Informed Trading Volume and Asset Prices:

The Role for Aggressive Investors[1]

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ABSTRACT

By studying the trading behavior of particularly *aggressive* investors, we provide new evidence on the joint determination of trading volume and asset prices that is consistent with the presence of informational advantages such as those theorized by Wang (1994). Using a unique Chinese data set of the most active daily market participants for each stock, we uncover the importance of a specific component of aggregate volume - we demonstrate that volume associated with particularly aggressive investor buying (selling) predicts large positive (negative) abnormal returns around key announcement dates. Critically, an advantage of our data is that we can also directly identify several plausible channels through which such an informational advantage could arise. Specifically, the abnormal returns are largest (in absolute terms) following announcement dates in the presence of aggressive pre-event traders who share the same geographic location as the firms in which they trade, and these effects are the most pronounced for stocks with the lowest analyst coverage or the smallest capitalizations. Further, we also find that particularly active traders located near relevant counterparties in an M&A transaction, new bank loan facility, or a key political change also exhibit informational advantages.

Key words: Informed trading volume, aggressive investor, geographic location, asset pricing

I. Introduction

Trading volume plays a critical role in asset pricing theory, and the examination of the joint properties of trading volume and returns has helped facilitate our collective understanding of the nature of price discovery. Specifically, a number of studies have explored the joint determination of volume and prices in the face of trading arising from (non-informational) hedging demands, while others have emphasized the implications of informational advantages possessed by various types of investors. For example, the seminal work of Grossman and Miller (1988) and Campbell, Grossman and Wang (1993) emphasize that market volume contains important information about future realized returns through a liquidity compensation channel, and returns generated by high volume tend to *reverse* themselves. In sharp contrast, Wang (1994) develops a heterogeneous-investor model with information asymmetry, and demonstrates that speculative trading volume from informed traders may engender return *continuation* effects around high volume periods as uninformed investors internalize their earlier misperceptions.

There are many empirical studies that test these theories (see, for example, Campbell, Grossman and Wang (1993), Conrad, Hameed, and Niden (1994), Cooper (1999), Lee and Swaminathan (2000), Llorente, Michaely, Saar, and Wang, (2002), and Gagnon and Karolyi (2009)). Testing for a volume–return dynamic that is consistent with an uninformed trading motive is relatively straightforward; simply put, return reversals manifest after high volume periods. However, successfully identifying a component of trading volume that is directly attributable to an informational advantage is considerably more challenging as it requires the identification of informed traders. Instead, researchers generally employ a consolidated measure of volume across all traders to provide an indirect test. For example, Llorente, Michaely, Saar, Wang (2002) provide empirical support for return continuation effects (rather than reversals) in the face of overall high volume periods. As their evidence is particularly true for firms potentially characterized by high informational asymmetry (such as firms with small capitalizations, high bid-ask spreads, or limited analyst coverage), one can perhaps indirectly infer the presence of an informational advantage.

Employing a unique Chinese dataset, this study provides a more direct test of the presence of informational advantages (such as those theorized by Wang (1994)) by studying the trading behavior of particularly *aggressive* investors before value-relevant corporate events.[3] Our tests have three advantages in identifying the role of informed trading in determining the price-volume relationship. First, our dataset can identify the investors contributing the most to aggregated market volume. Each trading day for each listed stock, the Shanghai Stock Exchange provides a non-public report to which we have special access on the trading activity for the top ten most active trading accounts in terms of both net purchases and net sales. If extreme volume indicates private information, investors in our data are the largest contributors. Second, we study trading before corporate events as this is likely a period over which information asymmetry is most pronounced (Chae, 2005). Specifically, we focus on trades prior to potentially value-relevant announcements in a manner similar to Kaniel et al. (2012); while that paper focuses largely on earnings announcements, we consider a broader collection of corporate and political events. Third, our data allow us to not only identify retail investors who can easily trade aggressively if/when they are informed (as they are not institutions with large positions that are difficult to maneuver (Kaniel et al. (2012)), but we also know their locations, the locations of the firms in which they trade, and the locations of certain relevant counterparties. That is, we can go further than many other papers that examine the role for informational advantages in the joint determination of

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[3] While there are many studies that consider the potential for informed trading, a common theme shared by these studies is the focus on a *particular* type of investor. Kaniel et al. (2012), among many others, focus on the degree to which individual investors trade on value-relevant information. Also, Asquith et al. (2005), Boehmer et al. (2008), and Engelberg et al. (2012) examine short sellers, Kelley and Tetlock (2013) examine retail investors, and Yang and Zhang (2009) focus on short-term institutional investors.

volume and returns. We directly identify several plausible geographic-based channels through which an informational advantage could arise.

Consistent with the presence of an informational advantage, we demonstrate that volume associated with particularly aggressive investor buying (selling) predicts large positive (negative) abnormal returns around key announcement dates. Our evidence indicates that pre-event trading by top ten trading accounts does in fact predict returns on and after various announcement dates. For example, we find that stocks heavily accumulated by aggressive investors in the ten days prior to all events, on average, exhibit abnormal returns that exceed the abnormal returns of stocks heavily sold by about 1.3% in the two-day event window around announcements and 2.5% over the next trading month. These effects are especially pronounced for some events, such as M&A activity, where the abnormal return difference is nearly 11% over the next trading month. The statistically significant results are consistent with the idea that, in aggregate, aggressive investor trading prior to potentially value-relevant announcements contains pertinent information.

While we demonstrate evidence suggestive of informational advantages possessed by the most aggressive investors, we also consider several alternative hypotheses to address the robustness of our conclusions. First, we rule out the possibility that the abnormal returns associated with aggressive trading around events are driven by simple price reversals occurring during the post-event window. Second, we embed our empirical exercise within a multivariate regression in which we can more easily control for other possibly confounding factors; our results are qualitatively unchanged. Finally, we address the question as to whether our findings are driven by liquidity provision rather than informational advantages. Following Kaniel et al. (2012), we decompose the cumulative abnormal returns following aggressive individuals' trading prior to key announcement into a component that is attributed to (non-informational) liquidity provision and a component that is attributed to trading on private information or skill.

We conclude that most of the abnormal return that we document is attributable to the private information possessed by aggressive market participants.

Critically, the top ten trading accounts data also permit an identification of the location from which the investors submit the trades. Since Coval and Moskowitz (2001), Hau (2001), Ivkovic and Weisbenner (2005), and Baik et al. (2010), among many others, explore the degree to which informational advantages might reflect location, we assess whether reduced acquisition costs associated with geographic proximity might be a channel through which our return predictability effects arise. In addition to focusing on the most aggressive investors in total, we build upon this idea by disaggregating our data based upon the location of the listed firms as well as the location of the most aggressive investors themselves. Across all the various events we consider, we find that aggressive pre-event trading by investors who share the same home city (and, in some cases, the same home province) with the headquarters of the firms in which they trade consistently demonstrates the most significant and economically meaningful return predictability.

While a reduced information acquisition cost associated with geographical proximity seems the most plausible conclusion one can draw, we go further by exploring whether the return predictability effects are even more pronounced for subsets of firms based on what we might expect *ex ante*. By dividing the sample of listed firms into groups based on their analyst coverage or firm size, we focus on those firms for which information acquisition would be the most valuable. While we continue to observe that the strongest return predictability results across various events manifest when the aggressive traders are nearby the relevant listed firm, the locational effects are generally largest for the subsets of firms with low analyst coverage or small size.

To further corroborate the importance of locational advantages, we focus on a subset of events (namely, bank loans, M&A activity, and changes in relevant government officials) for which there is an important counterparty involved in the origin of potentially value-relevant information. In the case of a newly issued bank loan, there is the issuing bank. In an M&A deal, this is the counterparty involved in the deal. Finally, around a change in a government official, this is a higher-level government body in the Chinese context which makes the decision. If proximity to the origin of information in our sample of aggressive investors is the primary reason behind the informational advantage that we document, investors close to the location of the relevant counterparty may also exhibit significant return predictability stemming from an informational advantage. We find this to be the case.

As a final exercise, we obtain additional investor-level data from one brokerage firm active in China. These data confirm that the event periods during which branch-level data appears in the top ten list of most active trading accounts is consistent with a dominant role for one or two extremely aggressive individual investors. Second, we can also confirm that the branch-level individual investors are largely located nearby the firms in which they trade

Our study contributes to several literatures. First, we offer a novel contribution to the price-volume literature by identifying informed volume, thereby testing Wang's (1994) theory on the joint determination of trading volume and asset prices in the presence of informed traders. Unlike previous empirical studies, we directly identify the aggressive investors who contribute the most to aggregated trading volume, and we infer their information advantage from their trades' return predictability around key corporate events.

Second, we contribute to a growing literature on the presence of informational advantages among retail investors. (such as Kaniel et al. (2008), Kaniel et al. (2012), Kelley and Tetlock (2013)). We present new evidence on the information advantages possessed by the most aggressive retail investors who together constitute a significant fraction of daily trading volume. Previous studies conduct tests on a sample of retail investors usually obtained from one or several brokerage firms. One disadvantage of this approach is that retail investors' trading skills and/or informational advantages might vary across brokers, and previous contradicting evidence could simply reflect variation in the segments of retail investor population that are sampled (see Kelley and Tetlock 2013). Our top ten trading account dataset allow us to identify a subset of the most aggressive investors across the entire retail investor population.

Finally, our study enriches the literature on home investors by documenting a plausible channel through which aggressive investors' advantages might arise – geographic proximity to the source of information generation, either in the form of the invested firms or relevant counterparties. The informational advantage of event counterparties provides a particularly novel perspective on the degree to which such advantages are gained through proximity to the source of information generation.

The rest of the paper proceeds as follows. Section 2 describes the data sample and our measurement of aggressive trading activity. Section 3 provides evidence on the relation between pre-event individual investor trading and subsequent abnormal returns. We also consider several alternative hypotheses to address the robustness of our conclusions on the presence of informational advantages among the most active traders. Section 4 examines the role for geographical proximity as a channel through which informational advantages arise. Section 5 employs an additional investor-level dataset to shed light on the nature of our top ten accounts data used throughout the study. Finally, Section 6 concludes.

II. Data and Measurement

A. Background and sample

We employ a unique dataset that permits an exploration of the informational advantage of a subset of particularly aggressive investors who disproportionately contribute to trading volume. Prior to providing relevant summary statistics on the nature of our trading data, a bit of institutional detail is required.

The Chinese stock market is based on an order book driven system. There are two channels through which investors can submit orders to the Shanghai or Shenzhen stock exchanges. The first is through brokers, who have trading accounts registered with the relevant exchanges. Investors submit orders to branches across the country, and then brokers upload these orders to the exchanges' order book system through their accounts. As a consequence, brokers act as the bridge between investors and markets. All individual investors and General Legal Entities trade through this channel. The second channel is through investors' own trading accounts on the stock exchanges. All mutual funds and some institutional investors trade through this direct channel. To give a sense of relative magnitudes, Table 1 (Panel A) reports the fraction of total volume attributed to each channel. For example, the first channel accounts for 87.17% (83.21% from individuals and 3.96% from General Legal Entities) of total market volume in 2008, whereas the second channel accounts for 12.83% (9.94% from Mutual Funds and 2.89% from Specialized Institutions) [Shanghai Stock Exchange Statistics Annual (2009)]. In our smaller sample of aggressive investors, about two-thirds of the top ten investors come from brokers (the first channel, in aggregate) with the remaining third coming from funds (the second channel, in aggregate).

Each trading day for each listed stock, the Shanghai Stock Exchange reports the trading activity for the top ten most active trading accounts in terms of both net purchases and net sales (either brokerage branches or mutual funds) employing these two channels. This non-public report, to which we have special access, yields twenty active trading accounts for each stock on each trading day. We focus on this subset of traders to isolate the potential informational advantage of the most aggressive investors, their locations, and the locations of the firms in which they trade.[4]

More specifically, our sample period covers 373 trading days from 28th June 2007

[4] To be transparent, we observe the trading decisions of only these specific groups of investors. Top ten is arbitrary, but this cutoff is determined by the reporting exchange. While this cutoff does permit the characterization of the most aggressive investors on each side of the market, we do not observe the trading patterns of the remaining market participants.

to 31st December 2008. The sample includes all 851 stocks listed on the Shanghai Stock Exchange. For each day and each stock, we obtain the trading volume of total purchases, total sales, net purchases and net sales from the top ten trading accounts (branches or mutual funds). To be clear, while we observe the trading behavior of the most aggressive funds, we do not observe the direct behavior of the most aggressive individuals. Rather, we observe the aggregated trading activity of the brokerage branches through which these individuals trade. While some aggregation is taking place, brokerage branch activity is nevertheless an important signal about individual trader aggressiveness, and the data do permit an exploration of regional branch variation that may be correlated with important informational advantages.[5] We exploit this regional variation in our empirical setup.

To better demonstrate the nature of our data, we present an example of a stock prior to a value-relevant corporate event. The particular company is Zhejiang China Commodities City Ground Co., Ltd, and its stock code is 600415. Its main business is real estate development and commodity sales. The stock experienced a suspension of trading from December 11th, 2007 to March 4th, 2008 due to an ongoing unreported corporate event (a restructuring, in this case). On March 5, 2008, the company announced that it would issue shares to its controlling shareholder, Yiwu State-owned Assets Investment Co., Ltd., in exchange for a real estate project. It is a common practice in the Chinese stock market that, prior to a listed company announcing an important corporate event that might be particularly value-relevant, stock trading is suspended for a certain period ranging from a few hours to several months, depending on the type and importance of events. The purpose of the regulator (China Securities Regulatory Commission, CSRC) establishing this rule was to mitigate information asymmetry and prevent insider trading. Interestingly, our branch-level data allows us to observe that

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[5] In Section V, we employ an additional investor-level dataset to help shed light on the importance of individual traders in the determination of top ten trading accounts.

some investors nevertheless start aggressively trading even before the suspension. The Appendix shows the top ten net buying and selling branches or mutual fund accounts from our database on the last trading day of stock 600415 prior to suspension, December 10th, 2007. Figure 1 presents a visual representation of the trading magnitudes and geographical origins. Specifically, the aggressive net buying from several accounts located in the firm's home city, Yiwu, is especially interesting. In the three subsequent trading days after the suspension, stock 600415 then hit three daily return upper limits (10% per day) in a row, exhibiting cumulative raw and market-adjusted returns of 30%.

While this example is intriguing, we next provide a sense of the *aggregate* importance of the subset of investors we do observe. Table 1 (Panel B) reports the percentage of total trading volume from the top ten accounts. While we observe on any given day detailed trading activity only for the top ten accounts (branches or funds), we do divide all figures by the total daily volume for each stock which we collect from the China Stock Market & Accounting Research (CSMAR) database system. Collectively, the top ten brokerage and fund trading account volumes together make up almost 30%, on average, of the net purchase and sale totals, with the largest fraction emanating from the aggregated daily brokerage accounts. Second, across most of the days (between the 5th and 95th percentiles), the fraction of total trading attributable to the top ten accounts ranges from between 10 to 60% (but can be as large as 100% of trading volume for any given day in the extreme). Taken together, the accounts that serve as the focus of our study represent a central component of equity market trading on the Shanghai exchange. Further, the breakdown across brokerages and funds reinforces the widespread perception of the importance of individual traders in the Chinese equity market context. As an example, the Shanghai Stock Exchange Statistics Annual (2009) reports that about 83% of the total volume is associated with individual trading, in sharp contrast to the dominant role played by institutional investors in the United States context.

It is important to note that there is significant variation in who enters the top ten groups. For each branch (or fund), we calculate the percentage of its appearance in the top ten accounts for each stock across all the relevant trading days. We then calculate the mean of each branch's or fund's percentage across all the stocks in our sample. Figure 2 shows the histogram of the calculated mean of all the branches and funds. The frequency of the top ten branches or funds appearing is extremely heavy in the left tail; clearly, the top ten accounts data is not dominated by a small number of very large branches. Instead, the data are dominated by many branches, each of which do not appear frequently.

As mentioned, the data also permit a focus on regional variation. Coval and Moskowitz (2001), Hau (2001), Ivkovic and Weisbenner (2005) and Baik et al. (2010), among many others, explore the degree to which informational advantages might reflect geographic proximity, possibly due to reduced local information acquisition costs. In addition to focusing on the most aggressive investors in total, we build upon this idea by also disaggregating the data based upon the location of the listed firms as well as the location of the most aggressive investors. Specifically, we observe the headquarter location of the various listed firms and the location of each brokerage branch within China. On the location of the 851 listed firms traded on the Shanghai exchange during our sample period, 634 have headquarters in cities other than Beijing (79) and Shanghai (138) – with a wide range of dispersion throughout the country. Since we also have information on the location of the brokerage branches, we will exploit this variation by focusing on the trading activity in geographically proximate firms of the most aggressive investors prior to various value-relevant events.

In addition to being able to identify the most active traders on any given day, we also observe their location (at least aggregated to the branch level as mentioned above). If investors submit orders through brokerage branches (i.e., the first channel), the location of these branches can be identified according to the branches' names. Our assumption is that the individual investors are also located near the branch that they employ for trading purposes.[6]

Table 2 reports data on the percentage of trading volume (buys and sells, separately) associated with the top ten accounts based upon the locations where the orders of the top ten trading accounts are submitted. To keep things simple, we provide a breakdown of the fraction of total volume attributed to the top ten accounts along two dimensions. First, we split firms by their headquarter location (we split the headquarter data into Beijing, Shanghai, and other). Second, for each listed firm's trading, order locations have been categorized as Beijing, Shanghai, home (based upon the order submitted to a branch in the same city as the listed company's headquarters), same province (based upon the order submitted to a branch in the same province as the city of the company's headquarters), other cities, and fund. That is, we specifically identify the cases when the most aggressive investors are located in the same city or province as the headquarters of the particular firm in which they are trading. On the last category: if investors, such as mutual funds and some other institutional investors, submit orders through their own accounts on the Shanghai stock exchange (i.e., the second channel), we classify their location simply as "fund" since we do not know where the fund is located.[7]

For both net purchases and sales, we observe that the fraction of daily volume of listed firms headquartered in either Beijing or Shanghai is, on average, significantly associated with aggressive (top ten) trading volume emanating from brokerage branches located in Beijing, Shanghai and/or other cities. This is consistent with the aggregated data we presented in Table 1. Recall that on any given day we observe detailed trading

[6] Because investors need to physically visit their branch for a number of procedural reasons, this assumption is consistent with anecdotal evidence. Further, it is true under Chinese securities market regulation that an individual investor can have only one account in the Shanghai Stock Exchange during this time period. This reduces the likelihood that some very sophisticated investors split trades across other remote branches. While it is presumably feasible that an investor uses others' accounts to trade, any significant departure from the validity of our assumption will only reduce the likelihood that we find significant evidence of locational advantages. In Section V, we employ an additional investor-level dataset to confirm the geographic location of individual traders.

[7] We collect mutual fund company data from Wind. By the end of 2008, there are sixty six mutual fund companies, thirty of which are from Shanghai, fourteen from Shenzhen, sixteen from Beijing, and six from elsewhere. Given the limited nature of the fund data, we do not exploit this regional variation.

activity only for the top ten accounts (branches or funds); however, like Table 1, we again divide all figures by the total daily volume for each stock across the entire market. For Beijing and Shanghai firms, more than 2.5% and 5.7% of total daily volume is associated with net purchases or sales, respectively, from top ten brokerage branches from the same city. Interestingly, even for firms headquartered in cities other than Beijing or Shanghai, more than 1% of total daily volume is, on average, associated with top ten brokerage branches from the same city or province. Taken together, these figures suggest that traders in close geographical proximity to firms' headquarters may play an important role in particularly aggressive trading. Finally, in all cases, trading by funds that enter the top ten calculation also plays an important role in daily volume. In a manner similar to Kaniel et al. (2012), we will explore whether these subsets of aggressive funds and/or traders, local or otherwise, display informational advantages by focusing on their behavior around value-relevant corporate and political events.

To operationalize this, we collect data for each firm based on several key corporate or political events. First, we collect corporate event days associated with (1) earnings announcements, (2) revisions in earnings forecasts, (3) the announcement of merger and acquisition activity, (4) the announcement of a new bank loan, (5) the date of a market trading suspension[8], and, finally (6) the announcement of a lawsuit. Data on the first five events types are obtained from CSMAR. Data on lawsuit announcements are taken from the RESSET Financial Research Database; we only retain the lawsuits that are marked as "important." Second, we manually collect dates associated with any changes in government officials (more detail in Section 3). Last, stock price, trading volume, and market capitalization data for each firm are collected from CSMAR.

[8] The data on market suspensions do require some explanation. On the Chinese exchanges, there are usually five reasons for a trading suspension: firms 1) do not report decisions made by shareholders' meeting; 2) convene shareholders' meeting, regular or special; 3) experience abnormal fluctuation of its stock price; 4) do not report important announcements which are not related to shareholders' meeting; and 5) report important announcements which are not related to shareholders' meeting. We retain the fifth category because others do not involve unscheduled new information.

Tables 3 and 4 report summary statistics on the distributions of events across listed firms. First, Table 3 provides statistics on the number of events per listed firm. All firms, on average, are associated with about fourteen events of the various types over our sample period; the 5^{th} (95^{th}) percentile is seven (twenty five) events per firm. There is some important variation between firms. One hundred and eighty five firms experience fewer than ten events, whereas 120 experience more than twenty. We will explore the interplay between stock prices and aggressive (top ten) trading behavior around these events, but we will examine the variation across event type (since informational advantages may potential vary across event type) as well as in association with geographical proximity.

Table 4 provides a temporal, by month, presentation of event arrival as well as a breakdown of the different events into each type. The first column demonstrates the temporal breakdown of the event arrivals across all event types in aggregate. While there are a few months associated with significantly larger amounts of event arrivals, the event arrivals appear to be relatively well populated in each month of our sample period. The remaining columns provide a breakdown of the events by type. While we measure nearly 12,000 events in total, more than 4,500 of them are associated with earnings announcements. While there are relatively few lawsuit related events, the other event types are well represented in the data, both in aggregate and through time. Taken together, we have a representative sample of events that are generally thought to be value-relevant. We will next explore the degree to which aggressive traders, as captured by our top ten accounts, exhibit an informational advantage by examining their trading in concert with the relevant equity price dynamics around these events.[9]

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[9] When we pool all the event types together, it is possible that some events for a particular firm are temporally quite close. One way to deal with this concern is to examine each event type separately; we consider this in subsequent section in a fashion similar to Kaniel et al. (2012), who consider scheduled earnings announcement. Of course, the usual concern in any event study that other relevant events appear during the event window remains. Our standard error construction is also explained below.

B. Trading imbalance measure

To operationalize our assessment of the role for aggressive trading, we first need to measure the relative importance of our top ten accounts for aggregate trading around these key events. We begin by computing an *imbalance* measure, similar to Kaniel et al. (2012), to construct a daily abnormal net trading series. For each listed firm *i*, we subtract the value of the net shares sold by aggressive investors from the value of net shares bought, and divide by the average daily volume over the sample period. We then subtract the daily average of the imbalance measure over the sample period to get an abnormal aggressive investors' net trading measure, which is more suitable for examining trading patterns around various events. Specifically, we define $\boldsymbol{AINT_{i,t}}$ for listed firm *i* on day *t* as:

$$AINT_{i,t} = Aggressive\ Imbalance_{i,t} - \frac{1}{T} \sum_{\substack{all\ days\ in \\ 6/28/2007-12/31/2008}} Aggressive\ Imbalance_{i,t}$$

where

$$Aggressive\ Imbalance_{i,t} = \frac{Aggressive\ investors\ net\ buy\ dollar\ volume_{i,t} - Aggressive\ investors\ net\ sell\ dollar\ volume_{i,t}}{Average\ daily\ dollar\ volume\ over\ the\ sample\ period_i}$$

We define cumulative abnormal net trading of aggressive investors over the period [t, T] as

$$AINT_i[t, T] = \sum_{k=t}^{T} AINT_{i,k}$$

where the period is defined relative to the event announcement date (day 0). For example, *AINT*[–10,–1] is the cumulative abnormal net trading of aggressive investors from ten days prior to the event announcement to one day prior to the announcement. The relevant questions are then whether we observe (a) an abnormally large amount of net purchases or sales emanating from the most aggressive investors in the days leading up to key corporate and political events and, if so, (b) do these trades predict future stock returns?

III. Return Predictability of Aggressive Investors' trading

This section investigates the informational advantage of aggressive investors by studying the degree to which any return predictability is associated with abnormally large trades in the days leading up to key corporate and political events. The method that we adopt is similar to Kaniel et al. (2012). First, we sort all events into quintiles according to net trading volume by aggressive investors in the ten trading days prior to the announcement as dictated by our *AINT*[–10,–1] measure. Quintile 1 contains the stocks that aggressive investors sold the most in the days leading up to the event, and quintile 5 contains the stocks that aggressive investors purchased the most. We then compute for each event the cumulative abnormal return (*CAR*) over various periods by subtracting the return on the Shanghai Composite Index from the return of the stock.[10] Since each period may contain multiple events, we cluster events at weekly level for *CAR*[0,1] and *CAR*[0,6], at monthly level for *CAR*[0,11] and *CAR*[0,21]. Given the possibility for some overlap in events, this means that we place into a cluster the events that happen in the same week or month for a particular firm.

When calculating standard errors, a cluster is seen as an observation.

[10] For robustness, we also measured the *CAR* by instead subtracting a size-based portfolio return. The key results are similar.

Specifically, we employ the following Rogers standard error (see Petersen (2009)):[11]

$$AVar(\beta) = \frac{N(NT-1)\sum_{i=1}^{N}(\sum_{t=1}^{T} X_{it}\varepsilon_{it})^2}{(NT-k)(N-1)(\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}^2)^2}$$

To obtain the mean *CAR* for an individual quintile, we regress the *CAR* on a constant and retain its Rogers standard error. To obtain the difference between Quintiles 1 and 5, we regress the *CAR*s on a constant and an indicator variable that takes the value of one for Quintile 5 and zero for Quintile 1 and use its coefficient and Rogers standard error.

Table 5 reports the estimated cumulative abnormal returns (*CAR*s). Across the sample of all events taken together, a trading imbalance associated with the top ten accounts demonstrates strong return predictability across all event windows. For example, over a one day period, the cumulative abnormal return (*CAR*[0,1]) for stocks with events associated with large net purchases by aggressive investors in the days leading up to the event (Q5) is 1.3% larger than for stock with events associated with large net sales by aggressive investors (Q1). This is also highly statistically significant. Statistically significant effects are also present for cumulative return differences between Q5 and Q1 stocks for longer horizons out to 21 days, and the cumulative return effect is also larger. The evidence suggests that a trading imbalance in the days leading up to materially relevant events emanating from the most aggressive investors is associated with realized returns subsequent to the event; these aggressive investors may posses certain informational advantages.

Despite this evidence, we have so far only viewed the results from an extremely aggregated perspective. There may be differences in the informational advantages among these aggressive investors across different event types as well as across

[11] Kaniel et al. (2012) employ the Fuller–Battese (1974) methodology, designed for standard panel data, to correct for temporal clustering. However, it is not suited to our data because a stock may have several events within a week or a month.

geographical proximity. Table 5 also presents evidence on the *CAR*s across Q5 and Q1 stocks separating out the different event types. Among the various types of events, aggregate *AINT*[–10,–1] (Q5-Q1 firms) really only exhibits statistically and economically significant return predictability for a subset of events: the announcement of M&A activity, a new bank loan, a trading suspension, or a change in the local governor. Recall that a stock-specific trading suspension is often instituted in advance of the arrival of value relevant information, so this result is particularly interesting. We do not find evidence on the aggregate return predictability associated with aggressive traders for earnings announcement or changes in earnings forecasts; however, in no case have we yet exploited the potential for interesting variation in the geographic location of the various firms and investors. Nevertheless, uncovering return predictability associated with aggressive traders aggregated across all events in aggregate warrants further exploration. Before turning to geography, we first perform several additional tests in a fashion similar to Kaniel et al. (2012) to evaluate the robustness of the key results we have presented so far.

First, we check whether the patterns we identity are driven by short-term return reversals, as documented by Jegadeesh (1990) and Lehmann (1990). We divide the sample into five groups according to the *CAR* over the ten days prior to the event, and then we investigate the return predictability of *AINT*[–10,–1] within each group. That is, Table 6 presents event-based *CAR*s over either event day 0 to 1 (Panel A) or 0 to 21 (Panel B) associated with differences in aggressive trading imbalances in the ten days leading up to the event. These post-event windows used to measure the *CAR* represent the two extremes presented in Table 5. The difference here is that we first separate the data into periods where the stock return was already abnormally negative or positive over the ten days leading up to the event. If the results on the return predictability of aggressive trading presented in Table 5 are entirely driven by return reversals, we should not expect to find a role for aggressive trading imbalances on future stock returns once we control for pre-event price dynamics.

Table 6 shows that the return predictability of *AINT*[–10,–1] exists across all groups delineated by pre-event *CAR*s for event window [0,1] (Panel A) and for three of the five groups for event window [0,21] (Panel B). The Q5-Q1 post-event *CAR*s based on pre-event aggressive trading imbalances are largely significant at, at least, the 10% significance level if not higher. Regardless of whether a stock, on average, exhibited a negative or positive abnormal return over the pre-event window, trading imbalances in the days leading up to materially relevant events emanating from the most aggressive investors remains associated with realized returns subsequent to the event. In sum, possible return reversals do not appear to be driving our results related to the most aggressive investors.

Second, we run a regression analysis to evaluate the return predictability of *AINT*[–10,–1] through a channel separate from the portfolio building analysis we have demonstrated so far. The advantage of a regression is that it permits one to control other potentially relevant factors. The dependent variable in the regression is the cumulative abnormal return over several different post-event windows, and the regressors include indicator variables for various events, the amount of aggressive investors' net trading prior to the event (*AINT*[-10,-1]), and past abnormal return (*CAR*[-10,-1]). Table 7 provides regression results. In sum, across all events taken together (presented in the first row), the coefficient on *AINT*[–10,–1] is highly statistically significant, regardless of the event window over which the effect is measured. We continue to uncover direct return predictability associated with abnormal trading among aggressive investors. Further, if we separate the results out into different events (presented in each subsequent row), many exhibit event-specific predictability results, though the more limited sample sizes clearly impacts statistical power.

Finally, we evaluate whether the return predictability of *AINT*[–10,–1] is caused by liquidity provision as opposed to an informational advantage. Following Kaniel et al.

(2012), for each day *t* during the sample period, we select all the stocks in our sample that did not experience any measured events in a 20-day window around that day. If the number of these stocks is not smaller than 200, we estimate the following three cross-sectional models:

Model 1: $CAR^i[0,21] = a_t + b_t * AINT^i[-10,-1] + c_t * CAR^i[-10,-1] + error$

Model 2: $CAR^i[0,21] = a_t + b_t * AINT^i[-10,-1] + c_t * CAR^i[-10,-1] + d_t * std^i[-10,-1] + error$

Model 3: $CAR^i[0,21] = a_t + b_t * AINT^i[-10,-1] + c_t * CAR^i[-10,-1] + d_t * std^i[-10,-1] + e_t * AINT^i[-10,-1] * std^i[-10,-1] + error$

The models provide estimated parameters that potentially describe the relation between net trading imbalance and future returns for each day in the sample period, separate from event dynamics.[12] To compute the *expected* abnormal return due to risk-averse liquidity provision around an event, we calculate aggressive investors' net trading, abnormal returns, and the standard deviation of returns for that stock during the pre-event period. We then multiply these variables by the parameter estimates for the date of the announcement to compute the different measures of the *expected* abnormal return based on the three estimated models. We follow this process for each event in our sample, and then compute a return component that is attributed to information/skill by taking the difference between the actual abnormal return and the estimate of the abnormal return due to liquidity provision.

Focusing on the longest post-event window, Table 8 provides several estimates of the cumulative abnormal return (*CAR*[0,21]) after the component potentially driven by

[12] If the number of these stocks is smaller than 200, we directly set the model parameters at 0, as this cannot likely provide a reliable estimate (we also consider 150 as the bar, and this version yields qualitatively similar results).

liquidity provision is extracted. In Panel A, we sort all events into quintiles according to aggressive investors' net trading in the ten trading days prior to the announcement (*AINT*[–10,–1]). In Panel B, we do the same but only for instance where we have more than 200 observations to estimate the three models. In each Panel, the relevant quantities of interest are the columns labeled *CAR*-*ECAR*, with one version for each of the three models (that is, we present the *CAR* just as it appeared in Table 5 and three estimates of *ECAR*). Regardless of the sample size or the model employed to measure the expected liquidity compensation, the results demonstrate that after adjusting for liquidity provision, *AINT*[–10,–1] continues to exhibit significant return predictability.

In summary, we provide strong collective evidence that the trading imbalance of aggressive investors in our sample demonstrate significant and robust return predictability across various event windows. This finding is consistent with Wang's (1994) theory on the joint determination of trading volume and asset prices in the presence of informed traders. Here, we identify a particular component of overall volume that appears, on average, to be informed. However, we have yet to provide concrete evidence on the origin of this informational advantage. While such identification will naturally prove somewhat elusive, we turn to additional sources of variation in the data to shed light on what might indeed be going on.

IV. Origin of Aggressive Investors' Informational Advantage

A. Return predictability and geographic proximity

In this section, we exploit additional variation in the data to potentially provide an answer to the question as to why aggressive investors might posses the informational advantage suggested by the return predictability shown in the previous section. As mentioned above, one possible explanation is the reduced information acquisition cost associated with geographical proximity. Indeed, there are existing studies which show that investors close to firms possess significant informational advantages (see Coval and Moskowitz (2001), Hau (2001), Ivkovic and Weisbenner (2005), and Baik et al. (2010), among others). Therefore, we explore whether the informational advantage of aggressive investors relates to their location and the location of the firms in which they trade. Since our dataset permits the identification of the location of brokerage branches, we categorize all investors in our sample into five groups as Beijing, Shanghai, home city, home province, fund, and other cities according to their location and the stocks they trade. Recall the discussion surrounding Table 3 for more details on these classifications.

We examine the degree to which our documented return predictability varies across the trading behavior of aggressive investors from different locations. Table 9 reports the results on the difference in *CAR*s across various post-event windows between the Q5 (large net purchases) and Q1 (large net sales) for aggressive investors in the ten days leading up to the events (*AINT*[-10,-1]). The first group presents the return differences for all events, and the first row simply repeats the Q5-Q1 quantity reported in Table 5. The remaining rows separate the abnormal trading by the location of the aggressive investor (and possibly that of the listed firm). For example, "home province" or "home city" denotes that we are reporting the Q5-Q1 *CAR* differences only for those listed firms for which the pre-event aggressive investor imbalances are located in the same province or city, respectively, as the listed firm. The other groups (fund, Shanghai, Beijing, other) simply denote the location of the trader, and the Q5-Q1 *CAR* differences reported there are associated with abnormal pre-event trading only for investors from those groups. Interestingly, while there are a few statistically and economically significant effects associated with these other sets of aggressive traders (grouped by location), the largest and most robust effects are associated with aggressive pre-event traders who are located in geographical proximity to the firms in which they trade. The aggregate figures presented earlier appear to mask some important variation related location.

We go a step further, and disaggregate these location-based findings by event type. Each subsequent section in the table provides the Q5-Q1 *CAR* differences over various post-event windows, where we have disaggregated the data both by event type (announcements associated with earnings, M&A activity, etc.) and by the location of the most aggressive investors. This is a large table, but contains some of the most important results in the paper. Each section is separated by event type, and within each section, we observe the return predictability associated with different groups of pre-event aggressive traders. Within each section sorted on event type, the first row provides the exact same Q5-Q1 *CAR* difference that was provided in Table 5 for the baseline return predictability analysis associated with that event type. As a reminder, only a subset of the event types demonstrated a consistent return pattern associated with aggressive pre-event trading when aggregated across all aggressive investors. However, for each event type separately, we now examine the Q5-Q1 *CAR* difference across various subgroups based on the location of the most aggressive traders. It is quite interesting to note that for almost all events (even those such as earnings announcements that did not exhibit statistically significant return predictability when aggregated across all aggressive investors), we now observe that aggressive trading imbalances emanating from traders who are located in the same city (and sometimes same province) as the listed firm are associated with statistically and economically significant return predictability. In contrast, there isn’t a clear pattern of robust return predictability associated with aggressive investors from funds, Beijing, Shanghai, or elsewhere across the various event types. These results provide important corroborating evidence that the return predictability that we detect around value-relevant corporate and political events in the aggregated data seems to be largely isolated to local investors.

Across all the various events we consider, we find that among all groups, home investors consistently demonstrate the most significant and economically meaningful return predictability. The reduced informational acquisition cost associated with geographical proximity seems the most plausible conclusion one can draw. However, we go further by exploring whether the return predictability effect is even more pronounced for subsets of firms based on what we might expect *ex ante*.

B. Firm characteristics and the value of information

We next focus on those firms for which information acquisition would be the most valuable. Specifically, we divide the sample of listed firms into groups based on their analyst coverage (measured using data from Wind) or firm size (measured using data from CSMAR**).** These firm-level characteristics serve as proxies for information asymmetry, and we expect that there will be higher return predictability from *AINT*[–10,–1] for the firms with limited analyst coverage and the smallest sizes. On analyst coverage, we sort firms into below and above median coverage groups; the median analyst coverage is five analysts in our sample.[13] On size, we consider groups of firms based on small, medium, and large market capitalization. The relevant cutoffs are the 40^{th} percentile (274,000,000 CNY) and the 70^{th} percentile (678,000,000 CNY).

Table 10 reports the return predictability associated with aggressive investors separated across these different groups of firms. In the interests of brevity, we focus solely on the Q5-Q1 *CAR*[0,1] difference.[14] For presentation, we arrange the results in three ways: first, we continue to separate the data into the various events; second, we again consider aggressive investor activity classified by the location of the traders; and finally, we now further split the results into groups of listed firms based on their analyst coverage and size.

As before, the first set of results presents the Q5-Q1 *CAR* differences for all events in aggregate. Table 10 shows that the *CAR* differences associated with

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[13] For every stock, we measure the number of analysts following the firm in 2007 and 2008 to proxy for analyst coverage. The 25^{th} percentile is zero analyst coverage, the 50^{th} is five, and the 75^{th} is 12. The maximum number of analyst following one firm is 52, so there is clearly a wide degree of cross-sectional variation in analyst coverage.

[14] Evidence (not reported) for the other post-event windows is qualitatively similar.

aggressive trading prior to all events, in aggregate, are considerably larger for firms with low analyst coverage and small market capitalizations. This result is consistent with the expectation that the informational advantage may be most pronounced for the stocks with the least attention. The remaining rows separate the predictability effects associated with abnormal pre-event trading by the location of the aggressive investor. For all events, "home province" or "home city" again signify that we are reporting the Q5-Q1 *CAR* differences only for those listed firms for which the aggressive investors are located in the same province or city, respectively. The other groups (fund, Shanghai, Beijing, other) again describe the location of the trader and the Q5-Q1 *CAR* difference reported there is associated with abnormal pre-event trading only for investors in those groups. Interestingly, while we already observed that the Q5-Q1 *CAR* differences associated with aggressive trading emanating from branches nearby the listed firm are sizeable, this table shows that these predictability effects are much larger for firms with low analyst coverage and small size. The predictability effects from trading associated with other locations are largely statistically insignificant. Aside from confirming the informational advantages of local investors, these results demonstrate that the effects are most pronounced precisely for the firms for which information acquisition is likely most valuable.

As in earlier tables, the remaining sets of results separate the data into the various event types. A consistent theme emerges. While we continue to observe that the strongest return predictability results across various events manifest when the aggressive traders are nearby the relevant listed firm, the *CAR* differences are generally larger for firms with low analyst coverage or small size.

C. Counterparties and informational advantages

As a final analysis in this section, we focus on a subset of events (namely, bank loans, M&A activity, and changes in relevant government officials) for which there is an important counterparty involved in the origin of potentially value-relevant information. In the case of a newly issued bank loan, there is the issuing bank. In an M&A deal, this is the counterparty involved in the deal.[15] Finally, around a change in a government official, this is a higher-level government body in the Chinese context which makes the decision. If proximity to the origin of information is the primary reason behind the informational advantage that we document in our sample of aggressive investors, investors close to the location of the relevant counterparty may perhaps also exhibit significant return predictability stemming from an informational advantage. We replicate the structure of our earlier analysis on the variation in return predictability across the different measures of aggressive pre-event trading delineated by location, but in this case we replace the relevant location as being near the headquarter of the listed firm to being near the relevant counterparty.

First, Table 11 provides evidence on the return predictability associated with aggressive pre-event trading around new bank loans (Panel A) and M&A (Panel B) events. As in earlier tables, we focus on the Q5-Q1 *CAR* differences, where the *CAR*s are measured across different post-event windows. As before, the rows in each case describe the particular group of aggressive investors for which we measure trading imbalances, *AINT*[-10.-1]. Here, we include aggressive investors from the same cities or provinces as the relevant counterparties. For the new bank loan events in Panel A, we find that aggressive trading activity among investors from the city of the counterparty bank headquarters has significant return predictability across all the event windows (carefully excluding those from the listed firms home province). For M&A activity in Panel B, we find that aggressive trading activity among investors from the city of the counterparty in the deal has significant return predictability across all event windows (again, carefully excluding those from the listed firms home province). Taken together,

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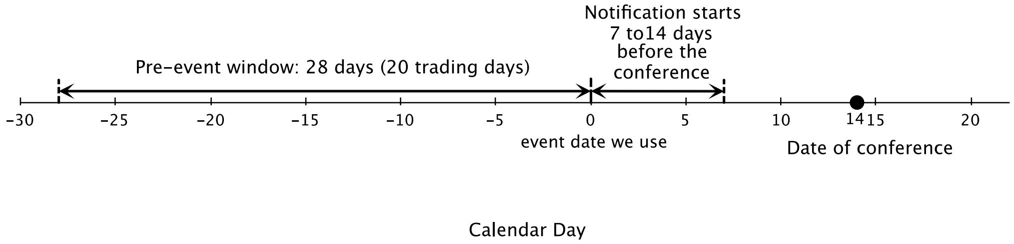
[15] An additional counterparty that would be quite interesting is the investment bank helping to facilitate the deal; however, we do not observe this level of detail.

it appears the informational advantage of investors in proximity to relevant counterparties is also present. This represents a novel and more nuanced feature of the general evidence on locational advantages than has been presented elsewhere in the literature.

Finally, we consider a political event associated with the change in local governors. Given the important role the state plays in the allocation of resources in China, this political shift likely represents an important and value-relevant event. Further, the decision to remove a governor takes place in a body of higher-level government officials, residing in Beijing or elsewhere (more on this below). The only tricky aspect of this important event is that the relevant dates are not as clear-cut as those of corporate events. There is a date when the nomination of the new governor is formally announced and becomes public, but the information has already circulated prior to that moment. We collect via the internet (Xinhuanet.com and people.com.cn) all changes in the top two governors of a province or a city, and then collect the dates of the conferences where the changes were formally announced. However, prior to these conferences, the superior officials would first make the expected changes known to the public and seek opinion. This period, which we call notification, lasts seven days. After notification, the conference would be held within another seven days to formally announce the change. So, the actual date when the information first becomes public is usually the 7th to 14th day prior to the date of the formal conference. To make sure what we capture is not fully public information and the trading imbalance we calculate is indeed a proper *ex-ante* imbalance, we use the 14th day prior to the conference as the event date. The following timeline describes this process:



Here, we define the counterparty investors associated with changes in governor events as follows. For a change in an urban governor, all firms with headquarters located in the city are thought to be potentially impacted. For a change in a provincial governor, we consider the firms in that province. We regard as "counterparty cities" the cities of the political superiors who made the changes. For changes in higher-level provincial governors, this is presumed to come from Beijing directly; for the changes in urban governors, the corresponding provincial capitals are employed.

Table 12 provides evidence on the return predictability associated with aggressive pre-event trading around changes in government officials. As in earlier tables, we focus on the Q5-Q1 *CAR* differences, where the *CAR*s are measured across different post-event windows. The rows in each case describe the particular group of aggressive investors for which we measure trading imbalances. Here, we include aggressive investors from the counterparty cities described above. Panel A includes all the government official changes in the sample. We find that the trading imbalance associated with investors from the counterparty city, either Beijing or the provincial capital using the rule described above, is economically significant for return predictability and is statistically significant in three of the four post-event windows. We also find that this effect is important even if we focus on the counterparties cities excluding investors from the firm's home city.

Finally, we divide the sample into set of state-owned (Panel B) and private (Panel C) firms. Given the particular importance of local connections in the allocation of resources for state-owned firms, we expect that the value-relevance of a change in local officials should be more pronounced for state-owned relative to private firms. Comparing Panels B and C, we indeed find that the return predictability associated with aggressive trading by investors located in the counterparty cities is highly significant in all event windows for state-owned firms, while we do not uncover significant predictability for private firms. Further, these effects are quite sizable, representing some of the largest CAR differences reported in the paper. Essentially aggressive investors near the relevant seats of power in the Chinese context appear to maintain a significant informational advantage. As with the evidence presented above on bank loans and M&A activity, the evidence on changes in important political positions also represents a novel feature of the general evidence on locational advantages, as well as provides some interesting, but more specific, evidence on the nature of the Chinese informational environment.

V. Brokerage Account Data

As a final exercise, we augment our analysis with an additional dataset on individual investor trading accounts to help shed light on the nature of top ten trading branch or fund data that have thus far been used in our study. While this more detailed dataset is only available for one brokerage firm in China, it nonetheless permits a cleaner identification of the individual traders and their locations anytime one of that brokerage firm's branches appears in the top ten list.

To provide some detail, our investor-level trading account data from this one brokerage firm come from 47 branches across 17 regions, where a "region" means a province (e.g., Liaoning), a municipality (e.g., Beijing), or an autonomous region (e.g., Xinjiang). The investor trading account data for this brokerage firm cover the full sample period (from 28th June 2007 to 31st December 2008) corresponding to the top ten data employed throughout the paper. There are 7,436 observations for which our branch-level data with full investor-level trading records also appear in the top ten list in the ten-day pre-event window used in the earlier analysis. Therefore, there are 7,436 stock-day-branch observations that are fully matched. For this matched sample, we know exactly how each individual investor trades in the stock through that branch to collectively make the branch appear on top ten list of trading for that particular stock.

Given this more detailed investor-level data, the first question we want to investigate is the composition of the individual trading that makes the specific branch appear in the top ten aggregated list. Is the notion of aggressive investor that we have promoted throughout the paper (using branch-level data) indeed reflective of one or two extremely aggressive investors trading through that branch or is it instead dominated by a group of investors trading in the same direction? To address this, we calculate the ratio of net trading imbalance of the top one or two investors to the total net trading imbalance of the branch on the specific days when a branch appears in top ten list for a particular stock.[16] Figure 3 plots the histogram of this ratio across the 7,436 observations of matched sample; Panel A provides a histogram for this ratio using only the top investor, whereas Panel B provides the same for the top two investors together. From these figures, it is clear that the top one or two investors dominate the trading associated with the overall branch on the day when the branch appears as a top ten net trader for the stock. For example, in more than 78% (94%) of the matched sample, the top one (two) investor(s) contribute more than 75% to the net trading imbalance for the particular brokerage firm for which we have data. This clearly indicates that the top ten branch and fund data potentially represent a small number of investors who trade aggressively before corporate events, corroborating our notion of aggressive individual investors.

Next, we compare the trading aggressiveness of these top investors during event and non-event periods. Table 13 reports the average of the top individual investors' net trading imbalance scaled by the average trading volume of the stock in the sample period. During the event period, when these investors make the branch appear on the top ten list for any stock, their net trading imbalance represents 1.60% of the average daily trading volume. Further, the top investor's net trading imbalance is 1.52% of the average daily trading volume across the full ten-day period prior to our events. That is, we average across not only the days branch is on the top ten list, but also the other days the top investor trades during the ten day period before events. The top investors are clearly

[16] This ratio can be above one if the top investors' net trading is in the opposite direction of the net trading imbalance of the rest of investors in the branch who also trade on the same stock.

important market participants around this time period. Last, we show that these top individual investors' net trading imbalance is 0.61% of average daily trading volume during non-event periods, less than half that in the event period. This comparison demonstrates that when top individual investors create a situation in which a particular branch appears on the top ten list during an event period, those individual investors trade much more aggressively than otherwise. This pattern also appears in the sub-sample of home investors (versus others) in the matched sample.

As a final analysis, we examine the geographic location of the individual investors in our matched sample. In our primary study using brokerage-level top ten account data, we assume the investors who trade through a particular branch live in the same city. This is certainly likely as investors need to physically visit their branch for a number of procedural reasons, and this assumption is consistent with anecdotal evidence. However, the information on individual investors' trading in our matched sample allows us to verify this assumption (at least for the sub-sample associated with this one brokerage firm). Specifically, we obtain the identity card information of each individual investor attached to their trading account registration information, including their birthplace. In our matched sample, 2.72% of accounts are general legal entry and identity card information is not available. The remaining 97.28% of the accounts are individual investors. According to their identity card information, 80.31% (86.41%) of investors who trade through the 47 branches in our sub-sample are born in the same city (province) as the location of the branch. That is, 80% of the individual investors we assumed to be local according to the branch-level data are indeed geographically proximate to that city or province. Furthermore, these figures likely serve as a lower bound as those who were not born in the same city as the particular branch could also be local investors if they work or live in the same city. Collectively, our sub-sample analysis confirms both the fact that our notion of aggressive investor in the top ten data is indeed dominated by one or two particularly active traders, and second that these traders are largely located nearby the firms in which they trade.

VI. Conclusion

By studying the trading behavior of particularly *aggressive* investors, we provide new evidence on the joint determination of trading volume and asset prices that is consistent with the presence of informational advantages such as those theorized by Wang (1994). Using a unique Chinese data set of the most active daily market participants for each stock, we uncover the importance of a particular component of aggregate volume - we demonstrate that volume associated with particularly aggressive investor buying (selling) predicts large positive (negative) abnormal returns around key announcement dates.

Unlike many other papers in this literature that are forced to infer something about the presence of informational advantages from the joint evolution of trading volumes and returns, we can go a step further by uncovering a plausible channel through which informational advantages may arise. In particular, we provide evidence of an important role for geographical proximity. The abnormal returns that we document are, in fact, largest (in absolute terms) following announcement dates in the presence of aggressive pre-event traders who share the same location as the firms in which they trade. Further, these effects are the most pronounced for stocks with the lowest analyst coverage or the smallest capitalizations; these are likely the relatively opaque firms for which the returns to informational advantages are largest. Further, we document additional corroborating evidence on the importance of geography by uncovering the fact that particularly active traders located near relevant counterparties in an M&A transaction, new bank loan facility, or a key political change also exhibit informational advantages.

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Table 1 Comparison of trading volume between our sample and Shanghai Stock exchange

Table 1 reports the statistics of trading volume on the Shanghai Stock Exchange and our sample which includes the top ten trading accounts for all 851 stocks traded on Shanghai Stock Exchange from 28th June 2007 to 31st December 2008. Panel A reports the aggregate figures for the market and our sample. The unit of trading volume is in billion CNY. The information about the market is from Shanghai Stock Exchange Statistics Annual (2009). For our sample, we report the trading volume from two channels, namely broker and fund. Individual investors and General legal entity trade through this channel. Mutual funds and some other institutional investors such as insurance companies, pension funds, brokers' own trading accounts and Qualified Foreign Institutional Investors, trade through this channel. Panel B reports the Percentage of trading volume from our top ten accounts to the total trading volume on the Shanghai Stock exchange. For each stock and each day, the percentage of net buy and sell from top ten trading accounts divided by the total trading volume is calculated, and then the average of this percentage across all the trading days for each stock is calculated. This panel reports the distributional statistics on the average of percentage across all stocks. Within the top ten trading accounts, the trading volume has been further classified into broker and fund categories, through which trades have been executed.

Panel A

Year	Statistics	Market					Sample		
		Shanghai	Individual	General Legal Entity	Specialized Institution	Mutual Fund	All	broker	fund
2008	volume	36086	30027	1429	4630	3587	9403	6014	3389
	percentage	100%	83.21%	3.96%	12.83%	9.94%	100%	63.96%	36.04%
2007	volume	61087	52541	2211	6335	5082	7436	4615	2821
	percentage	100%	86.01%	3.62%	10.37%	8.32%	100%	62.06%	37.94%

Panel B

	Trading channel	Mean	Max	P95	Median	P5	Min
Buy	Broker	22.53%	100.00%	47.40%	19.69%	7.41%	0.34%
	Fund	5.52%	100.00%	36.90%	0.00%	0.00%	0.00%
	Total	28.02%	100.00%	61.41%	23.90%	9.59%	2.48%
Sell	Broker	23.89%	100.00%	48.14%	21.30%	8.53%	0.16%
	Fund	4.93%	100.00%	33.44%	0.00%	0.00%	0.00%
	Total	28.80%	100.00%	59.80%	25.17%	10.83%	2.75%

Table 2 The location of top ten trading accounts

The sample includes all 851 stocks traded on the Shanghai Stock Exchange from 28th June 2007 to 31st December 2008. This table reports the location where the orders of top ten trading accounts are submitted. Locations have been categorized to Beijing, Shanghai, home (the city of company's headquarter), same province (the cities in the same province as the city of the company's headquarter), other cities, and fund. The trading channels of the first five types are brokers' branches and the trading channels of the location type, "fund", are investors' own trading accounts in Shanghai stock exchange. These investors are mutual fund and some other institutional investors. All stocks have been classified into 3 groups according to their company headquarters' location. For each stock, day and location type, the percentage of trading volume from top ten trading accounts to total daily trading volume is calculated and then the average of percentage across all trading days for each stock is calculated. The reported percentage is the average of the percentage across all stocks.

Trade type	Company headquarter	Beijing	Shanghai	Home	Same province	Other cities	Fund
Buy	Beijing	2.53%	3.17%			13.34%	10.11%
	Shanghai	1.47%	5.74%			14.11%	4.33%
	Other	2.00%	3.78%	1.01%	1.34%	15.06%	5.21%
Sell	Beijing	2.89%	3.43%			14.51%	9.21%
	Shanghai	1.70%	6.01%			14.75%	4.07%
	Other	2.21%	4.06%	1.04%	1.37%	15.87%	4.59%

Table 3 The number of corporate and political events

This table provides the descriptive statistics on the number of events that stocks face during the sample period from 28th June 2007 to 31st December 2008. The type of events include: earnings announcements, revisions earnings forecasts, the announcement of merger and acquisition activity, the announcement of a new bank loan, the announcement of a lawsuit, the date of a market trading suspension, and the change of relevant government officials.

Stocks	Number	Mean	Max	P95	Median	P5	Min
All	850	13.5953	46	25	12	7	1
# of events<10	185	7.6378	9	9	8	5	1
10≤# of events<20	545	13.2679	19	18	13	10	10
20≤# of events	120	24.2667	46	34.5	22.5	20	20

Table 4 The distribution of corporate and political events

This table provides the number of events used in the analysis for each month during the sample period. The type of events include: earnings announcements, revisions earnings forecasts, the announcement of merger and acquisition activity, the announcement of a new bank loan, the announcement of a lawsuit, the date of a market trading suspension, and the change of relevant government officials.

		All Events	Earnings	Earnings Forecast	M&A	Bank Loan	Lawsuit	Suspension	Governor
2007	7	301	110	147	34	0	10	0	0
	8	1005	694	7	68	65	5	128	38
	9	397	0	16	73	94	4	210	0
	10	1402	794	109	31	40	6	186	236
	11	470	0	5	26	80	10	156	193
	12	459	0	27	83	88	7	130	124
2008	1	973	17	210	73	114	4	455	100
	2	406	105	10	40	63	3	114	71
	3	689	327	26	51	90	3	74	118
	4	1426	876	228	22	106	9	145	40
	5	226	0	7	33	105	9	53	19
	6	356	0	21	31	103	8	183	10
	7	609	100	182	50	133	10	125	9
	8	1028	736	9	19	97	1	146	20
	9	393	0	13	64	131	3	180	2
	10	1196	831	90	59	80	2	133	1
	11	290	0	0	53	94	2	43	98
	12	263	0	14	63	164	10	12	0
All Time		11889	4590	1121	873	1647	106	2473	1079

Table 5 Abnormal event returns and aggressive trading

This table presents an analysis of market-adjusted returns on and after various events (including earnings, earnings forecast, M&A activity, bank loans, lawsuits, trading suspensions and changes in local political officials) conditional on different levels of aggressive investors' net trading before the event. We employ a net trading measure similar to Kaniel et al. (2012). We first compute an imbalance measure, that is, subtracting the daily value of the shares sold by aggressive investors from the value of shares bought, then dividing by the average daily dollar volume over the sample period. We then subtract from the imbalance measure the daily average of imbalances over the sample period to get the net trading measure, and compute for each stock the cumulative net trading measure over the 10 days before the announcement. We sort all events into quintiles according to net trading in the 10 trading days prior to the announcement (AINT[–10,–1]) (quintile 1 contains the stocks that aggressive investors sold the most and quintile 5 contains the stocks that aggressive investors bought the most). We then compute for each event the CAR over certain periods by subtracting the return of Shanghai Composite Index from the return of the stock. Since each period contains multiple events, we cluster events at the weekly level for CAR[0,1] and CAR[0,6] and at monthly level for CAR[0,11] and CAR[0,21]. We report the estimated means with cluster-corrected t-statistics (in parentheses, testing the hypothesis of zero CAR).

Event	Quintile	[0,1]		[0,6]		[0,11]		[0,21]	
		mean	t	mean	t	mean	t	mean	t
All	Q1	-0.0106	-3.02***	-0.0110	-1.50	-0.0115	-0.96	0.0003	0.02
	Q5	0.0024	0.86	0.0120	2.09**	0.0176	1.64	0.0256	1.31
	Q5-Q1	**0.0130**	**4.53*****	**0.0230**	**3.63*****	**0.0291**	**3.30*****	**0.0254**	**2.59****
Earning	Q1	-0.0116	-1.92*	-0.0109	-0.94	0.0004	0.03	0.0091	0.37
	Q5	-0.0049	-1.55	0.0041	0.58	0.0104	1.12	0.0171	1.06
	Q5-Q1	**0.0067**	**1.21**	**0.0150**	**1.43**	**0.0100**	**0.70**	**0.0079**	**0.54**
Earning Forecast	Q1	0.0016	0.26	-0.0022	-0.17	0.0014	0.06	0.0300	1.02
	Q5	0.0091	1.69*	0.0031	0.18	0.0135	1.08	0.0424	1.81*
	Q5-Q1	**0.0075**	**1.21**	**0.0052**	**0.32**	**0.0121**	**0.68**	**0.0124**	**0.75**
M&A	Q1	-0.0156	-1.80*	-0.0101	-0.81	-0.0218	-0.94	-0.0349	-0.87
	Q5	0.0156	2.56**	0.0371	3.15***	0.0583	2.60**	0.0740	2.47**
	Q5-Q1	**0.0312**	**3.02*****	**0.0472**	**2.97*****	**0.0801**	**3.07*****	**0.1089**	**3.46*****
Bank Loan	Q1	-0.0024	-0.67	-0.0102	-1.32	-0.0129	-0.83	-0.0209	-0.73
	Q5	0.0023	0.66	0.0082	0.92	0.0097	0.51	0.0021	0.07
	Q5-Q1	**0.0047**	**1.23**	**0.0184**	**2.09****	**0.0227**	**1.97****	**0.0230**	**1.60**
Lawsuit	Q1	-0.0164	-1.16	-0.0053	-0.32	-0.0120	-0.38	0.0008	0.02
	Q5	0.0179	0.86	0.0519	1.37	0.0361	0.56	-0.0058	-0.07
	Q5-Q1	**0.0344**	**1.51**	**0.0572**	**1.59**	**0.0481**	**1.01**	**-0.0066**	**-0.10**
Suspension	Q1	-0.0152	-3.87***	-0.0246	-2.75***	-0.0239	-1.55	-0.0029	-0.12
	Q5	0.0045	0.88	0.0055	0.57	0.0095	0.68	0.0100	0.28
	Q5-Q1	**0.0198**	**4.14*****	**0.0301**	**2.93*****	**0.0334**	**3.30*****	**0.0129**	**0.69**
Governor	Q1	-0.0126	-1.31	0.0038	0.20	-0.0240	-0.64	0.0222	0.68
	Q5	-0.0033	-0.39	0.0181	1.31	0.0160	0.58	0.0619	2.02
	Q5-Q1	**0.0093**	**1.75***	**0.0143**	**1.49**	**0.0400**	**2.79*****	**0.0397**	**2.47****

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Abnormal event returns and price reversals

This table presents an analysis of market-adjusted returns following earnings announcements conditional on different levels of aggressive investors' net trading before the event (AINT[–10,–1]) and past returns. We construct the aggressive investors' net trading measure by first computing an imbalance measure and then subtracting the mean daily imbalance over the sample period. We sort stocks into five quintiles on the cumulative market-adjusted return in [–10, –1] (CAR[–10,–1]), and within each quintile we sort on aggressive investors' net trading before the event. We then compute for each stock the cumulative market-adjusted return in [0,1] in Panel A and [0,21] in Panel B. For each of the 25 categories, we cluster events at weekly level for CAR[0,1] and at monthly level for CAR[0,21]. We report the estimated means with cluster-corrected t-statistics (in parentheses, testing the hypothesis of zero CAR).

Panel A: Cumulative Abnormal Return in [0,1] Conditional on CAR[-10,-1] and AINT[-10,-1]							
		(Negative)		CAR[-10,-1]		(Positive)	
AINT[-10,-1]		Q1	Q2	Q3	Q4	Q5	Q5-Q1
Q1	Mean	-0.0074	-0.0089**	-0.0097***	-0.01**	-0.0208***	-0.0134*
(Selling)	t	(-1.39)	(-1.97)	(-2.86)	(-2.31)	(-3.65)	(-1.86)
Q2	Mean	-0.0061	-0.0026	-0.0138***	0.0019	-0.0064	-0.0003
	t	(-0.85)	(-0.71)	(-3.71)	(0.45)	(-1.44)	(-0.04)
Q3	Mean	-0.0104	-0.0047	-0.0068*	-0.0027	0.0057	0.0161**
	t	(-1.51)	(-1.12)	(-1.87)	(-0.67)	(1.26)	(2.13)
Q4	Mean	-0.0017	-0.0013	-0.0002	0.0024	0.0028	0.0044
	t	(-0.32)	(-0.32)	(-0.06)	(0.72)	(0.68)	(0.65)
Q5	Mean	-0.0008	-0.001	-0.0009	0.0016	0.006	0.0069
（Buying)	t	(-0.15)	(-0.29)	(-0.22)	(0.4)	(1.23)	(0.97)
Q5-Q1	Mean	0.0066*	0.0078*	0.0089**	0.0116***	0.0268***	
	t	(1.81)	(1.94)	(2.45)	(2.67)	(5.31)	

Panel B: Cumulative Abnormal Return in [0,21] Conditional on CAR[-10,-1] and AINT[-10,-1]							
		(Negative)		CAR[-10,-1]		(Positive)	
AINT[-10,-1]		Q1	Q2	Q3	Q4	Q5	Q5-Q1
Q1	Mean	0.0111	0.0158	-0.0043	0.0064	-0.061**	-0.0721**
(Selling)	t	(0.72)	(0.80)	(-0.18)	(0.24)	(-2.18)	(-2.51)
Q2	Mean	0.0418**	0.0132	0.0037	0.0309	0.0345	-0.0071
	t	(2.08)	(0.78)	(0.18)	(1.03)	(1.31)	(-0.25)
Q3	Mean	0.04	0.0296	0.0231	0.0365*	0.0631*	0.0234
	t	(1.62)	(1.58)	(1.01)	(1.76)	(1.90)	(0.63)
Q4	Mean	0.0585***	0.0109	0.0406**	0.0167	0.019	-0.0399
	t	(2.75)	(0.65)	(2.13)	(0.75)	(0.83)	(-1.44)
Q5	Mean	0.0514**	0.0237	0.0124	0.0417**	0.0111	-0.0403
（Buying)	t	(2.43)	(1.49)	(0.93)	(2.42)	(0.31)	(-1.02)
Q5-Q1	Mean	0.0403**	0.008	0.0167	0.0353*	0.0721***	
	t	(2.23)	(0.47)	(1.14)	(1.83)	(3.77)	

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7 Evaluating informational advantages

This table presents a regression analysis relating market-adjusted returns on and after the event to pre-event trading by aggressive investors. The dependent variable in the regressions is the cumulative abnormal return (CAR[0,1], CAR[0,6], CAR[0,11], CAR[0,21]), and the regressors include indicator variables for events, aggressive investors' net trading before the event (AINT[–10,–1]), and past abnormal returns (CAR[-10,-1]). We construct the net individual trading measure AINT[–10,–1]) by first computing a daily imbalance measure and then subtracting the mean daily imbalance over the sample period; we compute for each stock aggressive investors' cumulative net trading measure over the period before the announcement. In order to overcome potential econometric problems associated with contemporaneously correlated errors for events that are clustered in time, we cluster events at the weekly level for CAR[0,1] and CAR[0,6] and at monthly level for CAR[0,11] and CAR[0,21]. We report the estimated coefficient of AINT[–10,–1] with cluster-corrected t-statistics (in parentheses, testing the hypothesis of zero CAR).

Event	[0,1]		[0,6]		[0,11]		[0,21]	
	coefficient	t	coefficient	t	coefficient	t	coefficient	t
All	0.0041	5.91***	0.0079	5.15***	0.0102	6.64***	0.0097	3.85***
Earning	0.0035	2.71***	0.0077	2.67***	0.0090	3.88***	0.0094	1.75*
Earning Forecast	0.0058	2.79***	0.0087	2.21**	0.0121	3.66***	0.0055	1.14
M&A	0.0053	2.45**	0.0087	2.25**	0.0135	2.70***	0.0184	2.91***
Bank Loan	0.0029	1.84*	0.0092	2.58**	0.0075	1.50	0.0093	1.37
Lawsuit	0.0056	0.47	0.0084	0.39	-0.0102	-0.35	-0.0351	-1.18
Suspension	0.0060	5.11***	0.0101	4.83***	0.0117	5.04***	0.0076	1.57
Governor	0.0009	0.70	0.0035	1.77*	0.0074	2.07**	0.0104	2.64**

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8 The role for liquidity provision

This table presents a decomposition of market-adjusted returns following pre-event individual investor trading into a portion attributed to liquidity provision and a portion attributed to information (or skill). Following Kaniel et.al (2012), for each day t during the sample period we select all the stocks in our sample that did not have any event in a 20-day window around that day. If the number of these stocks is not smaller than 200, we estimate the following three cross-sectional models:

Model 1: $CAR^i[0,21] = a_t + b_t * AINT^i[-10,-1] + c_t * CAR^i[-10,-1] + error$

Model 2: $CAR^i[0,21] = a_t + b_t * AINT^i[-10,-1] + c_t * CAR^i[-10,-1] + d_t * std^i[-10,-1] + error$

Model 3: $CAR^i[0,21] = a_t + b_t * AINT^i[-10,-1] + c_t * CAR^i[-10,-1] + d_t * std^i[-10,-1] + e_t * AINT^i[-10,-1] * std^i[-10,-1] + error$

The models give us estimated parameters that describe the relation between net trading imbalance and future returns for each day in the sample period. If the number of these stocks is smaller than 200, we directly set the model parameters to 0. To compute the expected abnormal return due to risk-averse liquidity provision for an event, we calculate aggressive investors' net trading, abnormal returns and standard deviation of returns for that stock during the pre-event period. We then multiply these variables by the parameter estimates for the date of the announcement to compute the expected abnormal return. We follow this process for each event in our sample. We compute for each event a return component that is attributed to information/skill by taking the difference between the actual abnormal return and the estimate of the abnormal return due to liquidity provision. In Panel A, we sort all events into quintiles according to aggressive investors' net trading in the 10 trading days prior to the announcement (AINT[–10,–1]). In Panel B, we sort only the adjusted events (i.e., model parameter is not zero for that day) into quintiles according to aggressive investors' net trading in the 10 trading days prior to the announcement (AINT[–10,–1]). Since each period contains multiple events, we cluster events at monthly level. We report the estimated means with cluster-corrected t-statistics (in parentheses, testing the hypothesis of zero CAR).

Panel A: Return Decomposition into Liquidity Provision and Informational Components, Full Sample (11525 observations)

AINT[-10,-1]	CAR[0,21]		ECAR1[0,21]		CAR-ECAR1		ECAR2[0,21]		CAR-ECAR2		ECAR3[0,21]		CAR-ECAR3	
	mean	t	mean	t	mean	t	mean	t	mean	t	mean	t	mean	t
Q1 (Selling)	0.0003	0.02	0.0019	0.12	-0.0016	-0.19	0.0007	0.05	-0.0004	-0.05	-0.0015	-0.10	0.0018	0.21
Q2	0.0185	0.93	0.0003	0.03	0.0181	1.35	0.0001	0.01	0.0183	1.38	0.0000	0.00	0.0185	1.40
Q3	0.0335	1.86*	0.0036	0.43	0.0299	2.15**	0.0030	0.37	0.0305	2.22**	0.0030	0.36	0.0305	2.22**
Q4	0.0362	1.85*	0.0068	0.67	0.0294	2.16**	0.0058	0.57	0.0304	2.25**	0.0059	0.57	0.0303	2.24**
Q5 (Buying)	0.0256	1.31	0.0059	0.35	0.0198	2.98***	0.0047	0.28	0.0209	3.10***	0.0047	0.28	0.0209	3.03***
Q5-Q1	0.0254	2.59**	0.0039	0.86	0.0214	2.64**	0.0040	0.81	0.0213	2.63**	0.0063	1.19	0.0191	2.31**

Table-Continued

Panel B: Return Decomposition into Liquidity Provision and Informational Components, Adjusted Sample (5202 observations)

AINT[-10,-1]	CAR[0,21]		ECAR1[0,21]		CAR-ECAR1		ECAR2[0,21]		CAR-ECAR2		ECAR3[0,21]		CAR-ECAR3	
	mean	t	mean	t	mean	t	mean	t	mean	t	mean	t	mean	t
Q1 (Selling)	-0.0168	-0.57	0.0041	0.13	-0.0209	-2.47**	0.0015	0.05	-0.0183	-2.26**	-0.0033	-0.10	-0.0134	-1.42
Q2	-0.0038	-0.13	0.0008	0.03	-0.0046	-0.71	0.0003	0.01	-0.0041	-0.65	-0.0001	0.00	-0.0037	-0.59
Q3	0.0098	0.38	0.0093	0.44	0.0005	0.07	0.0079	0.37	0.0019	0.27	0.0077	0.36	0.0020	0.28
Q4	0.0290	1.09	0.0149	0.68	0.0141	1.47	0.0128	0.58	0.0162	1.78*	0.0129	0.58	0.0161	1.76*
Q5 (Buying)	0.0274	0.85	0.0111	0.35	0.0163	1.95*	0.0090	0.28	0.0184	2.02**	0.0090	0.28	0.0184	1.96**
Q5-Q1	0.0441	4.26***	0.0070	0.74	0.0372	3.37***	0.0075	0.77	0.0367	3.30***	0.0123	1.22	0.0319	2.62**

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9 Informational advantages and geographic proximity

This table presents an analysis of market-adjusted returns on and after various events (including earnings, earnings forecast, M&A activity, bank loans, lawsuits, trading suspensions, and the change in local political officials) conditional on different levels of net trading before the event. In addition to the entire investor group, we also present the analyses of six subgroups. We use the net trading measure similar to Kaniel et al. (2012). We first compute an imbalance measure, that is, subtracting the daily value of the shares sold by aggressive investors from the value of shares bought and dividing by the average daily dollar volume over the sample period. We then subtract from the imbalance measure the daily average of imbalances over the sample period to get the net trading measure, and compute for each stock the cumulative net trading measure over the 10 days before the announcement. We sort all events into quintiles according to net trading in the 10 trading days prior to the announcement (AINT[–10,–1]) (quintile 1 contains the stocks that aggressive investors sold the most and quintile 5 contains the stocks that aggressive investors bought the most). We then compute for each event the CAR over certain periods by subtracting the return of Shanghai Composite Index from the return of the stock. Since each period contains multiple events, we cluster events at weekly level for CAR[0,1] and CAR[0,6], at monthly level for CAR[0,11] and CAR[0,21]. We report the estimated means with cluster-corrected t-statistics (in parentheses, testing the hypothesis of zero CAR). We report just the row "Difference between Q5 and Q1".

Event	Investor	[0,1]		[0,6]		[0,11]		[0,21]	
		mean	t	mean	t	mean	t	mean	t
All	All	0.0130	4.53***	0.0230	3.63***	0.0291	3.30***	0.0254	2.59**
	Home province	0.0116	4.94***	0.0176	4.50***	0.0184	4.12***	0.0188	2.77***
	Home City	0.0125	5.02***	0.0189	4.29***	0.0237	4.81***	0.0256	4.67***
	Fund	0.0078	2.52**	0.0118	1.68**	0.0158	1.25	0.0121	0.97
	Shanghai	0.0043	2.10**	0.0072	2.05**	0.0079	1.82**	0.0018	0.29
	Beijing	0.0029	1.49	0.0034	0.91	0.0115	2.85***	0.0125	1.89*
	Other	0.0034	1.35	0.0097	2.22**	0.0136	2.88***	0.0055	0.73
Earning	All	0.0067	1.21	0.0150	1.43	0.0100	0.70	0.0079	0.54
	Home province	0.0101	3.61***	0.0125	2.84***	0.0101	1.90*	0.0060	0.88
	Home City	0.0111	3.69***	0.0125	2.17**	0.0154	2.66**	0.0124	2.25**
	Fund	0.0036	0.79	0.0054	0.55	-0.0011	-0.08	0.0029	0.23
	Shanghai	0.0040	1.86*	0.0089	2.04**	0.0057	1.85*	-0.0027	-0.36
	Beijing	0.0067	2.63**	0.0039	1.04	0.0086	1.43	0.0052	0.52
	Other	0.0006	0.18	0.0074	1.17	0.0056	0.82	-0.0131	-1.32
Earning Forecast	All	0.0075	1.21	0.0052	0.32	0.0121	0.68	0.0124	0.75
	Home province	0.0134	1.57	0.0191	1.63	0.0212	1.49	0.0145	0.82
	Home City	0.0210	2.89***	0.0344	3.55***	0.0405	2.98***	0.0412	1.92*
	Fund	0.0049	0.60	-0.0048	-0.29	0.0212	0.82	0.0185	0.75
	Shanghai	0.0051	0.90	0.0223	1.99**	0.0264	2.30**	0.0203	1.17
	Beijing	-0.0052	-0.68	-0.0055	-0.46	0.0142	1.00	0.0145	0.70
	Other	-0.0008	-0.15	0.0010	0.09	-0.0010	-0.06	-0.0117	-0.92

Table-Continued

M&A	All	0.0312	3.02***	0.0472	2.97***	0.0801	3.07***	0.1089	3.46***
	Home province	0.0237	2.77***	0.0494	3.78***	0.0564	2.52**	0.0456	1.26
	Home City	0.0240	2.73***	0.0461	3.22***	0.0627	2.67***	0.0697	1.77*
	Fund	-0.0005	-0.05	-0.0187	-0.93	0.0059	0.23	-0.0214	-0.74
	Shanghai	0.0004	0.05	0.0120	0.73	0.0150	0.83	0.0355	2.61**
	Beijing	0.0340	3.78***	0.0385	2.46**	0.0533	2.80***	0.0646	2.63***
	Other	0.0038	0.43	0.0017	0.13	0.0150	0.87	0.0366	2.31**
Bank Loan	All	0.0047	1.23	0.0184	2.09**	0.0227	1.97**	0.0230	1.60
	Home province	0.0070	1.79*	0.0075	1.02	0.0086	1.08	-0.0034	-0.22
	Home City	0.0092	2.24**	0.0136	1.69	0.0197	1.94*	0.0146	0.85
	Fund	0.0089	2.08**	0.0240	2.57**	0.0264	1.99**	0.0293	1.46
	Shanghai	0.0015	0.32	-0.0011	-0.13	0.0085	1.07	0.0080	0.52
	Beijing	0.0044	1.00	0.0142	1.74	0.0324	3.54***	0.0469	2.50**
	Other	-0.0022	-0.46	-0.0025	-0.28	0.0046	0.44	0.0035	0.20
Lawsuit	All	0.0344	1.51	0.0572	1.59	0.0481	1.01	-0.0066	-0.10
	Home province	0.0227	1.26	0.0389	0.86	0.0738	1.21	0.0682	1.01
	Home City	0.0551	2.82***	0.1261	2.56**	0.1520	2.44**	0.1582	2.18**
	Fund	-0.0025	-0.10	0.0117	0.36	-0.0171	-0.17	-0.1317	-1.00
	Shanghai	0.0166	0.70	0.0055	0.11	0.0185	0.28	0.0029	0.05
	Beijing	-0.0055	-0.28	-0.0631	-1.23	-0.0751	-1.22	-0.1628	-3.00***
	Other	-0.0022	-0.12	0.0106	0.35	-0.0237	-0.64	-0.0148	-0.30
Suspension	All	0.0198	4.14***	0.0301	2.93***	0.0334	3.30***	0.0129	0.69
	Home province	0.0144	2.70***	0.0288	2.99***	0.0275	2.11**	0.0357	1.82*
	Home City	0.0146	2.85***	0.0278	3.09***	0.0281	2.68***	0.0329	2.00**
	Fund	0.0114	1.60	0.0184	1.37	0.0248	1.46	0.0191	0.61
	Shanghai	0.0080	1.38	0.0139	1.62	0.0136	0.95	-0.0012	-0.10
	Beijing	-0.0077	-1.63	-0.0087	-1.00	-0.0069	-0.58	0.0005	0.04
	Other	0.0114	2.38**	0.0191	2.20**	0.0282	2.32**	0.0203	1.45
Governor	All	0.0093	1.75*	0.0143	1.49	0.0400	2.79***	0.0397	2.47**
	Home province	0.0034	1.07	0.0141	2.33**	0.0165	1.78*	0.0222	2.36**
	Home City	0.0069	1.76*	0.0082	0.79	0.0187	1.61	0.0332	2.85***
	Fund	0.0076	1.33	0.0138	1.53	0.0315	1.84*	0.0111	0.86
	Shanghai	0.0050	1.10	0.0011	0.14	0.0041	0.46	0.0097	0.52
	Beijing	-0.0003	-0.06	-0.0060	-0.60	0.0016	0.09	0.0013	0.06
	Other	0.0107	2.15**	0.0047	0.69	0.0226	1.55	0.0309	1.23

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10 Informational advantages, geographic proximity, and the returns to informational generation

This table presents an analysis of market-adjusted returns on and after various events (including earnings, earnings forecast, M&A activity, bank loans, lawsuits, trading suspensions, and the change in local political officials) conditional on different levels of net trading before the event. In addition to the entire investor group, we also present the analyses of six subgroups. We use the net trading measure similar to Kaniel et al. (2012). We first compute an imbalance measure, that is, subtracting the daily value of the shares sold by aggressive investors from the value of shares bought and dividing by the average daily dollar volume over the sample period. We then subtract from the imbalance measure the daily average of imbalances over the sample period to get the net trading measure, and compute for each stock the cumulative net trading measure over the 10 days before the announcement. We sort all events into quintiles according to net trading in the 10 trading days prior to the announcement (AINT[–10,–1]) (quintile 1 contains the stocks that aggressive investors sold the most and quintile 5 contains the stocks that aggressive investors bought the most). We then compute for each event the CAR over certain periods by subtracting the return of Shanghai Composite Index from the return of the stock. Since each period contains multiple events, we cluster events at weekly level for CAR[0,1] and CAR[0,6], at monthly level for CAR[0,11] and CAR[0,21]. We report the estimated means with cluster-corrected t-statistics (in parentheses, testing the hypothesis of zero CAR). We define low-analyst-coverage stocks as those whose numbers of analyst followers are below the median and high-analyst-coverage stocks as those whose numbers of analyst followers are above the median. We sort stocks into deciles by market capitalization and define small stocks as those in deciles 1, 2, 3, and 4, mid-cap stocks as those in deciles 5, 6, and 7, and large stocks as those in deciles 8, 9, and 10. We report just the row "Difference between Q5 and Q1" and the columns for CAR[0,1]

Event	Investor	Low Analyst Coverage		High Analyst Coverage		Low-High		Small Size		Medium Size		Large Size		Small-Large	
		mean	t	mean	t	mean	t	mean	t	mean	t	mean	t	mean	t
All	All	0.0155	4.68***	0.0093	2.68***	0.0063	1.67*	0.0173	4.56***	0.0097	2.44**	0.0093	2.60**	0.0079	2.21**
	Home province	0.0165	5.38***	0.0047	1.64	0.0118	3.33***	0.0159	4.66***	0.0097	2.21**	0.0065	2.23**	0.0094	2.07**
	Home City	0.0186	5.16***	0.0044	1.50	0.0142	3.37***	0.0189	4.54***	0.0112	2.57**	0.0052	1.68*	0.0137	2.86***
	Fund	0.0011	0.26	0.0065	1.96**	-0.0054	-1.23	0.0048	0.96	0.0075	1.44	0.0048	1.52	0.0001	0.01
	Shanghai	0.0056	1.82*	0.0032	1.00	0.0023	0.50	0.0038	1.10	0.0057	1.55	0.0049	1.29	-0.0011	-0.23
	Beijing	0.0013	0.46	0.0054	2.12**	-0.0041	-1.12	0.0013	0.49	0.0023	0.48	0.0089	2.78***	-0.0076	-1.70*
	Other	0.0025	0.63	0.0044	1.68*	-0.0020	-0.40	0.0052	1.30	0.0008	0.22	0.0034	1.11	0.0018	0.36
Earning	All	0.0104	1.53	0.0047	0.97	0.0057	1.06	0.0133	1.98	-0.0005	-0.08	0.0080	1.85*	0.0053	1.21
	Home province	0.0110	2.47**	0.0121	3.93***	-0.0011	-0.20	0.0170	3.55***	0.0032	0.49	0.0072	1.80*	0.0098	1.90*

Table-Continued

Earning	Fund	0.0168	4.32***	0.0086	2.21**	0.0082	1.63	0.0186	3.53***	0.0086	1.48	0.0088	1.96**	0.0098	1.95*
	Shanghai	0.0016	0.38	-0.0012	-0.26	0.0029	0.56	0.0032	0.66	0.0037	0.58	-0.0005	-0.11	0.0037	0.57
	Beijing	0.0036	0.94	0.0035	0.85	0.0001	0.02	0.0050	1.14	0.0017	0.36	0.0066	1.48	-0.0016	-0.21
	Other	0.0054	1.36	0.0084	2.85***	-0.0030	-0.55	0.0049	1.37	0.0004	0.06	0.0103	2.23**	-0.0054	-0.78
	All	0.0020	0.30	-0.0020	-0.63	0.0039	0.51	0.0037	0.62	-0.0083	-2.37**	0.0022	0.52	0.0015	0.24
Earning Forecast	All	0.0066	0.87	0.0022	0.24	0.0044	0.34	0.0021	0.24	0.0178	1.34	0.0088	0.81	-0.0067	-0.47
	Home province	0.0240	2.56**	-0.0011	-0.09	0.0250	2.18**	0.0248	1.91*	0.0158	1.21	-0.0041	-0.28	0.0289	1.73*
	Home City	0.0324	3.29***	0.0082	0.98	0.0242	2.21**	0.0404	3.36***	0.0209	2.12**	0.0006	0.06	0.0398	3.44***
	Fund	0.0050	0.35	0.0062	0.60	-0.0012	-0.07	-0.0048	-0.23	0.0106	0.75	0.0073	0.59	-0.0121	-0.46
	Shanghai	0.0110	1.61	-0.0046	-0.51	0.0156	1.32	-0.0007	-0.09	0.0215	2.11**	-0.0014	-0.16	0.0007	0.06
	Beijing	0.0047	0.44	-0.0088	-0.67	0.0135	0.79	0.0001	0.01	-0.0137	-1.13	0.0039	0.33	-0.0037	-0.25
	Other	-0.0002	-0.02	0.0023	0.23	-0.0025	-0.14	0.0134	1.01	-0.0047	-0.64	-0.0102	-0.85	0.0237	1.08
M&A	All	0.0335	3.29***	0.0025	0.25	0.0309	2.08**	0.0376	2.92***	0.0335	1.27	0.0048	0.37	0.0328	1.65
	Home province	0.0321	3.43***	0.0048	0.48	0.0272	2.46**	0.0317	2.93***	0.0252	1.73*	0.0117	0.72	0.0200	1.12
	Home City	0.0262	2.73***	0.0146	1.12	0.0116	0.86	0.0286	2.61**	0.0193	1.17	0.0039	0.25	0.0248	1.45
	Fund	-0.0169	-1.13	-0.0033	-0.28	-0.0136	-0.71	-0.0186	-1.11	0.0124	0.80	-0.0049	-0.34	-0.0137	-0.60
	Shanghai	0.0106	0.96	-0.0009	-0.08	0.0115	0.70	0.0076	0.60	0.0071	0.45	0.0013	0.08	0.0063	0.29
	Beijing	0.0382	3.23***	0.0177	1.62	0.0205	1.30	0.0358	3.44***	0.0400	1.45	0.0009	0.07	0.0349	1.98**
	Other	0.0045	0.35	0.0158	1.56	-0.0113	-0.66	0.0009	0.09	0.0141	0.56	0.0045	0.26	-0.0036	-0.18
Bank Loan	All	0.0052	0.81	0.0123	2.28**	-0.0071	-0.88	0.0124	1.40	0.0056	0.78	0.0043	0.59	0.0081	0.80
	Home province	0.0147	2.58**	-0.0027	-0.48	0.0175	2.17**	0.0141	1.95*	0.0096	1.40	-0.0014	-0.21	0.0155	1.57
	Home City	0.0178	2.72***	-0.0009	-0.15	0.0178	1.87*	0.0141	1.54	0.0178	2.49**	-0.0041	-0.62	0.0181	1.58
	Fund	-0.0010	-0.15	0.0162	2.74***	-0.0172	-1.94*	0.0109	1.13	0.0058	0.77	0.0086	1.29	0.0023	0.20
	Shanghai	0.0141	2.26**	-0.0040	-0.68	0.0182	2.52**	0.0115	1.36	0.0014	0.20	0.0027	0.36	0.0088	0.90

Table-Continued

Bank Loan	Other	0.0009	0.17	0.0054	0.85	-0.0045	-0.58	0.0081	0.85	0.0055	0.72	0.0017	0.28	0.0063	0.57
	All	-0.0032	-0.45	0.0006	0.10	-0.0039	-0.38	-0.0029	-0.32	-0.0068	-0.71	0.0008	0.11	-0.0036	-0.35
Lawsuit	All	0.0425	1.73*	0.0317	0.91	0.0108	0.34	0.0405	1.62	0.0259	0.80	-0.0328	-2.10**	0.0733	2.93***
	Home province	0.0182	0.92	-0.0094	-0.60	0.0276	1.16	0.0293	1.32	0.0259	0.58	0.0093	0.22	0.0200	0.71
	Home City	0.0738	3.00***	-0.0196	-0.70	0.0934	3.09***	0.0701	2.65**	0.0120	0.21	0.0150	10.11***	0.0550	2.02**
	Fund	-0.0156	-0.53	0.0521	1.42	-0.0678	-1.72	-0.0548	-1.35	0.0736	3.53***	-0.0351	-3.26***	-0.0197	-0.43
	Shanghai	0.0232	0.85	0.0321	3.94***	-0.0089	-0.31	0.0342	1.16	0.0239	0.89	-0.0165	-1.06	0.0507	1.59
	Beijing	-0.0077	-0.42	0.0025	0.09	-0.0102	-0.40	-0.0138	-0.68	-0.0111	-0.47	0.0023	0.10	-0.0161	-0.65
	Other	0.0090	0.42	0.0075	0.21	0.0015	0.04	0.0071	0.30	-0.0119	-0.39	-0.0108	-0.60	0.0179	0.73
Suspension	All	0.0153	2.83**	0.0229	2.69***	-0.0076	-0.71	0.0181	3.02***	0.0130	1.29	0.0289	3.00***	-0.0108	-0.95
	Home province	0.0170	2.82**	0.0017	0.16	0.0153	1.37	0.0171	2.50**	0.0062	0.54	0.0117	0.97	0.0054	0.42
	Home City	0.0208	3.26***	0.0029	0.32	0.0179	1.66*	0.0201	2.63**	0.0043	0.41	0.0118	1.06	0.0083	0.64
	Fund	-0.0053	-0.44	0.0197	1.94*	-0.0250	-1.76*	-0.0025	-0.14	0.0152	1.22	0.0227	2.57**	-0.0252	-1.24
	Shanghai	0.0103	1.90*	0.0032	0.26	0.0071	0.62	0.0040	0.65	0.0096	0.98	0.0140	0.93	-0.0100	-0.70
	Beijing	-0.0106	-1.60	0.0024	0.25	-0.0130	-1.07	-0.0124	-2.12**	-0.0083	-0.85	0.0079	0.83	-0.0204	-1.71*
	Other	0.0105	1.61	0.0186	2.05**	-0.0081	-0.75	0.0104	1.41	0.0177	2.03**	0.0169	1.61	-0.0064	-0.50
Governor	All	0.0063	1.02	0.0076	0.97	-0.0013	-0.13	0.0078	1.12	0.0181	1.59	-0.0073	-0.88	0.0151	1.41
	Home province	0.0088	1.67*	-0.0044	-0.94	0.0132	1.89*	0.0019	0.38	-0.0001	-0.01	0.0123	1.37	-0.0104	-0.89
	Home City	0.0099	1.87*	0.0014	0.24	0.0085	1.14	0.0054	0.88	0.0019	0.25	0.0010	0.09	0.0045	0.32
	Fund	0.0065	0.79	-0.0058	-0.76	0.0124	1.21	0.0092	0.90	0.0149	1.13	-0.0078	-0.56	0.0169	0.94
	Shanghai	-0.0073	-1.09	0.0189	2.11**	-0.0262	-2.44**	-0.0050	-0.56	0.0143	2.06**	0.0185	1.75*	-0.0236	-1.68*
	Beijing	0.0049	0.66	-0.0015	-0.21	0.0064	0.93	-0.0019	-0.19	-0.0111	-1.11	0.0231	1.97**	-0.0249	-2.96***
	Other	0.0045	0.66	0.0131	1.70*	-0.0086	-0.75	0.0061	0.79	0.0176	1.63	0.0133	1.55	-0.0072	-0.71

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 11 Counterparties and information

This table presents an analysis of market-adjusted returns on and after bank loan and M&A events conditional on different levels of net trading before the event. For bank loan events, according to geographic locations, we group investors into 6 groups:1) home city, the investors from cities of listed companies' headquarters; 2) bhead_city, the investors from cities of corresponding banks' headquarters; 3) bhead_outprovince, the investors from cities of corresponding banks' headquarters excluding those in the home province; 4) bbranch_city, the investors from cities of corresponding banks' branches; 5) bbranch_outprovince, the investors from cities of corresponding banks' branches excluding those in the home province; 6) outall, the investors from neither cities of listed companies' headquarters nor corresponding banks' headquarter or branches. For restructure events, according to geographic locations, we group investors into 4 groups:1) home city, the investors from cities of listed companies' headquarters; 2) coparty_city, the investors from cities where counter parties are located; 3) coparty_outcity, the investors from cities where counter parties are located excluding those in the home city; 4) outall, the investors from neither cities of listed companies' headquarters nor those where counter parties are located. We use the net trading measure similar to Kaniel et al. (2012). We first compute an imbalance measure, that is, subtracting the daily value of the shares sold by aggressive investors from the value of shares bought and dividing by the average daily dollar volume over the sample period. We then subtract from the imbalance measure the daily average of imbalances over the sample period to get the net trading measure, and compute for each stock the cumulative net trading measure over the 10 days before the announcement. We sort all events into quintiles according to net trading in the 10 trading days prior to the announcement (AINT[–10,–1]) (quintile 1 contains the stocks that aggressive investors sold the most and quintile 5 contains the stocks that aggressive investors bought the most). We then compute for each event the CAR over certain periods by subtracting the return of Shanghai Composite Index from the return of the stock. Since each period contains multiple events, we cluster events at weekly level for CAR[0,1] and CAR[0,6], at monthly level for CAR[0,11] and CAR[0,21]. We report the estimated means with cluster-corrected t-statistics (in parentheses, testing the hypothesis of zero CAR).

Panel A: Counterparty in Bankloan Events

Investor	[0,1]		[0,6]		[0,11]		[0,21]	
	mean	t	mean	t	mean	t	mean	t
Homecity	0.0092	2.24**	0.0136	1.69*	0.0197	1.94*	0.0146	0.85
Bhead_city	0.0050	1.03	0.0215	2.97***	0.0333	3.56***	0.0505	2.82***
Bhead_outprovince	0.0036	0.70	0.0216	3.21***	0.0327	3.48***	0.0539	3.31***
Bbranch_city	0.0021	0.53	0.0137	1.96*	0.0184	1.65	0.0265	1.30
Bbranch_outprovince	-0.0035	-0.64	0.0076	0.83	0.0081	0.69	0.0291	1.49
Outall	0.0095	2.09**	0.0248	2.73***	0.0337	2.81***	0.0358	2.23**

Panel B: Counterparty in M&A Events

Investor	[0,1]		[0,6]		[0,11]		[0,21]	
	mean	t	mean	t	mean	t	mean	t
Homecity	0.0240	2.73***	0.0461	3.22***	0.0627	2.67***	0.0697	1.77*
Coparty_city	0.0252	2.82***	0.0509	3.45***	0.0640	2.60**	0.0774	1.93*
Coparty_outcity	0.1037	2.28**	0.1142	1.66*	0.1259	1.35	0.1664	1.61
Outall	0.0136	1.39	0.0074	0.47	0.0257	1.10	0.0426	1.78*

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 12 Political Events and information

This table presents an analysis of market-adjusted returns on and after bank loan events conditional on different levels of net trading before the event. According to geographic locations, we group investors into 4 groups: 1) home city, the investors from cities of listed companies' headquarters; 2) coparty_city, the investors from cities where corresponding political centers are located; 3) coparty_nothome, the investors from cities where corresponding political centers are located, excluding those in the home city; 4) outall, the investors from neither cities of listed companies' headquarters nor those where corresponding political centers are located. According to actual controllers, we group firms into two categories, state-owned enterprises and private firms. We use the net trading measure similar to Kaniel et al. (2012). We first compute an imbalance measure, that is, subtracting the daily value of the shares sold by aggressive investors from the value of shares bought and dividing by the average daily dollar volume over the sample period. We then subtract from the imbalance measure the daily average of imbalances over the sample period to get the net trading measure, and compute for each stock the cumulative net trading measure over the 10 days before the announcement. We sort all events into quintiles according to net trading in the 20 trading days prior to the announcement (AINT[–20,–1]) (quintile 1 contains the stocks that aggressive investors sold the most and quintile 5 contains the stocks that aggressive investors bought the most). We then compute for each event the CAR over certain periods by subtracting the return of Shanghai Composite Index from the return of the stock. Since each period contains multiple events, we cluster events at weekly level for CAR[0,1] and CAR[0,6], at monthly level for CAR[0,11] and CAR[0,21]. We report the estimated means with cluster-corrected t-statistics (in parentheses, testing the hypothesis of zero CAR). We report just the row "Difference between Q5 and Q1".

Panel A: Full Sample

Investor	[0,1]		[0,6]		[0,11]		[0,21]	
	mean	t	mean	t	mean	t	mean	t
Homecity	0.0047	0.76	-0.0040	-0.32	0.0183	1.58	0.0288	1.58
Coparty_city	0.0093	2.41**	0.0115	1.21	0.0360	2.39**	0.0367	2.22**
Coparty_nothome	0.0076	1.36	0.0177	1.73*	0.0424	2.53**	0.0392	1.86*
Outall	0.0031	0.34	-0.0071	-0.61	0.0064	0.40	0.0001	0.01

Panel B: State-owned Enterprises

Investor	[0,1]		[0,6]		[0,11]		[0,21]	
	mean	t	mean	t	mean	t	mean	t
Homecity	0.0055	0.82	-0.0054	-0.55	0.0143	1.19	0.0405	2.24**
Coparty_city	0.0146	3.04***	0.0251	2.27**	0.0586	3.60***	0.0539	3.04***
Coparty_nothome	0.0135	2.36**	0.0321	2.79***	0.0673	3.81***	0.0553	2.79***
Outall	-0.0031	-0.26	-0.0088	-0.54	0.0061	0.30	-0.0098	-0.33

Panel C: Private Firms

Investor	[0,1]		[0,6]		[0,11]		[0,21]	
	mean	t	mean	t	mean	t	mean	t
Homecity	0.0091	0.97	0.0056	0.26	0.0340	1.96*	-0.0008	-0.04
Coparty_city	-0.0010	-0.10	-0.0141	-0.93	-0.0117	-0.44	0.0001	0.00
Coparty_nothome	0.0010	0.10	-0.0107	-0.69	-0.0108	-0.39	0.0038	0.10
Outall	0.0121	1.25	-0.0055	-0.69	0.0067	0.32	0.0164	0.79

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

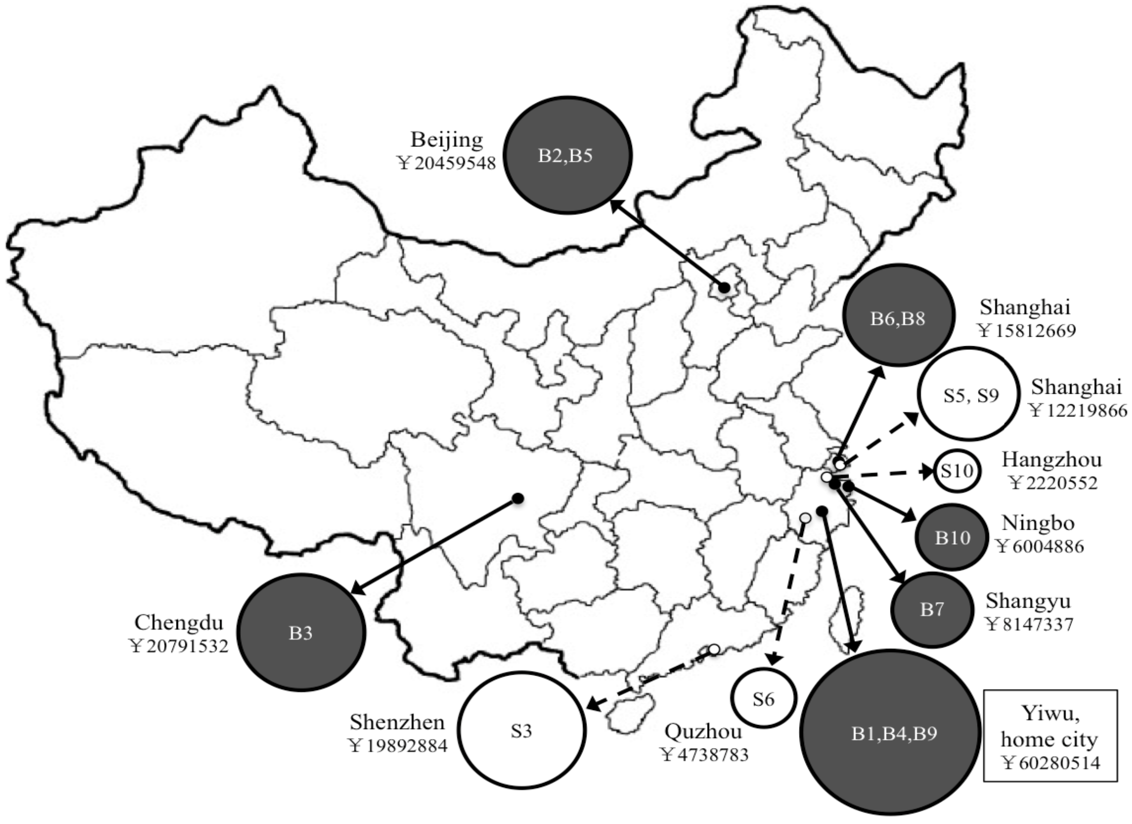
Table 13 Trading aggressiveness of the top investor

This table reports the average of net trading imbalance of the top individual investor during event and non-event periods. Each investor's net trading imbalance on a stock is scaled by the average trading volume of the stock in the sample period. The second column reports the average of the scaled net trading imbalance from the top investor when they make the branch appear on the top ten list during the ten day period prior to key events. Column 3 reports the average of the scaled net trading imbalance from the top investor during the ten day period prior to key events, where the top investors make the branch appear on top ten list at least once during this period. Column 4 reports the average of the scaled net trading imbalance from top investor during non-event periods. Home investors are the investors whose trading branch is in the same city as the headquarter of listing company of stocks they trade. Others refer to rest of investors in our matched sample.

	top ten during event periods	event-periods	non-event periods
Total	0.0160	0.0152	0.0061
Home	0.0177	0.0160	0.0070
Others	0.0158	0.0151	0.0059

Figure 1. Data example.

This figure provides an example of the data employed in the paper. We show aggressive investors' trading of the stock 600415 on 12/10/2007. The aggressive investors consist of brokerage branches of security companies and funds. B1 through B10 represent the top ten net buyers and S1 through S10 represent the top ten net sellers. Their locations are provided in the map. The grey (white) circles represent net buyers (sellers). The size of the circle reflects the total volume of net buyers or sellers in a city. Due to lack of identities of funds, their trading is not located in the map. Inside the circles are the branches or funds contributing to the corresponding volumes.



Top 10 net sellers		***City***	***Volume***
B1	Jiangbing North Road Branch	Yiwu	￥43643269
B2	Renmin North Road Branch	Chengdu	￥20791532
B3	Anyuanli Branch	Beijing	￥10939970
B4	Huagong Road Branch	Yiwu	￥9593823
B5	Banjing Road	Beijing	￥9519578
B6	Fuxing Middle Road Branch	Shanghai	￥8600908
B7	Baiguan Town Branch	Shangyu	￥8147337
B8	Xianxia Road Branch	Shanghai	￥7211761
B9	Chouzhou North Road Branch	Yiwu	￥7043422
B10	Xiaowen Street Branch	Ningbo	￥6004886
Top 10 net sellers		***City***	***Volume***
S1	Fund		￥71514515
S2	Fund		￥38238893
S3	Jingtian South Road Branch	Shenzhen	￥19892884
S4	Fund		￥16575412
S5	Haining Road Branch	Shanghai	￥8163000
S6	Shang Street Branch	Quzhou	￥4738783
S7	Fund		￥4300273
S8	Fund		￥4280000
S9	Fuxing East Road Branch	Shanghai	￥4056866
S10	Yanan Road Branch	Hangzhou	￥2220552

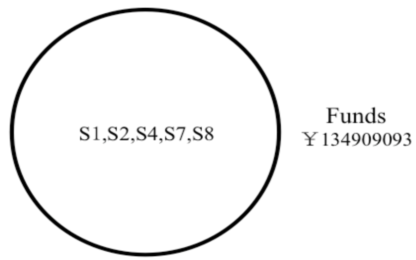


Figure 2. The average rate of appearing among the top ten investors.

For each branch (or fund), we calculate the percentage of its appearance in the top ten accounts for each stock across all the trading days of the stock. We then calculate the mean of each branch's or fund's percentage across all the stocks. In our dataset, there are 32850 accounts, 4842 of which are branches and 28008 of which are funds. Figure 2 shows the estimated histogram of the calculated mean of all the branches and funds.

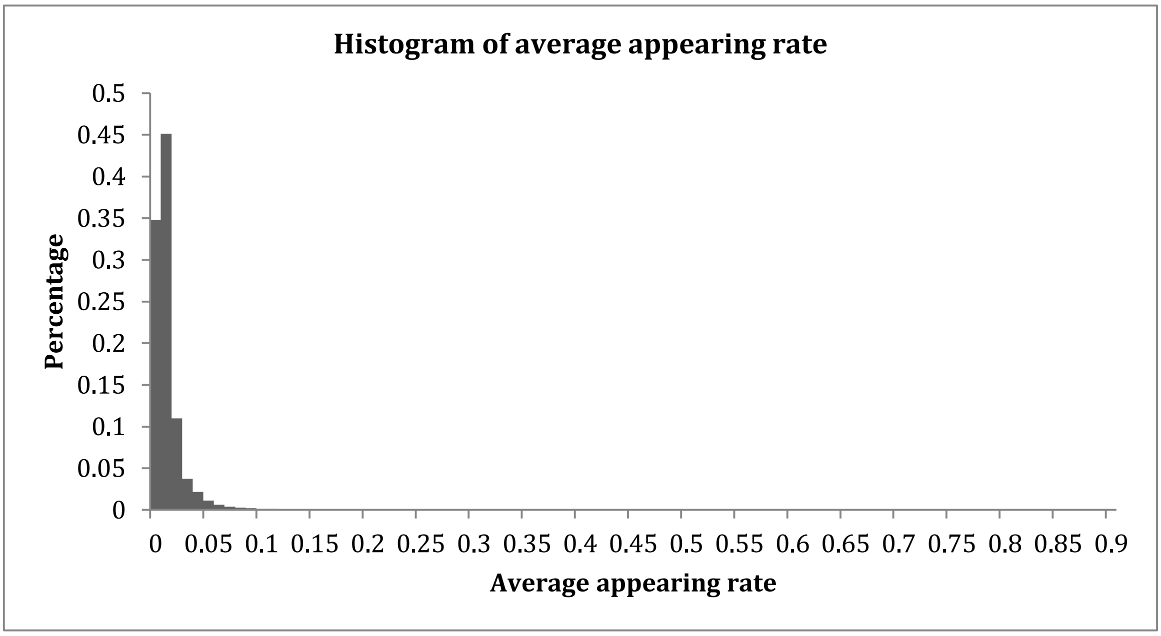


Figure 3. Contribution of the top investors

Figure 3.A (3.B) plots the histogram of the ratio of net trading imbalance of the top one (two) investor(s) to the total net trading imbalance of the branch on the specific days when a branch appears in top ten list for a particular stock.