldkamp (2009) argue that investors choose to process more information about local stocks. Consistent with this argument, investors are shown to search more often for local firms through Google (Chi and Shanthikumar (2014)) and to pay more attention to local stocks (Mondria and Wu (2013)).

Another stream of literature examines whether information advantages can earn local investors additional profits. Most studies give positive answers. Superior local performance has been documented for both institutional investors (Coval and Moskowitz (2001)) and individual investors (Ivković and Weisbenner (2005); Massa and Simonov (2006)). Similar conclusions come from evidence of other countries, such as South Korea (Choe et al. (2005)) and Indonesia (Dvorak (2005)). These findings are mostly based on the information from checking investors' investment accounts.

Instead of using investment account data, we investigate this issue by focusing on investor attention. This idea is motivated by the literature on attention-based investment decision making. Attention is a scare cognitive resource and limited attention has been documented to influence investors' decision making. For example, Odean (1999) argues that when choosing from thousands of alternative stocks, investors with limited attention have to constrain their searches to stocks that have recently caught their attention. Barber and Odean (2008) suggest that attention may exert a more profound influence on choice than preferences when there are many alternatives and the search costs are high. Sicherman et al. (2014) document that patterns in the observed trading can be partially attributed to the patterns in investor attention. Huang et al. (2013) find investors pay more attention to local equities than those of non-local companies. According to these studies, investors should pay attention to certain stocks before making investment decisions and then limit their investments to this set of stocks.

An extensive literature has investigated the importance of investor attention in financial markets. Earlier empirical studies use several indirect variables to proxy investor attention. Examples are extreme returns (Barber and Odean (2008)), abnormal trading volume (Hou et al. (2009)), advertising expenses (Chemmanur and Yan (2011); Lou (2014)), media coverage (Barber and Odean (2008)) and price limits (Seasholes and Wu (2007)). More recent studies propose some new measures for attention. For example, Da et al. (2011) introduce Search Volume Index (SVI) provided by Google trends and Huang et al. (2013) propose the posting volume on the Internet stock message boards. In this study, we use message posts instead of SVI as an attention mesure for a couple of reasons. First, as mentioned by Vozlyublennaia (2014), the measure from Google SVI suffers from the problem that searching for information is not related with stock trading behavior. In this perspective, postings on stock message boards are more informative and can better reflect individual investors' attention. Also, it should be noted that Google is not popular in China, with a search share of less than 15%[3].

[3] This statistics is from CNZZ, the largest provider for Chinese online web traffic statistics. The most widely-used search engine in China is Baidu, having an over 60% market share. However, Baidu did not provide the aggregate search volume data until 2011 and the current Baidu Index only covers a relatively small number of stocks, about 180.

A number of studies have investigated the link between investor attention and security prices. Barber and Odean (2008) argue that individual investors are net buyers of attention-grabbing stocks and that their attention-driven buying patterns should generate a short-term positive price pressure. This implies that more attention from investors can temporarily inflate stock prices, followed by a subsequent reversal. Consistent with this theory, Da et al. (2011) find that an increase in investor attention predicts a higher initial price and an eventual price reversal. Lou (2014) argues that advertising attracts investor attention and documents that an increase in advertising spending is associated with a temporary rise in retail buying and abnormal stock returns, followed by lower future returns. Mayer (2014) provides further supporting evidence to the attention-driven buying theory by identifying exogenous source of variation in investor attention. These studies examine the effect of aggregate attention on asset pricing, whereas ours investigates attention from locals relative to non-locals. The recent work by Andrei and Hasler (2015) theoretically and empirically document that investor attention and uncertainty are important determinants of asset prices. They show that stock return volatility and the risk premia increase with investor attention and uncertainty. Using media coverage to measure attention, Liu et al. (2014) find that pre-IPO attention has a long-term influence in the value of the stock. Bali et al. (2014) document the asset pricing implications of liquidity shocks and propose that an inattention-based theory is capable of explaining both short-term and long-term return predictability of liquidity shocks.

Our paper is also related to the emerging body of literature on the role of stock message boards in financial markets. Using data from message boards, researchers examine some important variables in financial markets, such as trading volume (Antweiler and Frank (2004); Sabherwal et al. (2011)), market volatility (Antweiler and Frank (2004)), investor sentiment (Das and Chen (2007); Sabherwal et al. (2011)) and divergent opinions among investors (Chang et al. (2015)). The evidence shows that it is worth understanding stock message posting activities.

3. Data Description

Our stock message data are from Guba Eastmoney[4]. According to the statistics for unique visitors and page views, Guba Eastmoney is the most popular stock message board in China. This site provides a unique message board for every stock. Figure 1 provides a screenshot of the message board for Shanghai Airport (600009). On Guba Eastmoney, investors are allowed to read, post and reply to stock messages without having to register. Registered posters are identified by their registered account ID, while unregistered participants are identified by their IP address. As shown in Figure 1, most authors are unregistered posters. About 86% of the postings in our sample are from users identified by their IP addresses, and this figure hardly varies across provinces. We use a "Web-scraper" program to download stock message posting information. Each piece of posting information includes (1) a unique ID number; (2) the number of clicks; (3) the number of replies; (4) the title of the original post; (5) the author of the post (either the registered account ID or the IP address); (6) the content of the post; (7) the date of the post; and (8) the time of the post.

[Insert Figure 1 here]

We use IP-address geolocation technology, specifically the QQ database, to locate each poster who is identified by his or her IP address. We only retain messages with IP addresses that indicates a location in mainland China. Consequently, each message poster in our sample is matched with one of the 31 regions (provinces, autonomous regions and municipalities) in

[4] The address of this website is http://guba.eastmoney.com.

mainland China[5]. Following previous research, we use the region in which a firm’s headquarter is located as its region. In this paper, "local investors" ("non-local investors") of a company means investors who are (are not) located in the same region as the firm. The locations of company headquarters are taken from the Wind Database.

Our sample period is from June 2007 to May 2013. We exclude stocks that were suspended for more than 1 year consecutively during this period. We also require that Wind data be available for at least 6 months before the inclusion of the firm in the sample. The final data set covers 2,399 A-share listed stocks, of which 936 are traded on the Shanghai Stock Exchange and 1,463 are traded on the Shenzhen Stock Exchange. As some companies conducted their IPOs during our sample period, the number of firms in our sample varies across years. Table 2 reports the unbalanced structure of our sample. We report the descriptive statistics of stock message postings in Table 3. National postings for a firm are postings from all regions in mainland China and local postings are those from the company’s local province.

We obtain financial data, trading data on individual stocks, analyst following information and data on the CSI300 from the Wind Database. We download the deposit interest rate of the RMB from the official website of the People’s Bank of China. We obtain our news data from China InfoBank.

[Insert Table 1 here]

[Insert Table 2 here]

[Insert Table 3 here]

4. Construction of Attention Measures

[5] These regions are mutually exclusive.

In this paper, we use relative attention (*RA*) to measure the level of attention paid to a particular stock by locals relative to non-locals. The relative attention for firm *i* is defined as:

$$RA_i = ln\left(1 + \frac{number\ of\ postings\ for\ firm\ i\ from\ its\ local\ province}{total\ number\ of\ postings\ for\ firm\ i\ from\ mainland\ China}\right) \quad (1)$$

where *ln*(•) is the natural logarithm function and an increase in it shows that local investors are posting more messages about the stock than non-local investors[6]. As we assume that postings are a measure of investor attention, it follows that an increase in this measure means an increase in local investors' attention to a stock compared with non-local investors. By definition, this measure is always nonnegative. Panel A in Table 4 provides the descriptive statistics of relative attention. It shows that this measure is nonnegative, with a mean of 0.1022.

[Insert Table 4 here]

To measure unusual changes in relative attention, we construct an abnormal attention measure. Abnormal attention is usually measured as the difference between current attention and the normal value of attention in the previous few periods[7]. Following the literature, we define *ARA* for firm *i* in week *t* as its *RA* in week *t* subtracted by the median of its *RA* in the previous five weeks[8]. That is,

$$ARA_{it} = RA_{it} - median(RA_{it-1}, RA_{it-2}, RA_{it-3}, RA_{it-4}, RA_{it-5}) \quad (2)$$

The median over preceding periods represents the normal level of relative attention. *ARA* can capture unusual variations in attention to a stock by locals relative to non-locals. A higher *ARA*

[6] One may argue that it is more precise to use clicks-weighted numbers than the simple number of message postings to construct the relative attention measure because the weighted numbers may incorporate attention from the posters as well as the readers. However, our sample does not allow us to construct such measures because the number of clicks only represent the views until a point of time—the day when we collected the sample—and it is not time-series data.

[7] See, for example, Da et al. (2011) and Mondria and Wu (2013).

means that compared with their respective normal level, local investors' attention is much higher than that of non-locals. In other words, an increase in *ARA* indicates that local investors are paying abnormally high attention to a stock while non-local investors are not. The use of *ARA* also allows us to make comparisons across stocks. Panel A in Table 4 gives the descriptive statistics for *ARA*. Its value varies from -0.6857 to 0.6790, with a mean of 0.0052. Figure 2 shows that the density distribution of *ARA* is distributed around zero.

[Insert Figure 2 here]

We also report the summary statistics of *ARA* for firms in different industries and regions. Chinese listed companies are classified into 13 industries according to the *Guidance for Industry Classification of Listed Companies* released by the China Securities Regulatory Commission (CSRC)[9]. Panel B in Table 4 shows that the mean of *ARA* differs across industries, from 0.0034 in Finance and Insurance to 0.0056 in IT. Moreover, the companies in our sample are headquartered in the 31 regions (provinces, autonomous regions and municipalities) in mainland China, which have many different characteristics. Thus, it is possible that some of these regional characteristics may influence our results. For example, it is reasonable to expect that investors in more developed regions can access the Internet more easily and thus post more messages on stock message boards. Poor provinces and provinces with smaller population may have fewer local investors and thus have lower *ARA*. Panel C in Table 4 shows that the mean of *ARA* varies across region from 0.0020 in Qinghai to 0.0065 in Zhejiang.

5. Can Abnormal Relative Attention Reflect Local Information Advantage?

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[8] Our main results remain unchanged when we use other periods, such as 4 weeks and 6 weeks.

[9] The listed companies are disproportionately distributed in these sectors. Almost 60% of the firms are categorized into Manufacturing.

Having defined *ARA*, we examine whether this measure can reflect the information advantages that local investors possess. When local investors obtain advantageous information about a local stock, they are likely to pay more attention on this specific stock. In our setting, the local investors may spend more time to read and respond to the message postings about this local stock, leading to an abnormal increase in the number of local postings and thus an increase in our *ARA* measure. It should be noted that it is possible for the local investors to post something that is totally unrelated to the advantageous information they have received, but the unconscious posting behavior could still represent the increasing attention from local investors and reveal the fact that they obtain more information than non-local investors.

Following the analysis above, it is reasonable to argue that *ARA* tends to exhibit an upward trend before information-induced attention-grabbing events, and a downward trend following the weakening of local information advantages. In this section, we confirm this proposition using upper price limit events and public news release events.

5.1. Upper Price Limit Events

To ensure financial stability and the healthy development of the stock market, the Chinese stock exchanges have imposed limits on daily equity price movement since December 16, 1996. The daily price limit means that the price of a stock can only move within a certain range of the previous day's closing price. The daily price limit in China (except the day of a stock's IPO) is ±10% for most stocks ("Normal" stocks) and ±5% for a few stocks labeled as "special treatment stocks" ("ST" stocks)[10]. When a stock hits its price limit, trading is still allowed to continue but order prices must be within the prescribed range.

[10] For a detailed description of "ST" stocks, see Section 6.3.3.

A stock may hit its upper price limit for a variety of reasons. First, economic policies play a vital role in security markets, and the release of policies that are beneficial to the stock market or to specific individual stocks may contribute to upper price limit events. For example, Searainbow Holding (000503), a company focusing on electronic commerce, hit its upper price limit on February 6, 2009 due to a policy that encouraged the development of the electronic information industry. Second, a company's operating performance is believed to affect the value of its stock, and good performance is one of the highest contributing factors to upper price limit events. In addition, a reorganization of material assets will cause a stock to hit its upper price limit because these asset transaction activities are often associated with better performance in the future. Moreover, economic globalization has made markets around the world more interactive. In recent years, the stock markets and futures markets in other countries have had a greater influence on Chinese A-share markets. For example, the successive rise in the price of aluminum futures on the London Mental Exchange (LME) led to the upper price limit event of China Aluminum (601600) on July 17, 2009.

Upper price limit events are appropriate events to fulfill our purpose for at least two reasons. The first is that many price limit events are induced by the arrival of new information. Phylaktis et al. (1999) confirm the information hypothesis, which assumes that the true equilibrium price and volatility are driven by the arrival of information. They argue that if the true equilibrium price falls beyond the price limit range, the price limit will be hit. Fama (1988) also attributes the delaying effect of price limits on the adjustment of stock prices to the information about changes in fundamental values. The second reason is that price limit events are attention-grabbing events. Using a sample from the Shanghai Stock Exchange in China, Seasholes and Wu (2007) show that stocks hitting their upper price limits have high returns, high volumes and much news coverage, which are the three characteristics of attention-grabbing stocks documented by Barber and Odean (2008).

Despite the above mentioned benefits, we also note that some price limit events may be associated with information that is equally available to and processed by local and non-local investors. To eliminate these noisy events, we use several criteria to filter the price limit events. First, the stocks should not have hit their upper price limits during the 60 days before the event. Given that price limit events can draw much attention from investors, we use this requirement to exclude the possibility that two consecutive limit events interact with each other. Second, the stocks should not have been suspended during the 60 days before the event. During a suspension, the information contributing to the upper price limit event probably becomes available to all investors and attracts much attention from both local and non-local investors. Third, we require that the cumulative change in the closing price in the 5 days before the event must be less than 20%. There are 1,144 price limit events that satisfy all of these criteria[11].

If local investors are better informed, meaning that they can obtain private information or process value-relevant public information before (Hirshleifer and Teoh (2003)) and better than (Van Nieuwerburgh and Veldkamp (2009)) distant investors, they will tend to have information advantages before upper price limit events and pay more attention to these stocks than non-local investors. Local investors' advantages are expected to generate an increase in *ARA*. Therefore, our first hypothesis is:

Hypothesis I: *Abnormal relative attention (ARA) increases before upper price limit events.*

[11] Price limit events are determined using the daily closing price. We obtain similar results when using the daily highest price.

To test this hypothesis, we examine the trends in *ARA* preceding price limit events. We display the cross-sectional mean and median of *ARA* around the week of the upper price limit (Week 0) in Table 5, Panel A and Figure 3. Consistent with our intuition, this graph displays an upward trend in the mean of *ARA* before price limit events. In fact, *ARA* rises by almost 50% in two weeks, from 0.0063 in Week -3 to 0.0093 in Week -1, indicating that local investors are paying an abnormal amount of attention to these stocks relative to non-local investors. The jump during the event week is in line with the evidence in Seasholes and Wu (2007). As upper limit events draw much attention from non-local investors, *ARA* is then expected to decrease dramatically. Similarly, we observe an increase in the median of *ARA* before price limit events. These results suggest that locals are better informed and pay more attention than distant investors to stocks that will hit their upper price limits in a few days.

[Insert Table 5 here]

[Insert Figure 3 here]

[Insert Figure 4 here]

We also examine the behavior of *ARA* around the lower price limit events. As shown in Figure 4, we neither find significant changes in *ARA* before the lower price limit events, nor a consistent pattern for the mean and the median. This asymmetric behavior of *ARA* prior to the upper and lower price limit events is not surprising because good news rather than bad news is more likely to induce an increse in *ARA*.

5.2. Public News Release Events

Next, we provide additional evidence by looking at it the other way round—by examining the decrease in *ARA*. If higher *ARA* indicates greater local information advantages, then one may expect *ARA* should decline when the local information advantages disappear.

Some studies have examined the effect of public news releases and documented that the release of news stories can weaken local information advantages. For example, Diamond and Verrecchia (1991) show that more informative disclosures reduce the information advantage of privately informed traders. Tetlock (2010) proposes and tests a model of individual stock prices in which a public news story eliminates the information asymmetry between informed and uninformed traders. Similarly, Bushee et al. (2010) find that greater press coverage reduces information asymmetry around earnings announcements. Following these studies, we suggest our second hypothesis:

Hypothesis II: *Abnormal relative attention (ARA) will decrease after the release of news.*

Our news dataset is the daily news feed from China InfoBank. This database provides up-to-date information on economic news from China. It provides full-text access to daily news from more than 1,000 leading newspapers and trading magazines in China. We collect news articles for each firm whose ticker symbol is mentioned in the title. We only retain news articles published in the *China Securities Journal*, *Shanghai Securities News*, *Securities Times* and *Securities Daily*. These are the most popular and influential press providing news in security markets in China. All A-share listed companies use at least one of the four papers as their information disclosure newspaper. To avoid the interaction between successive news releases, we require that the interval between consecutive news stories should be more than four weeks. We define a week as an news release event week for a stock if our dataset records news for the stock in that particular week. Panel B in Table 5 reports the cross-sectional means and medians of *ARA* around the news release event weeks (Week 0). They are also plotted in Figure 5. This graph shows a downward trend in both measures from Week -1 to Week 3. It is not surprising to find that *ARA* drops significantly from Week -1 and Week 0 because news coverage can grab much attention from uninformed non-local investors. Consistent with Hypothesis II, *ARA* continues to decline from Week 0 to Week 3, regardless of whether we measure it by sample mean or median. The mean of *ARA* experiences a decrease of 35%, from 0.0040 to 0.0026, during this period. The median drops from 0 in Week 0 to -0.0018 in Week 3. These results imply that local information advantages become weaker after news releases.

[Insert Figure 5 here]

In conclusion, the evidence from upper price limit events and news release events shows that local investors can gain access to advantageous information, and that such information advantages can be observed in investor attention.

6. Does Abnormal Attention Predict Returns?

As local investors are better informed, they may obtain private information or pay attention to value-related information before non-local investors. Thus, one may expect that local information advantages will lead to an increase in *ARA* and that the market will not fully react to the information at the time when it catches the attention of these informed investors due to the inattention of non-local investors. This implies that an unusual increase in relative attention may precede the adjustment in market price, leading us to expect that *ARA* can predict stock returns.

Although the advantageous information that local investors obtain may be either good or bad news, we argue that it is more likely that good news will catch their attention and cause an increase in *ARA*. We posit that this is the case for several reasons. First, the existence of short-sale constraints (Diether et al. (2002); Nagel (2005)) prevents individual investors from shorting stocks when they are pessimistic about them. As a result, individual investors are more likely to ignore bad news than good news. Second, Barber and Odean (2008) prove that individual investors are more likely to buy attention-grabbing stocks than to sell them. Their evidence suggests that individual investors tend to allocate more attention to stocks about which they have positive expectations. Following these studies, we expect that unusual increases in relative attention tend to be associated with subsequent increases rather than decreases in price[12]. Thus, we propose the following hypothesis:

Hypothesis III: *Stocks with higher abnormal relative attention (ARA) will have higher future returns*.

In this section, we first test this hypothesis using regression analysis. In addition, we examine the role of stock names. Finally, we provide several robustness checks.

6.1. Regression Analysis

We run a Fama-MacBeth (1973) cross-sectional regression to test Hypothesis III. We follow Daniel et al. (1997) to compute the characteristic-adjusted returns and use it as the dependent variable. Daniel et al. (1997) develop benchmarks for stock returns based on the size, book-to-market and momentum characteristics of these stocks. Each week, we match each stock with one of the 125 characteristic-based portfolios. The stock returns in excess of benchmarks, the evaluated portfolio returns, are used as our DGTW returns, which are more precise performance measure compared with the raw excess returns.

In addition to *ARA*, we incorporate a set of control variables into the regression. Their definitions are displayed in Table 1 and the summary statistics of these variables are reported in Table 6. To control for the well-documented size and book-to-market effects, we incorporate Size and B/M. Size is the logarithm of the market capitalization of tradable shares, which is reported in 100 millions. B/M is the ratio of book-value to market-value. Previous studies use

[12] Our findings that *ARA* increases significantly before the upper price limit events but not before the lower price limit events support this viewpoint.

trading volume (turnover) to measure investor attention[13]. Hou et al. (2009) find that price momentum profits are higher among high volume stocks. We include Turnover, the stock turnover rate, to control for the effects of trading volume on return.

[Insert Table 6 here]

We also control for some characteristics that might be related to local information advantages. Stocks that are followed by many analysts and that are covered by many news reports are likely to attract much attention from individual investors. Local investors may have fewer information advantages concerning these stocks. Thus, we include Analyst and Media in the regression. Analyst is defined as the number of analysts following a stock in each month. Media is the monthly number of news reports published in the *China Securities Journal*, *Shanghai Securities News*, *Securities Times* and *Securities Daily* in which the firm's ticker symbol is contained in the title.

The information environment of a firm may exert an effect on the local information advantage. A firm with better corporate transparency may offer less advantageous information for local investors. Share price informativeness, measured by firm-specific return variation, is widely used (Fernandes and Ferreira (2008)) to examine corporate transparency. We define the share price informativeness measure, Prinfo, as in Fernandes and Ferreira (2008). For firm *i* in year *t*, we run a time-series regression of its 52 firm-specific weekly excess returns on the corresponding market excess returns and obtain the goodness-of-fit measure($R^2_{i,t}$). Firm-specific excess returns are the returns of individual stocks that are in excess of the risk-free return, where the risk-free return is the 3-month deposit interest rate of the RMB. The market excess return is the weekly return of the CSI300 index minus the risk-free return. Following Fernandes and

[13] See, for example, Hou et al. (2009), Gervais et al. (2001) and Barber and Odean (2008).

Ferreira (2008), we measure the share price informativeness of firm *i* for year *t* by the logarithm of firm-specific return variation ($1-R^2_{i,t}$) relative to market-wide return variation($R^2_{i,t}$).

We incorporate three variables from Coval and Moskowitz (1999): current ratio (Currt), return on assets (ROA) and employment figures (Lnemp). Currt is defined as the ratio of current assets to current liabilities and captures the short-term financial health of a firm. ROA is computed as earnings before interest and tax divided by total assets and is used as a measure of accounting performance. Lnemp is the logarithm of the number of employees in the firm. We also add the growth rate of sales in the past 3 years (Growth) because companies with high growth rate may attract much attention from investors and the literature documents the difference in return between value stocks and growth stocks.

Also, Ivković and Weisbenner (2005) show that a household generates an excess return from its local holdings relative to its non-local holdings, and that the excess return to local investment is smaller among stocks in the SP500 index. They attribute this difference to the fact that those firms tend to experience less information asymmetry between local and non-local investors. Like firms in the SP500 index in the US, the firms in the CSI300 index are better known across China. Therefore, we include CSI300, a dummy variable, to identify whether a firm is in the CSI300 index or not.

Peng and Xiong (2006) propose a category-learning model, in which limited investor attention leads to category learning. They argue that because investors have limited attention, they tend to process more market and sector-wide information than firm-specific information. It is possible that firms in certain industries such as Finance and Insurance draw attention from investors across the country while companies in some industries attract more local attention. Thus, we introduce a dummy variable for industries to consider industry effects. Table 4 Panel C shows that *ARA* varies considerably across regions. To prevent our results from being dominated by a small group of stocks that are headquartered in a particular region, we use a dummy variable indicating the regions in which firms are located to control for region characteristics.

The regression results are reported in Table 7. The regression coefficients are first estimated across sections and then averaged over time. The standard errors are computed using the Newey-West (1987) formula with three lags. The returns are annualized and reported as percentages. In the first regression, we regress the DGTW return in week *t*+1 on the *ARA* and the control variables. All of the variables are cross-sectionally demeaned so that the regression intercepts are 0. We also standardize the independent variables. The result shows that *ARA* is significantly positive at the 1% level. This implies that stocks with higher *ARA* earn higher returns in following week. A one standard deviation increase in *ARA* leads to a 1.28% higher annualized return in the following week.

[Insert Table 7 here]

We also examine the predictive power of *ARA* for stock returns over longer periods. In the other four regressions, the dependent variables are the DGTW returns in week *t*+2, week *t*+3, week *t*+4 and the average DGTW return from week *t*+5 to *t*+12. However, we do not find a significant coefficient for *ARA* in these regressions, implying that its predictive power diminishes after one week.

For robustness, we also use a panel regression with a firm-level fixed effect to explore the relationship between *ARA* and stock returns. We compute the *t*-statistics using standard errors clustered by firm. The results of the panel regressions are similar to those of the cross-sectional regressions. To save space, we do not report these results here, they are available from the authors upon request.

To conclude, we show that *ARA* helps to forecast short-term returns and that stocks with higher *ARA* will generate significantly higher returns in the following week. The results validate our Hypothesis III.

6.2. The Role of Stock Name

Some stocks in China use ticker symbols which indicate their location. These are "local-name stocks". For example, Shanghai Airport (600009) indicates that this company is located in Shanghai. Contrary to the traditional notion that stock names are irrelevant to firm value, recent evidence reveals the role of stock names in attracting investors' attention and consequently influencing stock prices. Cooper et al. (2001) prove that a transfer to names related to the Internet in 1998 and 1999 positively influenced stock prices, while Cooper et al (2005) show that the stock market reacts positively to a deletion of the Internet-related name during the burst of the Internet bubble. Bae and Wang (2012) find that during the China stock market boom in 2007, stocks listed on US stock exchanges with the word "China" in their names received more attention from investors and that these stocks outperformed other stocks. Huang et al. (2013) document that local bias in investors' attention is stronger for local-name stocks. Thus, we conjecture that the extent to which *ARA* influences future returns may vary according to whether stock names include localities. If local-name stocks attract more attention from local investors, the information asymmetry between local and non-local investors on these stocks might be higher, which will lead to a stronger effect of our *ARA* measure. Our fourth hypothesis is as follows:

Hypothesis IV: *Abnormal relative attention (ARA) exerts a stronger effect on local-name stocks*.

In our sample, 449 stocks (20.80%) are local-name stocks. To test Hypothesis IV, we use a dummy variable that takes a value of 1 if the firm's ticker symbol indicates its local province. We add the interaction of *ARA* with this dummy variable into the regressions from the previous section, with the DGTW return in week *t*+1 as the dependent variable. Table 8 reports the results of the name effect test. The primary coefficient of interest is that on the interaction term, *ARA**Name. We find that the estimate for this coefficient is significantly positive, implying that the slope of *ARA* for local-name stocks is greater than that from our baseline model.

[Insert Table 8 here]

6.3. Robustness Tests

In this subsection, we conduct several tests to confirm the robustness of our principal results. We consider the effects of post share, trading time, special treatment firms and large outliers. We also check whether our results are robust to an alternative definition of returns. These results are reported in Table 9[14].

[Insert Table 9 here]

6.3.1. Post Share

Guba Eastmoney is the most popular stock message board in China and is widely used by users across China. Figure 6 illustrates the number of posts per capita in each region, calculated as the total number of posts from a region divided by the average population during the sample period in this region. It shows that the number of messages per capita is basically the same in most regions. However, the number of posts in regions such as Shanghai (123.74) and Tibet

[14] For simplicity, we only report the results for the DGTW return in week *t*+1. For all of the robustness tests, the results for the DGTW returns in other weeks are similar to our basic results. The omitted results are available from the authors upon request.

(3.35) deviates far from the regional median (15.55). To exclude the possibility that our results are driven by particular regions with extreme numbers of posts, we report the results for the subsample after removing the two regions with the highest share of posts (Shanghai and Beijing) and the two regions with the lowest share of posts (Tibet and Inner Mongolia). Regression (1) in Table 9 shows that this omission does not materially alter our conclusions.

[Insert Figure 6 here]

6.3.2. Trading Time

The content of posting activity during trading time may be somewhat different from that during closing time. With a sample of stocks listed on the NYSE and Nasdaq, Antweiler and Frank (2004) show that message posting tends to be concentrated during work hours, when the stock markets are open. The Shanghai Stock Exchange and Shenzhen Stock Exchange are open from 9:15 a.m. to 3:00 p.m. Beijing time, with a lunch break from 11:30 a.m. to 1:00 p.m. Consistent with their conclusion, we find that the percentage of messages posted during trading time is higher than that during non-trading time (Figure 7). It is possible that messages posted during trading hours contain more value-related information. To test the robustness of our results, we calculate *ARA* with stock messages posted during trading time and rerun the regressions. As shown in Table 9, Regression (2), the results are similar to those in Table 7.

[Insert Figure 7 here]

6.3.3. Special Treatment Stocks

To improve Chinese listed companies' corporate governance and protect investors' interests, in 1998 the CSRC introduced a policy that some Chinese listed firms should be classified as Special Treatment (ST) firms. Typically, a firm will be labeled as an "ST" firm if it had a negative audited net profit in the previous two consecutive fiscal years or it had a negative audited net worth in the previous fiscal year[15]. "ST" firms are usually financially distressed firms that are believed to be more risky. These firms are subject to more stringent monitoring by regulators and investors (Bai et al. (2002)). Therefore, investors may pay particular attention to these firms. In our sample, 308 (12.84%) stocks experienced special treatment during the sample period. To show that our primary results are not influenced by this particular group of stocks, we exclude these stocks in Table 9, Regression (3). We do not find any material difference between these results and those in Table 7.

6.3.4. Outliers

As another robustness test, we truncate the returns to their three-standard-deviation values and rerun the regressions in Table 7. As shown in Table 9, Regression (4), the results remain virtually unchanged, implying that our results are not driven by large outliers.

6.3.5. Alternative Returns

We also rerun the regressions using raw excess returns as the dependent variable. The raw excess returns are defined as the difference between stock returns and the risk-free return, where the risk-free return is the 3-month deposit interest rate of the RMB. Regression (5) in Table 9 suggests that our conclusions are robust to this alternative return measure.

7. Is Abnormal Attention Related to Risk?

To examine the effect of abnormal attention after controlling for well-documented risk factors, we construct long-short portfolios sorted by *ARA*. Each week, we first divide the stocks into two portfolios using the median of *ARA*: Portfolio High consists of stocks with *ARA* above

[15] Besides these main reasons, a firm may be subjet to special treatment for serveral other abnormalities. See the *Rules Governing the Listing of Stocks on Shanghai Stock Exchange* and the *Rules Governing the Listing of Stocks on Shenzhen Stock Exchange* for details of the regulations.

the breakpoints and Portfolio Low consists of stocks with *ARA* below the breakpoints. We then form a zero-investment portfolio (Portfolio High-Low) that goes long on Portfolio High and short on Portfolio Low. The equally weighted returns in the week following its formation are used to measure the portfolio's performance[16].

We repeat the process described above for each week and obtain a time series of returns for the three types of portfolios. The time-series returns are then regressed on the well-documented risk factors to yield the risk-adjusted alphas. Panel A in Table 10 reports the portfolio returns in excess of the risk-free return, together with the alphas from the CAPM model, the Fama-French (1993) three-factor model, the Carhart's (1997) four-factor model and the model with Carhart four factors as well as Pástor and Stambaugh (2003)'s liquidity factor. The table shows that Portfolio High-Low earns significantly positive risk-adjusted alphas in all models, implying that stocks with a high *ARA* outperform other stocks. This confirms our findings from the previous regression analysis that greater *ARA* is associated with higher returns in the following week.

For robustness, we also examine portfolios with the quintiles of *ARA* as the breakpoints: Portfolio High are stocks with *ARA* in the highest quintile and Portfolio Low are stocks with *ARA* in the lowest quintile. Portfolio High-Low are still defined as longing Portfolio High and shorting Portfolio Low. As shown in Table 10 Panel B, the risk-adjusted alphas from these long-short portfolios provide evidence consistent with the previous results.

Table 10 demonstrates that the superior performance of stocks with high *ARA* persists after controlling for market, size, book-to-market and momentum factors. To further understand the sources of the *ARA* effect, we examine the performance of double-sorted, long-short portfolios.

---

[16] We do not find significant differences in the value-weighted returns of the portfolios, which is consistent with our finding that *ARA* plays a more important role in smaller firms which tend to have worse information environment.

Each week, we first sort stocks into trisections by firm characteristics and then form long-short portfolios based on *ARA*, as before, within each subsample. In this analysis, we control for the relevant characteristics by sorting and the risk factors by regression. This methodology allows us to identify the subsets of stocks in which the *ARA* effect is the strongest.

[Insert Table 10 here]

We argue above that *ARA* represents local investors' information advantages to some extent. This leads us to expect that the effectiveness of *ARA* varies across firms with different information environments. Specifically, the role of *ARA* might be more important for companies with worse information environments. To confirm this idea, we use two firm characteristics regarding information diffusion in the double-sorted analysis, firm size (Size) and analyst coverage (Analyst). According to Hong et al. (2000), information about smaller firms may spread slower than information about larger firms. Their argument is that investors facing fixed information acquisition costs tend to devote more effort to learning about stocks in which they can take large positions. Drawing from their conclusion, we speculate that *ARA* exerts a larger effect on smaller firms. Analyst coverage can not only attract attention from investors but also improve a firm's information environment. For example, Piotroski and Roulstone (2004) find that analysts' forecasts promote the incorporation of future earning news into stock price. Thus, the relationship between *ARA* and stock returns may be stronger for firms with fewer analysts following them.

Table 11 reports the results for the double-sorted analysis. Panel A reports the risk-adjusted alphas for long-short portfolios constructed by the median of *ARA*. Consistent with our expectation, we find that *ARA* exerts a stronger effect on firms with worse information environments, that is, smaller firms and firms with less analyst coverage. Moreover, we yield similar conclusions from the portfolios constructed by the quintiles of *ARA*.

[Insert Table 11 here]

To conclude, our findings in this section suggest that the effect of *ARA* is preserved after controlling for well-known risk factors. We also find that the effect is much stronger for firms with worse information environments, which confirms our previous argument.

8. Conclusion

This paper links local information advantages with investor attention and documents the asset-pricing implications of attention measures. Using postings on China's stock message boards as a proxy for investor attention, we construct *ARA* to measure the unusual patterns of attention paid to stocks by local relative to non-local investors. Using upper price limit events and public news release events, we first show that local information advantages can be reflected in investor attention.

We then document that the *ARA* predicts short-term returns: a one standard deviation increase in *ARA* indicates a 1.28% higher return in the following week. We find that the predictive power is stronger for local-name stocks. This result is not affected by post shares, trading times, special treatment stocks, large outliers or the definition of return. Furthermore, we show that a trading strategy based on the *ARA* yields significant alphas and that the effect of *ARA* is much stronger for companies with worse information environments.

The results have several implications. For example, we show that in addition to aggregate attention, the geographical dimension of investor attention is significantly associated with stock returns. The evidence indicates that investor attention reflects information acquisition. Our results also suggest that all investors are able to generate significant excess returns by following these abnormal variations in attention, which are measured by the publicly accessible stock message postings. One shortcoming of this study is that we can only distinguish local and non-local investors by provincial boundary. A more precise measurement could be based on the distance between cities.

We hope that this paper will inspire more innovative investigations. First, researchers could explore whether *ARA* is related to trading volume, volatility and investor sentiment, and so on. Second, it would also be interesting to investigate how investor attention affects market-wide and firm-specific information environments using our revealed attention measure. Finally, as stock message posting data provide information about clicks and replies, we expect such data to provide a setting in which to examine the relations between investor interaction, investor attention and information diffusion.

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点击 Click	回复 Reply	标题 Title	作者 Author	发表日期 Post Date	最后更新 Latest Update Date
308	0	受益观博人潮“酒金”	220.160.250.*	06-07	06-07 17:07
1669	25	机场真是绝了，每次有利好都下跌	60.173.6.*	06-07	06-07 14:59
529	1	应该要涨了	121.228.146.*	06-07	06-07 14:51
298	0	看看其他上海本地股就知道上海机场有多烂了	123.122.98.*	06-07	06-07 14:45
203	0	股指期货时代行情的特点	121.10.120.*	06-07	06-07 14:33
668	3	继续吧，我快要忍不住了	59.60.200.*	06-07	06-07 14:23
491	2	卖吧不是罪，吸吧不会罪！	半仓	06-04	06-07 13:44
409	2	有中邮这支全市最熊的基金在操盘，上海机场好不	118.212.158.*	06-07	06-07 12:42
417	1	呵呵，高抛的，破12的日子不远了，又可以补仓了	118.212.158.*	06-07	06-07 11:28
355	1	东航两个月后必超机场，大家快出手	116.253.4.*	06-07	06-07 10:51
288	0	空方太抠门，用1手打压	99.231.69.*	06-07	06-07 10:31
660	3	上海机场第一个跌停板将在今天华美登场	58.19.155.*	06-07	06-07 10:21
1130	5	交通运输：5月增长强劲 旺季即将来临	59.55.158.*	06-05	06-07 09:50

Figure 1 China’s Internet Stock Message Board Guba Eastmoney

This figure is a screenshot from Guba Eastmoney, the most popular Internet stock message board in China. The site provides a unique message board for every stock. It identifies registered posters by their registered account ID and unregistered users by their IP address.

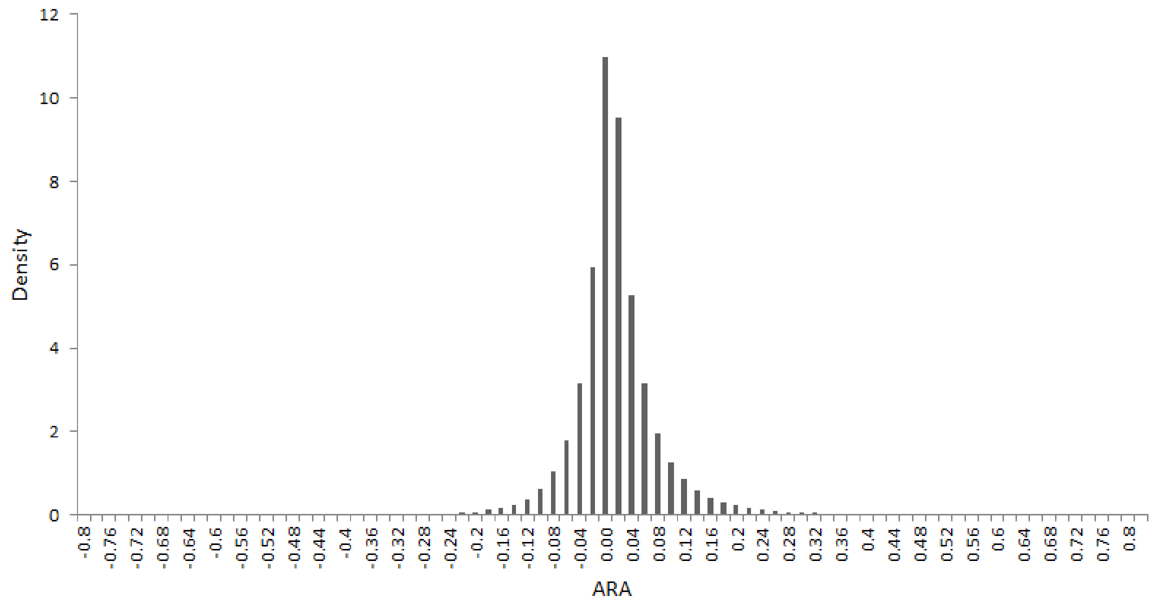

Figure 2 Density Distribution of *ARA*

This graph illustrates the density distribution of *ARA*. The sample consists of weekly data on 2,399 stocks from June 2007 to May 2013. This figure is plotted using 489,931 observations with a valid *ARA*.

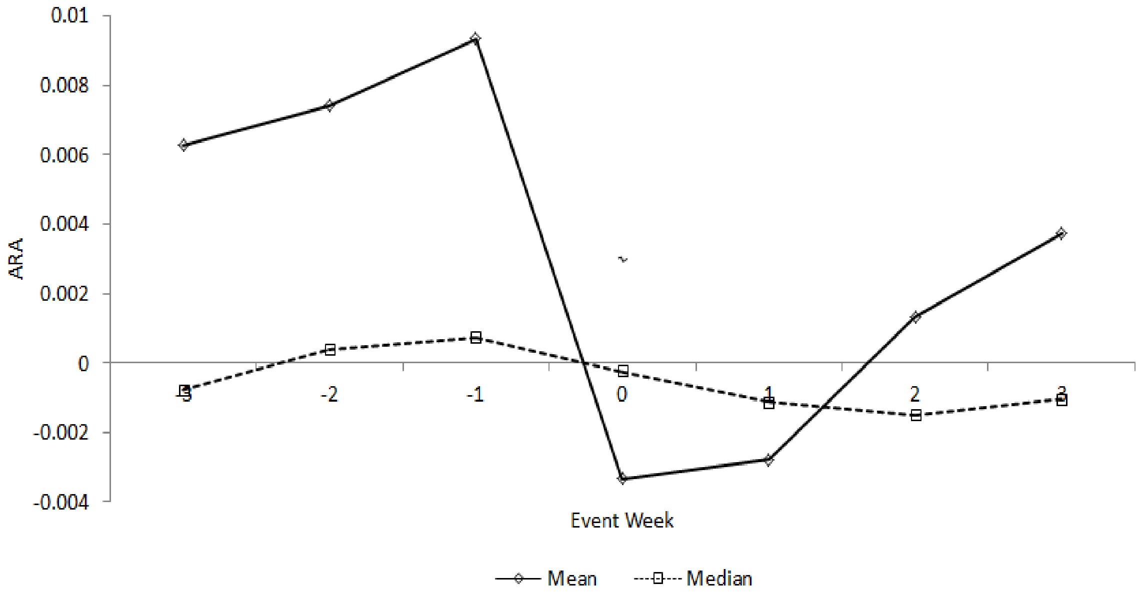

Figure 3 *ARA* around the Upper Price Limit Events

This graph plots the cross-sectional mean and median of *ARA* around the week of the upper price limit events. Week 0 is the week of the price limit events. There are 1,144 events in the sample.

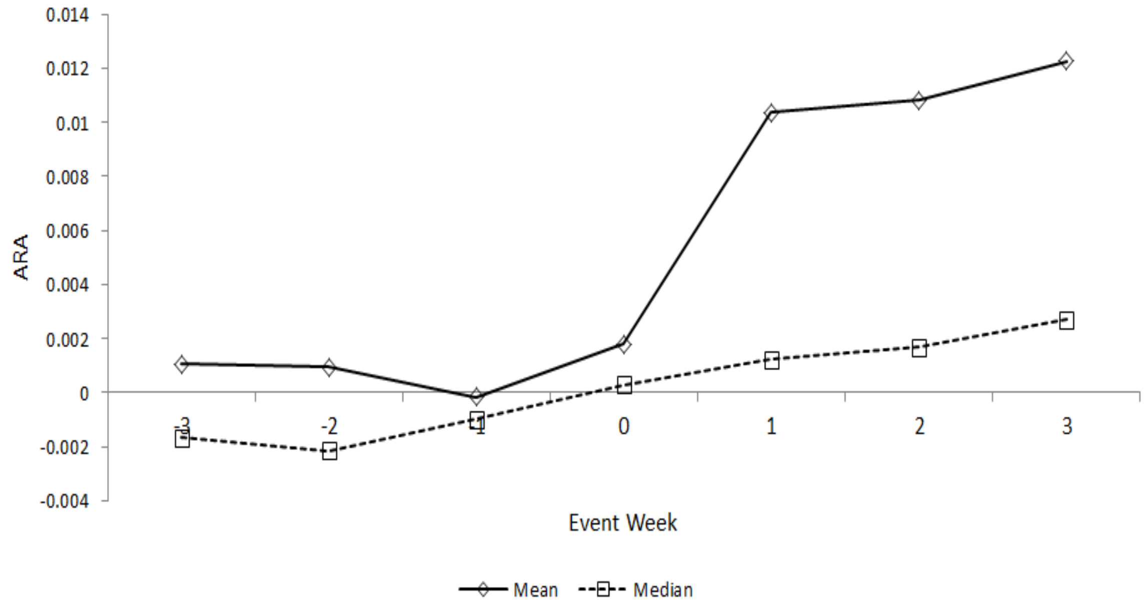

Figure 4 *ARA* around the Lower Price Limit Events

This graph plots the cross-sectional mean and median of *ARA* around the week of the lower price limit events. Week 0 is the week of the price limit events. There are 1,583 events in the sample.

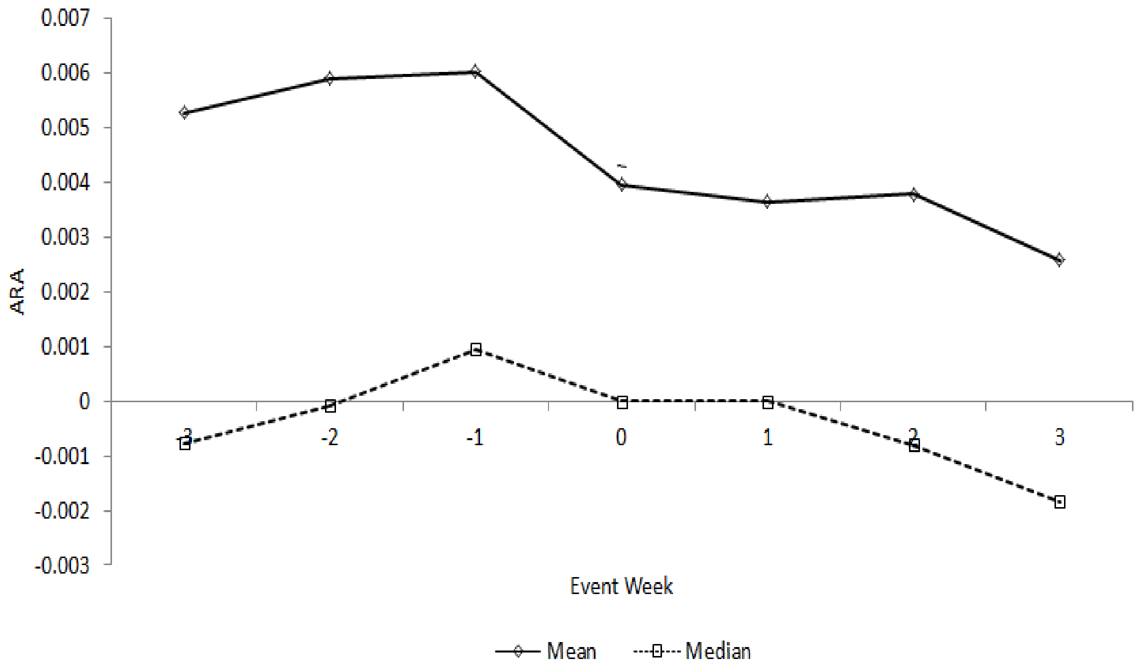

Figure 5 *ARA* around the News Release Events

This graph plots the cross-sectional mean and median of *ARA* around the week of public news releases (Week 0). Public news releases are defined in the text. There are 5,236 stock-week pairs of news releases in the sample.

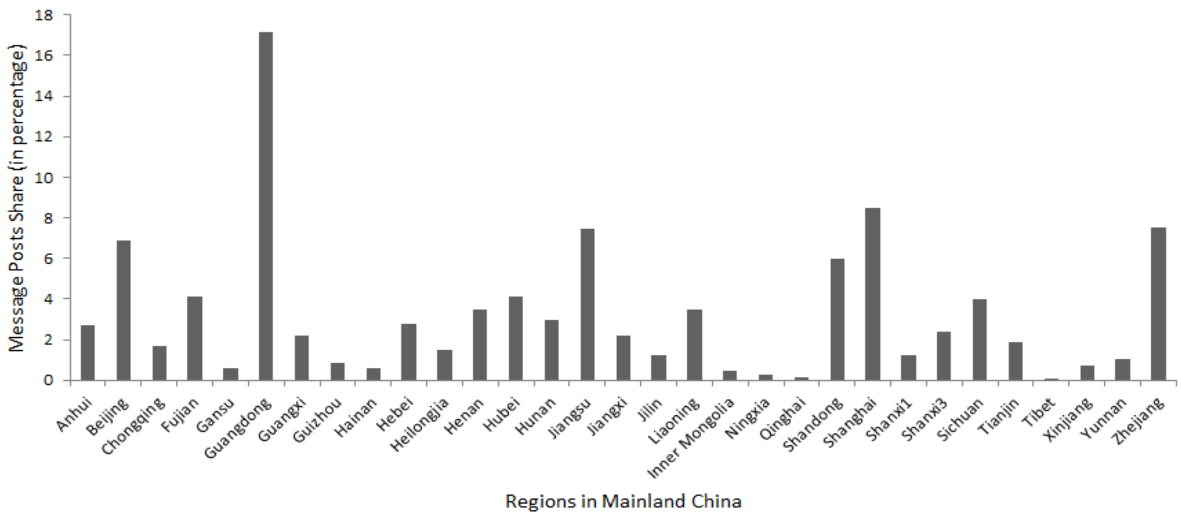

Figure 6 Regional Distribution of Message Posts

This graph plots the regional distribution of message posts. It shows the number of posts per capita in each region (province, autonomous region or municipality) in mainland China.

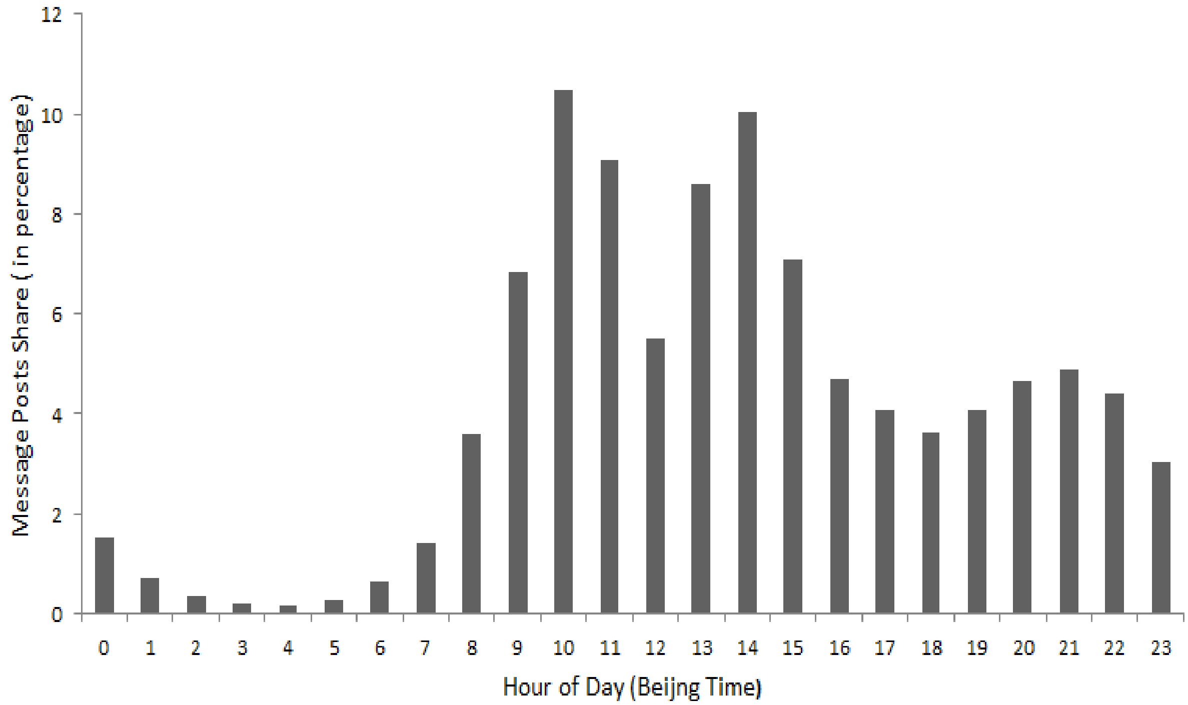

Figure 7 Hourly Distribution of Message Posts

This graph illustrates the hourly distribution of message posts. It shows the percentage of messages posted during each hour of the day.

Table 1 Variable Definitions

This table gives the definitions of the variables used in this paper.

Variable	Definition
Attention Variables	
RA	Relative attention
ARA	Abnormal relative attention
Control Variables	
Size	Logarithm of the market capitalization of tradable shares (in 100 million)
B/M	Ratio of book-value to market-value
Turnover	Stock turnover rate
Analyst	Number of analysts following a stock in each month
Media	Number of news reports with a title containing a firm's ticker symbol in each month
Prinfo	Share price informativeness
Currt	Ratio of current assets to current liabilities
ROA	Ratio of earnings before interest and tax to total assets
Lnemp	Logarithm of the number of employees in the firm
Growth	Percentage growth rate of sales in the past 3 years
CSI300	Dummy variable that takes the value of 1 if the firm is in the CSI300 index
Name	Dummy variable that takes the value of 1 if the firm's ticker symbol indicates its local province
Traditional Risk Factors	
Alpha	The Jensen's alphas from the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, or the model with Carhart four factors as well as Pástor and Stambaugh (2003)'s liquidity factor
MRF	Market return minus risk-free return
SMB	Size factor from the Fama-French (1993) three-factor model
HML	Book-to-market ratio factor from the Fama-French (1993) three-factor model
MOM	Momentum factor from the Carhart (1997) four-factor model
PSL	Liquidity factor from Pástor and Stambaugh (2003)

Table 2 Unbalanced Structure of the Sample

This table displays the unbalanced structure of our sample. We exclude stocks that were suspended consecutively for more than 1 year during this period. We also require that Wind data be available for at least 6 months before the inclusion of the firm in the sample. The final data set covers 2,399 stocks in the Chinese A-share markets. In this table, we report the number of firms in each year, the number of firm-week observations by week, the percentage of observations and the cumulative percentage of observations.

Year	Number of Stocks	Number of Observations	Percentage	Cumulative Percentage
2007	1,376	16,490	3.37%	3.37%
2008	1,510	56,488	11.53%	14.90%
2009	1,529	76,745	15.66%	30.56%
2010	1,805	82,614	16.86%	47.42%
2011	2,137	98,374	20.08%	67.50%
2012	2,362	109,982	22.45%	89.95%
2013	2,399	49,238	10.05%	100.00%
Total		489,931	100.00%	

Table 3 Descriptive Statistics for Stock Message Postings

This table provides the descriptive statistics for the stock message postings. It reports the number of firms, cross-sectional mean, standard deviation, minimum and maximum of the number of national postings and local postings for each firm. National postings for a firm are postings from all regions in mainland China and local postings are those from the company's local provinces. The sample period is from June 2007 to May 2013.

	Number of firms	Mean	Std. Dev.	Min	Max
National Postings	2,399	126,026.33	153,335.84	1,217	1,784,280
Local Postings	2,399	12,271.07	22,524.54	13	339,983

Table 4 Descriptive Statistics for the Attention Variables

This table provides the descriptive statistics for the attention variables. *RA* is relative attention, defined as in Equation (1). *ARA* is abnormal relative attention, which is *RA* in the current week minus the median of *RA* in the previous five weeks. Panel A reports the statistics for the entire sample. The sample includes 2,399 stocks listed on both the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The sample consists of weekly data on these stocks from June 2007 to May 2013. The statistics are calculated from observations with a valid *ARA*. Panel B displays the descriptive statistics for each industry. The industries are defined using sectors in the *Guidance for Industry Classification of Listed Companies* released by the CSRC. Panel C shows the statistics for every region in mainland China.

Panel A: All Sample

	Mean	Std. Dev.	Min	Median	Max	Observations
RA	0.1022	0.0952	0.0000	0.0735	0.6931	489,931
ARA	0.0052	0.0681	-0.6857	-0.0002	0.6790	489,931

Panel B: Subsamples Classified by Industry

	Number of firms	Mean of *ARA*	Std. Dev of *ARA*	Min of *ARA*	Max of *ARA*
Agriculture, Forestry, Livestock Farming, Fishery	45	0.0055	0.0604	-0.4243	0.6360
Communication and Cultural Industry	36	0.0052	0.0706	-0.5815	0.6381
Comprehensive	52	0.0045	0.0706	-0.5845	0.6129
Construction	51	0.0052	0.0704	-0.5927	0.6444
Finance and Insurance	41	0.0034	0.0499	-0.4556	0.6286
IT	195	0.0056	0.0719	-0.5850	0.6523
Manufacturing	1,442	0.0054	0.0671	-0.6857	0.6790
Mining	58	0.0038	0.0524	-0.6061	0.6419
Real Estate	124	0.0052	0.0706	-0.6432	0.6360
Social Services	76	0.0052	0.0789	-0.6585	0.6479
Transportation	75	0.0048	0.0698	-0.6235	0.6232
Utilities	72	0.0050	0.0684	-0.6721	0.5996
Wholesale and Retail Trade	132	0.0051	0.0738	-0.6843	0.6455

Panel C: Subsamples Classified by Region

Region	Number of firms	Mean of *ARA*	Std. Dev of *ARA*	Max of *ARA*	Min of *ARA*
Anhui	77	0.0059	0.0569	0.6469	-0.6721
Beijing	209	0.0053	0.0603	0.6539	-0.6592
Chongqing	34	0.0051	0.0604	0.6286	-0.4556
Fujian	85	0.0056	0.0636	0.6678	-0.6190
Gansu	24	0.0036	0.0306	0.3756	-0.1589
Guangdong	358	0.0049	0.0888	0.6154	-0.6702
Guangxi	29	0.0049	0.0606	0.6242	-0.3866

(Continued)

Table 4——Continued

Region	Number of firms	Mean of *ARA*	Std. Dev of *ARA*	Max of *ARA*	Min of *ARA*
Guizhou	19	0.0039	0.0362	0.4784	-0.2643
Hainan	24	0.0046	0.0393	0.6790	-0.2929
Hebei	47	0.0056	0.0593	0.6493	-0.6843
Heilongjiang	29	0.0044	0.0392	0.4898	-0.3915
Henan	63	0.0053	0.0690	0.6381	-0.6857
Hubei	81	0.0050	0.0638	0.5696	-0.6539
Hunan	70	0.0056	0.0615	0.6604	-0.6665
Jiangsu	225	0.0058	0.0717	0.6615	-0.6381
Jiangxi	32	0.0061	0.0643	0.6319	-0.5270
Jilin	38	0.0050	0.0569	0.6495	-0.5845
Liaoning	65	0.0052	0.0612	0.5934	-0.5447
Inner Mongolia	23	0.0027	0.0260	0.4475	-0.2724
Ningxia	11	0.0037	0.0329	0.3053	-0.2127
Qinghai	10	0.0020	0.0289	0.4353	-0.2866
Shandong	149	0.0054	0.0687	0.6379	-0.6169
Shanghai	196	0.0052	0.0768	0.6534	-0.5850
Shanxi1	32	0.0040	0.0528	0.6419	-0.6061
Shanxi3	37	0.0042	0.0580	0.6391	-0.5508
Sichuan	87	0.0046	0.0647	0.6592	-0.5927
Tianjin	38	0.0049	0.0540	0.6232	-0.5993
Tibet	10	0.0032	0.0224	0.3052	-0.0485
Xinjiang	38	0.0044	0.0432	0.5671	-0.3975
Yunnan	27	0.0041	0.0455	0.6022	-0.6585
Zhejiang	232	0.0065	0.0713	0.6678	-0.6123

Table 5 *ARA* around Event Weeks

This table reports the cross-sectional means and medians of *ARA* around upper price limit events and news release events. Panel A is the result for 1,144 upper price limit events. Panel B is the result for 1, 583 lower price limit events. Panel C is the result for 5,236 stock-week pairs of news releases. The symbols ***, ** and * denote that the cross-sectional mean is significant at the 1%, 5% and 10% significance level, respectively.

	Panel A Upper Price Limit Events			Panel B Lower Price Limit Events			Panel C News Release Events		
	Mean	t-stat	Median	Mean	t-stat	Median	Mean	t-stat	Median
-3	0.0063**	2.19	-0.0008	0.0010	0.47	-0.0017	0.0053***	5.36	-0.0008
-2	0.0074**	2.55	0.0004	0.0009	0.42	-0.0022	0.0059***	5.72	-0.0001
-1	0.0093***	2.90	0.0008	-0.0002	-0.07	-0.0010	0.0060***	6.12	0.0010
0	-0.0033	-1.41	-0.0002	0.0018	0.88	0.0003	0.0040***	3.86	0.0000
1	-0.0028	-1.08	-0.0011	0.0104***	4.84	0.0012	0.0036***	3.85	0.0000
2	0.0013	0.50	-0.0015	0.0108***	5.27	0.0017	0.0038***	3.92	-0.0008
3	0.0038	1.49	-0.0010	0.0122***	5.38	0.0027	0.0026***	2.66	-0.0018

Table 6 Summary Statistics for Control Variables

This table provides the summary statistics for the control variables. Size is the logarithm of the market capitalization of tradable shares (in 100 million). B/M is the ratio of book-value to market-value. Turnover is the stock turnover rate. Analyst is the number of analysts following a stock in each month. Media is the monthly number of news reports with a title containing the firm's ticker symbol. Prinfo is the share price informativeness measure in Fernandes and Ferreira (2008). Currt is the ratio of current assets to current liabilities. ROA is the ratio of earnings before interest and tax to total assets. Lnemp is the logarithm of the number of employees in the firm. Growth is the percentage growth rate of sales in the previous 3 years. The sample includes 2,399 stocks listed on both the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The sample consists of weekly data on these stocks from June 2007 to May 2013. The statistics are calculated from observations with a valid *ARA*.

	Mean	Std. Dev.	Min	Max	Observations
Size	3.3163	1.1578	-0.4879	9.9162	468,790
B/M	0.3297	0.2411	-9.2937	3.7120	468,714
Turnover	12.3930	13.3154	0.0041	237.4057	460,812
Analyst	1.6385	3.2542	0.0000	35.0000	488,937
Media	0.1000	0.5603	0.0000	32.0000	489,931
Prinfo	0.7732	1.1348	-2.1000	13.3551	484,854
Currt	2.6127	6.3717	0.0007	471.9664	480,835
ROA	3.7283	13.7097	-903.5402	769.7572	480,951
Lnemp	7.5299	1.5028	1.0986	13.2228	488,734
Growth	73.8744	120.9710	-100.0000	997.8117	435,829

Table 7 *ARA* and Stock Returns

This table reports the results of the Fama-MacBeth (1973) regression. The independent variables are defined in Table 1 and are calculated in week *t*. We use dummy variables to control for the industry effects and regional characteristics. For the sake of simplicity, we omit the coefficients of these dummy variables. The dependent variable is the characteristic-adjusted return as in Daniel et al. (1997) (DGTW returns). In the first four regressions, the dependent variables are the DGTW returns calculated in week *t*+1, *t*+2, *t*+3 and *t*+4. The fifth dependent variable is the mean DGTW return from week *t*+5 to *t*+12. The returns are annualized and reported as percentages. All of the variables are cross-sectionally demeaned and the independent variables are also standardized. The *t*-statistics, which are in parentheses, are adjusted for serial correlation and heteroskedasticity. The symbols ***, ** and * denote that the individual coefficient is significant at the 1%, 5% and 10% significance level, respectively.

Week	t+1	t+2	t+3	t+4	t+5 — t+12
ARA	1.284***	-0.308	-0.245	-0.025	-0.162
	(2.65)	(-0.51)	(-0.52)	(-0.05)	(-0.75)
Size	-14.809***	-8.849***	-6.740***	-6.304***	-4.111***
	(-8.43)	(-5.57)	(-4.47)	(-3.91)	(-3.99)
B/M	3.193***	1.961*	1.138	0.567	1.709**
	(3.15)	(1.85)	(1.08)	(0.51)	(2.18)
Turnover	-21.184***	-12.254***	-10.095***	-9.877***	-5.775***
	(-10.68)	(-7.19)	(-6.90)	(-6.77)	(-6.69)
Analyst	5.892***	4.149***	2.227*	1.452	0.468
	(6.01)	(4.18)	(1.97)	(1.50)	(0.57)
Media	2.730	1.813	2.388	-0.726	-0.962
	(1.10)	(0.79)	(0.85)	(-0.49)	(-0.88)
Prinfo	8.913***	10.228***	10.291***	9.487***	11.901***
	(3.52)	(4.06)	(3.90)	(3.76)	(6.74)
Currt	-0.412	-0.181	-0.423	-1.679*	-0.147
	(-0.38)	(-0.17)	(-0.44)	(-1.83)	(-0.18)
ROA	14.426***	16.438***	18.255***	16.714***	21.110***
	(3.78)	(4.00)	(3.97)	(3.39)	(4.37)
Growth	2.087***	1.817***	1.745***	1.170*	1.480***
	(3.08)	(2.70)	(2.72)	(1.86)	(3.56)
Lnemp	2.397***	1.612*	2.153***	2.382***	2.115***
	(2.78)	(1.94)	(2.79)	(2.90)	(3.95)
CSI300	1.961**	1.579**	1.499**	1.674**	0.959
	(2.48)	(2.13)	(2.03)	(2.05)	(1.47)
$AdjR^2$	8.00%	7.60%	7.50%	7.30%	11.00%

Table 8 Test of the Name Effect

This table displays the test results for the name effect. We add the interaction of *ARA* with Name into the cross-sectional regression, where Name is a dummy variable that takes the value of 1 if the firm's ticker symbol indicates its local province. The other independent variables are as defined in Table 1 and are calculated in week *t*. The dependent variable is the DGTW return calculated in week *t*+1. We omit the coefficients of the industry and region dummies for simplicity. All of the variables are cross-sectionally demeaned and the independent variables are also standardized. The *t*-statistics in brackets are adjusted for serial correlations and heteroskedasticity. The symbols ***, ** and * denote that the individual coefficient is significant at the 1%, 5% and 10% significance level, respectively.

ARA	0.915**
	(2.45)
Name	-3.610**
	(-2.36)
*ARA**Name	0.729***
	(3.67)
Size	-14.817***
	(-7.03)
B/M	3.338***
	(4.68)
Turnover	-21.190***
	(-14.58)
Analyst	5.795***
	(11.71)
Media	4.069***
	(2.69)
Prinfo	8.909***
	(8.77)
Currt	-0.391
	(-0.41)
ROA	14.658***
	(3.08)
Growth	1.981***
	(3.19)
Lnemp	2.422***
	(2.73)
CSI300	2.025***
	(4.65)
$AdjR^2$	8.00%

Table 9 *ARA* and Stock Returns: Robustness

This table presents the robustness test results. Regression (1) excludes regions with an extreme share of posts. Regression (2) uses a subsample during trading time. Regression (3) excludes special treatment stocks. In Regression (4), all of the stock-return observations are truncated to their three-standard-deviation values. The first three regressions use the DGTW return in week *t*+1 as the dependent variable. Regression (5) uses the results with the raw excess return in week *t*+1 as the dependent variable. The independent variables are as defined in Table 1 and are calculated in week *t*. All of the variables are cross-sectionally demeaned and the independent variables are also standardized. We omit the coefficients of the industry and region dummies for simplicity. The numbers in brackets are the *t*-statistics, which are adjusted for serial correlations and heteroskedasticity. The symbols ***, ** and * denote that the individual coefficient is significant at the 1%, 5% and 10% significance level, respectively.

Regression	(1)	(2)	(3)	(4)	(5)
Tests	Post Share	Trading Time	ST Stocks	Outliers	Raw Excess Return
ARA	0.982**	0.807***	1.071**	1.198**	1.037**
	(2.53)	(3.59)	(2.07)	(2.43)	(2.27)
Size	-13.087***	-15.883***	-15.548***	-12.833***	-23.175***
	(-7.59)	(-6.51)	(-9.29)	(-7.85)	(-10.78)
B/M	2.690***	1.679***	3.091***	2.725***	8.222***
	(4.42)	(2.96)	(3.06)	(2.85)	(5.32)
Turnover	-21.085***	-21.240***	-20.416***	-22.304***	-21.714***
	(-14.79)	(-7.27)	(-10.99)	(-11.60)	(-10.35)
Analyst	6.142***	6.290***	4.876***	6.094***	7.829***
	(8.59)	(6.23)	(4.47)	(6.69)	(6.40)
Media	0.541	0.367	3.823	2.748	-4.264
	(1.29)	(0.95)	(1.32)	(1.05)	(-0.61)
Prinfo	8.134***	9.680***	9.031***	5.697**	9.819***
	(6.04)	(7.44)	(3.50)	(2.40)	(3.20)
Currt	-0.043	0.087	-1.022	-0.240	0.056
	(-0.04)	(0.07)	(-0.94)	(-0.25)	(0.07)
ROA	15.766***	11.923***	8.261***	14.775***	8.827***
	(2.83)	(5.02)	(6.33)	(4.25)	(3.61)
Growth	1.734**	1.815***	2.010***	1.897***	2.384***
	(2.54)	(5.60)	(2.77)	(3.02)	(3.20)
Lnemp	2.821***	2.518***	0.993	2.357***	2.353***
	(3.06)	(5.41)	(1.13)	(2.90)	(2.85)
CSI300	1.325**	2.283***	2.436***	1.551**	4.178***
	(2.01)	(3.07)	(2.90)	(1.97)	(4.55)
No. of Obs.	276,873	340,416	284,987	312,871	340,416
No. of Firms	1,961	2,399	2,091	2,399	2,399
$AdjR^2$	7.50%	8.70%	8.70%	7.90%	12.20%

Table 10 Portfolio Performance: Single-Sorted

This table shows the risk-adjusted returns for equally-weighted portfolios sorted by *ARA*. Each week, we construct a high *ARA* portfolio (Portfolio High), a low *ARA* portfolio (Portfolio Low) and a long-short portfolio (Portfolio High-Low). In Panel A, a stock is divided into Portfolio High (Portfolio Low) if its *ARA* is above (below) the median of *ARA*. In Panel B, a stock belongs to Portfolio High (Portfolio Low) if it is in the highest (lowest) quintile of the sample sorted by *ARA*. Portfolio High-Low is a zero-investment portfolio that goes long on Portfolio High and short on Portfolio Low. We use the following-week portfolio returns to measure the performance. The risk-adjusted returns are portfolio returns in excess of the risk-free return, alphas from the CAPM model, alphas from the Fama-French model, alphas from the Carhart model and alphas from the model with Carhart four factors as well as Pástor-Stambaugh liquidity factor. The returns are annualized and reported as percentage. The *t*-statistics are reported in brackets. The symbols ***, ** and * denote that the portfolio return is significant at the 1%, 5% and 10% significance level, respectively.

Panel A: Portfolios Constructed by Medians

Portfolio	Ret-Rf	CAPM Alpha	Fama-French Alpha	Carhart Alpha	Pástor-Stambaugh Alpha
High	-5.05	2.10	-11.67***	-11.76***	-13.01***
	(-0.33)	(0.31)	(-3.26)	(-3.29)	(-3.73)
Low	-6.98	0.25	-14.11***	-14.12***	-15.42***
	(-0.45)	(0.04)	(-4.04)	(-4.01)	(-4.42)
High-Low	1.93*	1.85*	2.44**	2.36**	2.41**
	(1.71)	(1.68)	(2.23)	(2.13)	(2.16)

Panel B: Portfolios Constructed by Quintiles

Portfolio	Ret-Rf	CAPM Alpha	Fama-French Alpha	Carhart Alpha	Pástor-Stambaugh Alpha
High	0.41	7.35	-7.13*	-7.59**	-8.94**
	(0.03)	(1.04)	(-1.93)	(-2.08)	(-2.47)
Low	-4.01	3.05	-11.95***	-11.98***	-13.58***
	(-0.26)	(0.44)	(-3.33)	(-3.30)	(-3.78)
High-Low	4.43***	4.30***	4.81***	4.39***	4.64***
	(2.67)	(2.61)	(2.91)	(2.82)	(3.16)

Table 11 Portfolio Performance: Double-Sorted

This table reports the results for the double-sorted analysis. Each week, we first sort stocks into trisections by firm characteristics and then form long-short portfolios based on *ARA* as before within each subsample. We use two characteristics related to information environments in this analysis, that is, firm size (Size) and analyst coverage (Analyst). Panel A and Panel B consider portfolios constructed by medians and quintiles, respectively. We report the risk-adjusted alphas for long-short portfolios. The returns are annualized and reported as percentages. The *t*-statistics are reported in the brackets. The symbols ***, ** and * denote that the portfolio return is significant at the 1%, 5% and 10% significance level, respectively.

Panel A: Portfolios Constructed by Medians

Group	Excess Returns	CAPM	FF Three-Factor	Carhart Four-Factor	Pástor-Stambaugh Alpha
			By Firm Size		
Small	7.47***	7.32***	7.95***	7.17***	6.29***
	(4.03)	(3.98)	(4.18)	(3.85)	(3.88)
Medium	1.65	1.46	2.25	2.11	2.81
	(0.82)	(0.73)	(1.11)	(0.99)	(1.28)
Big	-1.70	-1.60	-1.40	-1.11	-1.03
	(-1.02)	(-0.97)	(-0.83)	(-0.69)	(-0.64)
			By Analyst Coverage		
Low	3.97**	3.77*	4.77***	4.21**	4.26**
	(2.12)	(2.19)	(2.66)	(2.26)	(2.23)
Medium	4.12	4.11	4.71*	5.49*	5.22*
	(1.59)	(1.59)	(1.74)	(1.95)	(1.87)
High	0.25	0.27	0.45	0.99	1.28
	(0.12)	(0.13)	(0.22)	(0.50)	(0.65)

Panel B: Portfolios Constructed by Quintiles

Group	Excess Returns	CAPM	FF Three-Factor	Carhart Four-Factor	Pástor-Stambaugh Alpha
			By Firm Size		
Small	13.26***	13.08***	14.20***	13.90***	13.26***
	(5.05)	(4.99)	(5.36)	(5.15)	(4.92)
Medium	0.07	-0.35	0.12	-0.77	0.91
	(0.02)	(-0.11)	(0.04)	(-0.26)	(0.37)
Big	-1.40	-0.94	-0.33	0.10	-0.31
	(-0.52)	(-0.37)	(-0.13)	(0.04)	(-0.11)
			By Analyst Coverage		
Low	8.06***	7.38***	8.38***	7.61***	8.84***

(Continued)

Table 11——Continued

	(3.21)	(3.06)	(3.33)	(3.07)	(3.72)
Medium	12.48***	12.37***	13.57***	14.28***	14.56***
	(3.38)	(3.40)	(3.74)	(3.82)	(3.90)
High	-2.22	-2.20	-1.92	-1.87	-2.00
	(-0.88)	(-0.87)	(-0.75)	(-0.73)	(-0.81)