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Christian T. Lundblad[2]

Department of Finance
Kenan-Flagler Business School
University of North Carolina at Chapel Hill
Chapel Hill, NC 27599-3490, USA,
Tel:+1 919-962-8441
E-mail: Christian_lundblad@unc.edu

Zhishu Yang

School of Economics and Management
Tsinghua University
Beijing, 100084, China
Tel.: +86-10-62771769
E-mail: yangzhsh@sem.tsinghua.edu.cn

Qi Zhang

Department of Economics and Finance
Durham University Business School
Mill Hill Lane, Durham DH1 3LB, UK.
Tel: +44 191 3345376
E-mail: qi.zhang2@durham.ac.uk

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[2] Corresponding author.

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ABSTRACT

We examine the trading behavior of particularly *aggressive* investors, those who contribute the most to daily trading volume, and provide new evidence that is consistent with the presence of informational advantages. Using a unique Chinese data set of the most active daily market participants for each stock, we demonstrate that aggressive investor buying (selling) predicts large positive (negative) abnormal returns, both unconditionally and, in particular, around key, value-relevant announcements. 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 announcements 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. We also find that particularly active traders located near relevant counterparties in an M&A transaction, a new bank loan facility, or a key political change also exhibit informational advantages. Finally, we find that a fraction of aggressive trading is unusually concentrated in individual stocks, suggesting that some component of the informational advantages that we document may reflect insider trading.

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

I. Introduction

The examination of the informational advantages possessed by various types of investors represents a central question in financial market research, as the associated findings have helped to facilitate our collective understanding of the nature of price discovery. For example, Asquith et al. (2005), Boehmer et al. (2008) and Engelberg et al. (2012) examine short sellers, Berkman et al. (2014) explore the performance of guardians behind children's accounts，Coval and Moskowitz (2001), Hau (2001), and Baik et al. (2010) explore local investors, Kaniel et al (2012) examine individual investors, Kelley and Tetlock (2013) consider retail investors, and finally, Yan and Zhang (2009) focus on short-term institutional investors.

In contrast to the extant literature, this study focuses on *aggressive* investors, defined for the purposes of this paper as those traders who contribute the most to daily trading volume. There are several reasons as to why aggressive investors might carry certain informational advantages. First, the simple observation that a collection of investors begins to trade aggressively, either in general or, especially, prior to major corporate events, deserves further scrutiny. Second, theoretical market microstructure studies often portray informed investors as aggressive; see, for example, the language employed by Holden and Subrahmanyam (1992, 1994) and Vives (1995). More recently, by generalizing Kyle's (1985) model to introduce stochastic volatility in noise trading, Collin-Dufresne and Fos (2016) demonstrate that informed, strategic investors choose to trade aggressively on their private information when sufficient market liquidity allows them to do so.[3] Third, empirical studies such as Kaniel et al. (2012) and Kelley and

[3] Our definition of aggressive investors is consistent with the meaning of "aggressive" in these theoretical studies. For example, in Holden and Subrahmanyam (1992) aggressive trading by multiple informed investors means that they trade in larger quantities than a monopolistic informed investor would otherwise choose. In Collin-Dufresne and Fos (2016), aggressive trading of informed investors refers to the fact that they trade larger volumes when markets are more liquid.

Tetlock (2013) find that individual (retail) investors appear to exhibit informational advantages. As Kaniel et al. (2012) point out, one reason that individual investors' trades exhibit return predictability is that individuals can aggressively trade on their information, while institutional investors may be more restricted, perhaps due to institutional constraints such as diversification mandates or litigation fears.

Despite the theoretical focus, data incompleteness has limited researchers' capacity to identify aggressive investors. That is, using largely U.S. market data, one is not generally able to observe the investors who contribute the most to daily trading volume across the market. Employing a unique Chinese dataset that permits the identification of the most aggressive investors, as we define them, we are the first to investigate their potential informational advantage. For 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. Therefore, our dataset can identify the aggressive investors who contribute the most to aggregated daily market volume. Furthermore, our data permit the identification of retail investors who can easily trade aggressively if/when they are informed (as opposed to institutions as in (Kaniel et al. (2012)). Finally, we also observe these aggressive investors' 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 informational advantages of various investors. We directly identify several plausible geographic-based channels through which an informational advantage could arise.

Consistent with the presence of an informational advantage of aggressive investors, we demonstrate that volume associated with particularly aggressive investor buying (selling) predicts large positive (negative) abnormal returns. Unconditionally, we demonstrate that trading by these top ten accounts predict future stock returns; that is, periods associated with abnormally large trading by aggressive investors (as a fraction of total volume) are associated with significant return predictability. Further, we show that return predictability is particularly pronounced around key, value-relevant corporate events. Pre-event trading by the 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.[4]

We also examine several measures of market quality during periods when aggressive investors trade and find that these investors are most active when the market is more liquid. This is consistent with an important prediction of the theoretical model in Collin-Dufresne and Fos (2016). Second, using additional data from the Shanghai Exchange, we shed some light on who is trading against these aggressive investors prior to value-relevant corporate events. We find that small investors generally trade against aggressive investors while large size investors trade alongside aggressive investors.

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[4] In the on-line appendix, 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), Malloy (2005), Ivkovic and Weisbenner (2005), Shive (2012), and Baik et al. (2010), among many others, explore the degree to which informational advantages might reflect location, we assess whether 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.

Geographic proximity as a key driver of informational advantages seems the most plausible conclusion one can draw. However, 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 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 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 capitalizations.

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 or agent 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 return predictability 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.

Any evaluation of our findings for the Chinese market, where insider trading rumors endlessly swirl, must acknowledge the potential for the informational advantages that we detect to be at least partially attributable to insider trading. Certainly, some of the interesting locational examples we provide might sway a reader to come to such a conclusion.

As a final exercise, we attempt to disentangle the informational advantages derived from a lower information acquisition cost associated with geographic proximity (what one might refer to as 'benign') from an unfair advantage associated with insider trading by locals. Employing the unique features of our detailed data and a novel empirical design to measure branches' aggressive trading on local stocks, we find that a fraction of aggressive trading is unusually concentrated in individual local stocks, suggesting that some component of the informational advantages that we document may reflect insider trading.

Our study contributes to several literatures. First, we contribute to the literature on investors' informational advantages by introducing to the list of informed investors a new candidate – aggressive investors who contribute the most to daily trading volume. Unlike previous studies, which usually focus on a particular type of investors (such as short sellers, short term institutions, etc.), we identify investors by the proportion to which they contribute to total trading volume. Our finding on aggressive investors' information advantage is consistent with a prediction from several theoretical studies including Holden and Subrahmanyam (1992, 1994), Vives (1995), and Collin-Dufresne and Fos (2016).

Second, our data permit the identification of aggressive retail and institutional investors, and we uncover the fact that the informational advantage of aggressive investors largely comes from retail investors. This finding contributes to a growing literature on the degree to which retail investors are informed (Kaniel et al. (2008), Kaniel et al. (2012), and Kelley and Tetlock (2013)). Previous studies conduct test based on various samples 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 the contradicting evidence found throughout the literature could simply reflect variation in the segments of retail investor population that are sampled (see Kelley and Tetlock 2013). Our top ten trading account data allows us to identify a subset of retail investors, the most aggressive across the entire retail investor population. Our finding is consistent with arguments that retail investors' trades exhibit informational advantages, but that the earlier focus on a more mixed population of retail investors may mask the fact that it is a subset that exhibits consistent return predictability.

Third, 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 physical proximity.

Finally, while the ability to detect the most aggressive investors can push forward our understanding of the nature of price discovery in a general sense, research such as this can also have important regulatory implications. To be clear, if an informational advantage is gained by skill or effort, then regulators should encourage such behavior to improve price discovery and market efficiency. However, if the informational advantage is instead a reflection of insider trading, illegal under securities laws, regulation should be considered to restrict it. Our study provides a new tool to detect potentially informed investors, as well as to further investigate the nature of their informational advantage as benign or otherwise.

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 individual investor trading and subsequent abnormal returns. Section 4 examines the role for geographical proximity as a channel through which informational advantages arise. Section 5 examines the potential role for insider trading. 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.[5]

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

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[5] 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 individual trading patterns of the remaining market participants. At the conclusion of section 3, we do explore the nature of the likely counterparties with some partially aggregated data obtained from another source.

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.[6] While some aggregation is taking place, brokerage branch activity is nevertheless an important signal about individual trader aggressiveness[7], and the data do permit an exploration of regional branch variation that may be correlated with important informational advantages.[8] 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. (stock code: 600415). Its main businesses are 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).[9] On March 5, 2008, the company announced that it would issue shares to its controlling shareholder, Yiwu State-owned Assets Investment

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[6] Because investors need to physically visit their branch for a number of procedural reasons, we assume that the individual investors are also located near the branch that they employ for trading purposes. 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. In Section V, we employ an additional investor-level dataset to confirm the geographic location of individual traders.

[7] We obtain additional investor-level data from one brokerage firm active in China. First, we confirm that the branch-level individual investors are largely located nearby the firms in which they trade. Second, these data also confirm that the event periods during which branch-level data appear in the top ten list of most active trading accounts is consistent with a dominant role for one or two extremely aggressive individuals in branches. 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 of the branches 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.

[8] 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.

[9] 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 securities regulator (China Securities Regulatory Commission, CSRC) established this rule to mitigate information asymmetry and to prevent insider trading.

Co., Ltd., in exchange for a real estate project and once trading resumes, the price appreciates significantly (hitting daily limits, effectively a circuit breaker, several days in row). Interestingly, our branch-level data allow us to observe that some investors nevertheless start aggressively trading even *before the suspension announcement* – this sort of trading deserves particular scrutiny. Figure 1 provides a visual representation of the top ten net buying and selling branches or mutual fund accounts from our database on the last trading day prior to the suspension. Specifically, a particular feature of the aggressive pre-suspension buying that we observe is that it originates from several accounts located in the firm's home city, Yiwu. Given that the stock significantly appreciates over the next several days after trading resumes, this local net buying suggests an informational advantage and episodes of concentrated, aggressive trading warrant further exploration.

While this example is intriguing, we next provide a sense of the *aggregate* importance of the subset of particularly active investors whom we 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 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.

It is also 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 are 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 and our example suggests a potential importance associated with location. 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.

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.[10]

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 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

[10] 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.

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, 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.[11]

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

[11] We report summary statistics on the distributions of events across listed firms in the online appendix.

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, so that

$$Aggressive\ Imbalance_{i,t} = \frac{Aggressive\ investors\ net\ buy\ dollar\ volume_{i,t} - Aggressive\ investors\ net\ sell\ dollar\ volume_{i,t}}{Average\ daily\ dollar\ volume\ over\ the\ sample\ period_i} \tag{1}$$

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:

$$AINT_{i,t} = Aggressive\ Imbalance_{i,t} - \frac{1}{T} \sum_{\substack{all\ days\ in \\ \text{sample}}} Aggressive\ Imbalance_{i,t} \tag{2}$$

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

$$AINT_i[t,T] = \sum_{k=t}^{T} AINT_{i,k} \tag{3}$$

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 advantages of aggressive investors by studying the degree to which return predictability is associated with abnormally large trades. We first explore the empirical relation between return predictability and aggressive trading across our entire sample. Do aggressive investors appear, on average, to maintain an informational advantage? Second, we conduct a conditional analysis by focusing on return predictability associated with aggressive trading 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 days, in the first approach, or specific key events, in the second, into quintiles according to net trading volume by aggressive investors. For each day of interest, we focus on the prior ten trading days prior to build our (signed) *AINT*[–10,–1] aggressive investor measure.[12] Quintile 1 contains the stocks that aggressive investors sold the most in the ten preceding days, and quintile 5 contains the stocks that aggressive investors purchased the most over that period. For each day, we then compute the cumulative abnormal return (*CAR*) over various periods by subtracting the return on the Shanghai Composite Index from the return of the stock.[13] Since each period over which we measure abnormal returns may contain multiple events, we cluster events at the weekly level for *CAR*[0,1] and *CAR*[0,6] and at the 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.

To obtain the mean *CAR* for an individual quintile, we regress the *CAR* on a constant. 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

[12] That is, we effectively treat each trading day as an event for the initial unconditional analysis.

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

Quintile 1 and use its coefficient. When calculating standard errors, we employ the following Rogers standard error (see Petersen (2009)):[14]

$$AVar(\beta) = \frac{T(\sum_{t=1}^{T} N_t - 1)\sum_{t=1}^{T}\left(\sum_{i=1}^{N_t} X_{it}\varepsilon_{it}\right)^2}{(\sum_{t=1}^{T} N_t - k)(T-1)\left(\sum_{t=1}^{T}\sum_{i=1}^{N_t} X_{it}^2\right)^2} \tag{4}$$

Where T is number of time period clusters, N_t is the number of events in cluster t, X_{it} and ε_{it} are the independent variable and residual for event i in cluster t. k is number of independent variables in regression.

A. Aggressive Investors and Information

Are periods of elevated trading among aggressive investors associated with return predictability? Table 3 reports estimated cumulative abnormal returns (*CAR*s) over several alternative windows conditional on different levels of aggressive investors' prior trading activity. In general, aggressive investors' trading is associated with subsequent return predictability. For example, over a two-day period, the cumulative abnormal return (*CAR*[0,1]) for stocks with large net purchases by aggressive investors over the 10 days leading up to a day (Q5) is 0.66% larger than for stocks with large net sales by aggressive investors (Q1). The statistical significance exists across all return window lengths, reinforcing the conclusion that aggressive investors maintain, on average, an economically and statistically significant informational advantage.

Before advancing to our exploration of the nature and possible origin of the information aggressive investors' might possess, we address how their high level of, likely informed, trading relates to market quality. To first establish a baseline for the Shanghai Stock Exchange, Table 4 (Panel A) provides summary statistics for several

[14] 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.

standard measures of market quality. BAS is the daily relative bid ask spread measured over various components of the order book. For example, BAS1 is computed as the difference between the closest (from the latest trade price) bid and ask prices, divided by their mean, averaged across the day. Similarly, BAS2 through BAS5 are computed using the distance between the second to fifth, respectively, closest bid and ask prices from the latest trade price in the same way. The data appear to be relatively standard in that the average bid-ask spread (BAS1) is 24 basis points, with an interquartile range from 11 to 29 basis points; the spreads naturally widen as you move out the order book. We also compute market depth (DEPTH 1) as the sum of the closest ask price multiplied by its corresponding selling volume and the closest bid price multiplied by its corresponding purchasing volume, averaged across the day. DEPTH 2 is the sum of the closest to fifth closest bid and ask prices from the latest trade price multiplied by their corresponding volumes, averaged across the day.

Next, we evaluate how aggressive trading relates to market quality. In Table 4 (Panel B), we sort all trading days into quintiles according to net trading on the day. For each trading day, we then compute the seven market quality measures detailed in Panel A. Panel B reports the mean of these market quality measures across each trading quintile. As mentioned above, quintile 1 and 5 contain the stocks that aggressive investors sold and bought the most, respectively, while quintile 3 contains stocks where aggressive trading is relatively limited. Interestingly, Panel B shows that the market quality measures, spreads and depth across various components of the order book, are significantly better for stocks in quintiles 1 and 5 than for stock in 3. At first glance, this result may be surprising; if aggressive investors trading is associated with return predictability due to the possession of an informational advantage, one might expect periods of high trading activity to be associated with elevated spreads and worsened market conditions. However, this result is consistent with the prediction of the theoretical model in Collin-Dufresne and Fos (2016), where informed investors strategically choose to trade when the market is more liquid. Collin-Dufresne and Fos (2015) study trading behaviors of activist investors and find similar evidence.

A. Return Predictability around Corporate Events

Next, we study trading before key corporate events as this is likely a period over which information asymmetry is most pronounced (Chae, 2005). Table 5 (rows 1 through 3) reports the estimated *CAR*s conditional on different levels of aggressive investors' net trading before a large collection of events. 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 two-day period, the *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 stocks 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. Notably, the magnitudes of the reported *CARs* around key corporate events are much larger than those presented in Table 3. This finding is consistent with the fact that information asymmetry is potentially much more pronounced prior to major corporate events relative to average periods of aggressive investor activity. 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 geographical proximity. Table 5 also presents evidence on the *CAR*s across stocks in quintiles Q5 and Q1, separating out the different event types. Among the various types of events, aggregate *AINT*[–10,–1] (Q5-Q1 firms) 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.[15]

Similar to Table 4 (Panel B), we continue to observe that, in the periods leading up to these events, the market is more liquid for stocks in quintiles Q1 and Q5 (the stocks aggressive investors sold or bought, respectively, the most before these events).[16] This is again consistent with the prediction of Collin-Dufresne and Fos (2016).

Finally, we shed light on who trades against aggressive investors before these various events. To do so, we employ another unique dataset from the Shanghai Stock Exchange, which reports, by groups, the proportion of a firm's investors holding different

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[15] We 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). 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. Finally, we evaluate whether the return predictability of AINT[–10,–1] is caused by liquidity provision as opposed to an informational advantage. Our results are robust to all these additional tests, and tabulated results are reported in online appendix.

[16] Tabulated results are reported in the online appendix.

numbers of shares for each stock for each day in our sample period. Using the groupings provided, we can, for example, characterize small size investors as holding less than or equal to 50,000 shares and large size investors as holding more than 100,000, with finer categories presented in Table 6. This dataset allows us to see the changes in holding proportions among various investors before events, especially when aggressive investors exhibit strong trading imbalances. Similar to our previous analysis, we sort all events into quintiles according to net trading volume by aggressive investors in the ten trading days prior to the announcement. 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 calculate the mean of the holding proportion changes of various investors across different share size holdings groups within the ten trading days before events for each quintile. We also calculate cluster-corrected *t*-statistics (cluster at monthly level, testing the hypothesis of zero holding change).

Results are reported in Table 6. Before the events when aggressive investors sold the most, small size investors *increased* their holding proportions, while large size investors did the opposite. For example, small size investors, characterized in groups as holding less than or equal to 1,000 shares, between 1,000 and 10,000 shares, and between 10,000 and 50,000 shares significantly increase their holdings by 0.28%, 1.41%, and 0.76% (collectively 2.45%) of total market capitalization, respectively, before the events aggressive investors sold the most (see Quintile 1 in Table 6). Prior to these same events, large size investors, characterized as holding between 100,000 and 500,000, 500,000 and 1,000,000, 1,000,000 and 5,000,000, 5,000,000 and 10,000,000, and larger than 10,000,000 shares significantly decrease their holding by 0.31%, 0.25%, 1.03%, 0.64%, and 0.29% (collectively 2.52%) of total market capitalization, respectively, before the events aggressive investors sold the most. The opposite is true prior to events when aggressive investors are disproportionately purchasing (see Quintile 5 in Table 6).

Taken together, we conclude that small investors trade against aggressive investors while some of large size investors trade alongside (or in some cases are) aggressive investors.

In summary, we provide strong collective evidence that the trading imbalance of aggressive investors in our sample demonstrates significant and robust return predictability across various event windows. We also find that these aggressive investors trade against small size investors. 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 possess 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 geographic proximity. Indeed, there are existing studies which show that investors close to firms possess significant informational advantages (see Coval and Moskowitz (2001), Hau (2001), Malloy (2005), Ivkovic and Weisbenner (2005), Shive (2010), 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 2 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 7 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 geographic proximity to the firms in which they trade. The aggregate event-based 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* given their information environment.

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.[17] On size, we consider groups of firms based on small, medium, and large market capitalization. The relevant cutoffs are the 40th percentile (274,000,000 CNY, $38,214,000) and the 70th percentile (678,000,000 CNY, $94,561,000).

Table 8 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.[18] 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 8 shows that the *CAR* differences associated with aggressive trading prior to all events, in aggregate, are considerably larger for firms with low analyst

[17] For every stock, we measure the number of analysts following the firm in 2007 and 2008 to proxy for analyst coverage. The 25th percentile is zero analyst coverage, the 50th is five, and the 75th 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.

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

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

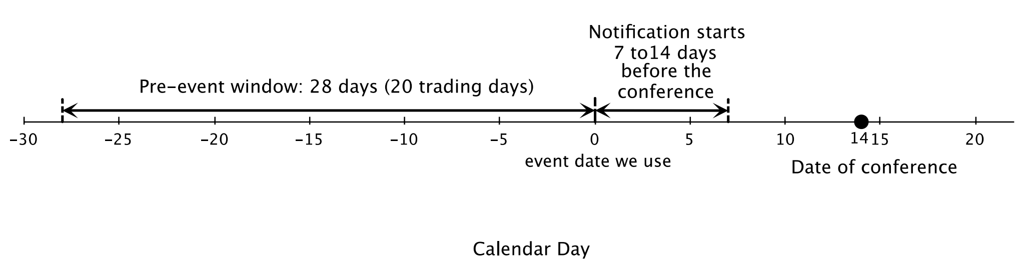
As a final analysis in this section, we focus on a subset of events (namely, bank loans, M&A activity, and changes in relevant government officials) for which there is an important counterparty involved in the origin of potentially value-relevant information. In the case of a newly issued bank loan, there is the issuing bank. In an M&A deal, this is the counterparty involved in the deal.[19] 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 9 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

[19] 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.

(again, carefully excluding those from the listed firms home province). Taken together, 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 10 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. Again, for this example, Beijing or the provincial capital represent a possible origin city for relevant political information. We also find that this effect is important even if we focus on the counterparty 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. Informational Advantages: Benign vs. Insider Trading

In this section, we attempt to disentangle the informational advantages that may be possessed by local aggressive investors derived from a lower information acquisition cost associated with geographic proximity (what one might refer to as 'benign') from an advantage associated with insider trading by locals. We hypothesize that situations in which aggressive investors gain an advantage through a reduced information acquisition cost associated with *geographic proximity* would likely yield trading activity across <u>many</u> of the firms in their home city. In contrast, if aggressive trading reflects insiders, an alternative hypothesis is that this information is presumably more firm-specific. In such instances, aggressive trading should be largely focused on a particular firm.

Specifically, we test whether the home investors who appear in the top ten list for a particular home stock also appear frequently in the lists for other local stocks. Or, is their trading activity largely concentrated in a particular nearby firm? Obviously, this is imperfect (for example, a political insider exploiting knowledge about an impending governor transition may trade multiple firms); however, an exploration of this hypothesis regarding insider trading is afforded by our unique data in way that would have been quite limited or simply impossible in earlier studies.

To illustrate the method, let's employ an example. For a branch in a particular city, we assume there are three listed local stocks, denoted by H1, H2, and H3. Imagine that the branch appears in the top ten list of H1, H2 and H3, 2, 3, and 4 times, respectively, over a relevant measurement window. The relative appearance frequencies (among all such appearances) on the top ten lists for these three stocks are 22%, 33%, and 44%. From here, one could envision an equal-weighted benchmark, essentially asking whether the elevated frequency for stock H3 is (statistically) suspicious. That is, one could establish a natural benchmark for which the frequencies should instead be 33% each. However, the average appearance frequencies of a branch across these stocks may naturally differ due to the fact that baseline trading levels are different across stocks. It may be more difficult for a branch to appear in the top ten lists of high trading volume stocks. Therefore, a proper comparison should at least adjust for the baseline nature of the stocks being traded.

We instead consider a more refined benchmark by also examining all the instances during which this branch appears in the top ten lists for stocks *outside* the home city. We divide all such instances into five groups based on the average daily trading volume of the non-local stocks in which they trade. This allows us to establish a natural relationship between the instances of appearing in the top ten lists with general stock trading in a manner quite separate from geographic proximity. Suppose that the appearances of the branch as a top 10 trader in each group of stocks ranked by overall volume, from lowest to highest, are 22%, 20%, 21%, 19% and 18%, across all such instances. Appearances naturally becomes less common, on average, in stocks traded more frequently. Now, we can link these general patterns to the particular local stocks traded by the branch. Assume that the average trading volume of stocks H1, H2, and H3 are most similar to the trading levels for groups 1, 3, and 5 based on the non-local distribution established above. If the branch's appearance frequencies in local stocks H1, H2, and H3 closely mirror its appearance frequencies in non-local stocks (i.e. trading in local and non-local stocks are similar, and local investors do not focus on some particular stocks), those local appearance frequencies should be similar to their non-home group peers (22%, 21%, and 18%).

With this benchmark in hand, we can now examine the extent to which aggressive trading of local stocks appears unusually concentrated. We employ the degree of cosine similarity[20] to calculate how similar the local trading vector (22%, 33%, and 44%) is to benchmark vector (22%, 21%, and 18%). The formula for calculating cosine similarity is as follows:

$$cosine\ similarity(V_1, V_2) = \frac{V_1 \cdot V_2}{|V_1||V_2|} \tag{5}$$

where $\cdot$ is the dot product which calculates the sum of products of corresponding elements from two vectors and $|V_1|$ and $|V_2|$ are the lengths of the vectors V_1 and V_2. If the branch somehow had the exact same appearance frequencies in local stocks as its benchmark (22%, 21%, and 18%) from non-local appearances, the cosine similarity between these identical vectors would be exactly one. Hence, we assume that appearances on the top ten lists for home city stocks that are, on balance, similar to the frequencies the same branches exhibit on non-local lists are an indication of trading on

[20] This technique originates from the field of textual analysis to calculate the similarity between two sets of texts (Kogan et al 1998). In recent years, it has been used in the economics, finance, and accounting literatures. For example, studies examine firm product similarity between companies by Hoberg and Phillips (2016), bank similarity based on 10-K Business Description section and MD&A disclosures by Robert M. Bushman et al (2017), similarity in IPO Prospectus by Hanley and Hoberg (2010, 2012), hedge fund portfolio analysis by Sias, Turtle, and Zykaj (2016), and portfolio similarity between insurance companies by Getmansky et al. (2017).

local information in a less concentrated manner consistent with relatively benign investors. In contrast, a trading pattern more concentrated in individual local stocks may be indicative of insider trading. Suppose we observe the most extreme local appearance frequency vector imaginable, (0%, 0%, and 100%) – this will exhibit a low cosine similarity value, denoted by *cosine_min*, relative to the benchmark (22%, 21%, and 18%). Any other (random) appearance frequency of the branch across home stocks should fall between *cosine_min* and one. To facilitate cross-branch and cross-city comparison, we calculate a standardized similarity measure as

$$standard\_cosine = \frac{\text{cosine\_similarity(home,benchmark)} - \text{cosine\_similarity(insider,benchmark)}}{1 - \text{cosine\_similarity(insider,benchmark)}} \quad (6)$$

where home refers to the vector of actual appearance frequencies across branches, while benchmark (insider) refers to the vector of appearance frequency of hypothetical perfectly benign (inside) trader.

The *standard_cosine* measure gauges the relative distance of a branch's home appearance between hypothetical insider and benchmark investors. We calculate *standard_cosine* for all branches.[21] To evaluate our findings, we plot the histogram of the calculated *standard_cosine* measure among branches in panel A of Figure 3. We observe that the distribution is significantly left skewed toward zero, indicating the presence of aggressive investors who appear more often in the top ten lists for local stocks in a rather concentrated manner, even when properly benchmarked. Given the sizeable advantage associated with geographic proximity that we document above, one might be tempted to conclude that such concentrated trading suggests the presence of local insider trading.

[21] To reliably employ our distance measure, we require a branch to appear at least 5 times in 2 or more home stocks to be included in the analysis. This eliminated about 30% of our branches.

Finally, to highlight the unusual nature of these distributions, we conduct a natural placebo test. For each branch, we randomly pick a city for which the branch appears in as top 10 investor (for at least two stocks from this city). For that randomly picked city, we do the exactly the same thing as we did for home city above. We calculate the *standard_cosine* of this branch in this random city and employ the same general non-local benchmark. We plot the histogram of this placebo measure across branches in panel B of Figure 3. In sharp contrast to the indications of concentrated home city trading that we observed in Panel A, we show here that the measure is much more skewed toward 1, indicative of far more balanced trading across stocks located in random (non-home) cities. Taken together, these pictures clearly demonstrate that aggressive trading in home stocks is much more concentrated in *particular* stocks than aggressive trading more broadly. While certainly not conclusive, this evidence does suggest that the informational advantages that we document in this paper are at least partially indicative of the existence of local insider trading.

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. 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, 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 geographic 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. Finally, we provide new, provocative evidence that suggests that the informational advantages that we document are at least partially attributable to the presence of local insider trading.

References

Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short interest, institutional ownership, and stock returns, *Journal of Financial Economics* 78, 243-276.

Baik, Bok, Jun-Koo Kang, and Jin-Mo Kim, 2010, Local institutional investors, information asymmetries, and equity returns, *Journal of Financial Economics* 97, 81-106.

Berkman, Henk, Paul D. Koch, and P. Joakim Westerholm, 2014, Informed trading through the accounts of children, *Journal of Finance* 69, 363-404.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2008, Which shorts are informed? *Journal of Finance* 63, 491-527.

Chae, Joon, 2005, Trading volume, information asymmetry, and timing information, *Journal of Finance* 60, 413-442.

Collin−Dufresne, Pierre, and Vyacheslav Fos, 2015, Do prices reveal the presence of informed trading? *Journal of Finance* 70, 1555-1582.

Collin−Dufresne, Pierre, and Vyacheslav Fos, 2016, Insider trading, stochastic liquidity, and equilibrium prices, *Econometrica* 84, 1441-1475.

Coval, Joshua D., and Tobias J. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811-841.

Engelberg, Joseph E., Adam V. Reed, and Matthew C. Ringgenberg, 2012, How are shorts informed? Short sellers, news, and information processing, *Journal of Financial Economics* 105, 260-278.

Fuller, Wayne A., and George E. Battese, 1974, Estimation of linear models with crossed-error structure, *Journal of Econometrics* 2, 67-78.

Hau, Harald, 2001, Location matters: an examination of trading profits, *Journal of Finance* 56, 1959-1983.

Holden, Craig W., and Avanidhar Subrahmanyam, 1992, Long−lived private information and imperfect competition, *Journal of Finance* 47, 247-270.

Holden, Craig W., and Avanidhar Subrahmanyam, 1994, Risk aversion, imperfect competition, and long-lived information, *Economics Letters* 44, 181-190.

Ivković, Zoran, and Scott Weisbenner, 2005, Local does as local is: Information content of the geography of individual investors' common stock investments, *Journal of Finance* 60, 267-306.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2008, Individual investor trading and stock returns, *Journal of Finance* 63, 273-310.

Kaniel, Ron, Shuming Liu, Gideon Saar, and Sheridan Titman, 2012, Individual investor trading and return patterns around earnings announcements, *Journal of Finance* 67, 639-680.

Kelley, Eric K., and Paul C. Tetlock, 2013, How wise are crowds? Insights from retail orders and stock returns, *Journal of Finance* 68, 1229-1265.

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

Lehmann, Bruce N, 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics* 105, 1-28.

Malloy, Christopher J, 2005, The geography of equity analysis, *Journal of Finance* 60, 719-755.

Shive, Sophie, 2012, Local investors, price discovery, and market efficiency, *Journal of Financial Economics* 104, 145-161.

Vives, Xavier, 1995, Short-term investment and the informational efficiency of the market, *Review of Financial Studies* 8, 125-160.

Yan, Xuemin Sterling, and Zhe Zhang, 2009, Institutional investors and equity returns: Are short-term institutions better informed? *Review of Financial Studies* 22, 893-924.

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 Unconditional return predictability of aggressive investors

This table presents an analysis of market-adjusted returns on and after each trading day conditional on different levels of aggressive investors' net trading before the day. 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 each trading day. We sort all trading days into quintiles according to net trading in the 10 trading days prior to the day (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 trading day the CAR over certain periods by subtracting the return of Shanghai Composite Index from the return of the stock. We cluster trading days 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).

Investor	Quintile	[0,1]		[0,6]		[0,11]		[0,21]	
		mean	t	mean	t	mean	t	mean	t
All	Q1	-0.0028	-1.31	-0.0054	-0.96	-0.0063	-0.53	-0.0028	-0.13
	Q2	0.0005	0.26	0.0053	0.99	0.0113	1.03	0.0259	1.38
	Q3	0.0025	1.39	0.0104	2.02**	0.0183	1.62	0.0353	1.84*
	Q4	0.0039	2.42**	0.0119	2.62***	0.0198	1.86*	0.0316	1.67*
	Q5	0.0038	2.62***	0.0081	2.08**	0.0114	1.20	0.0143	0.72
	Q5-Q1	0.0066	5.22***	0.0135	4.27***	0.0177	3.62***	0.0171	2.46**

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

Table 4 Market quality and aggressive trading

This table presents an analysis of market quality of each trading day conditional on different levels of aggressive investors' net trading on the day. 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 on each trading day. We sort all trading days into quintiles according to net trading on the day (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 trading day the marker quality measures. Panel A shows the summary statistics for each of the 7 market quality measures. BAS is relative bid ask spread. BAS1 is computed from the difference between the closest ask price from the latest trade price and the closest bid price from the latest trade price, divided by their mean, then averaged across the day. BAS2 to BAS5 is computed using the second to fifth closest bid and ask price from the latest trade price respectively in the same way. DEPTH 1 is the sum of the closest ask price from the latest trade price multiplied by its corresponding selling volume and the closest bid price from the latest trade price multiplied by its corresponding purchasing volume, then averaged across the day and scaled by the stock's average daily dollar volume over the sample period. DEPTH 2 is the sum of the closest to fifth closet bid and ask prices from the latest trade price multiplied by their corresponding volumes, then averaged across the day and scaled by the stock's average daily dollar volume over the sample period. Panel B reports the estimated means and cluster-corrected t-statistics (in parentheses). We cluster trading days at the weekly level.

Panel A: Summary statistics for market quality measures

Variables	Mean	Std	P10	P25	Median	P75	P90
BAS 1	0.0024	0.0015	0.0011	0.0014	0.0020	0.0029	0.0040
BAS 2	0.0059	0.0031	0.0028	0.0038	0.0052	0.0073	0.0099
BAS 3	0.0091	0.0046	0.0044	0.0059	0.0080	0.0113	0.0153
BAS 4	0.0123	0.0062	0.0059	0.0079	0.0108	0.0152	0.0206
BAS 5	0.0154	0.0078	0.0073	0.0099	0.0136	0.0190	0.0259
DEPTH 1	0.0037	0.0032	0.0012	0.0018	0.0029	0.0046	0.0070
DEPTH 2	0.0239	0.0201	0.0077	0.0116	0.0184	0.0297	0.0456

Panel B: Market quality conditional on aggressive trading

Investor	Quintile	BAS 1	BAS 2	BAS 3	BAS 4	BAS 5	DEPTH 1	DEPTH 2
		mean	mean	mean	mean	mean	mean	mean
All	Q1	0.0020	0.0049	0.0074	0.0100	0.0124	0.0049	0.0304
	Q2	0.0025	0.0062	0.0095	0.0128	0.0160	0.0032	0.0207
	Q3	0.0028	0.0071	0.0110	0.0149	0.0188	0.0026	0.0177
	Q4	0.0026	0.0064	0.0099	0.0133	0.0167	0.0031	0.0205
	Q5	0.0020	0.0050	0.0077	0.0103	0.0129	0.0047	0.0302
	Q5-Q3	-0.0008***	-0.0020***	-0.0033***	-0.0046***	-0.0059***	0.0021***	0.0125***
		(-8.72)	(-9.20)	(-9.44)	(-9.57)	(-9.68)	(16.55)	(15.60)
	Q1-Q3	-0.0009***	-0.0022***	-0.0036***	-0.0050***	-0.0063***	0.0023***	0.0127***
		(-9.66)	(-9.75)	(-9.87)	(-9.94)	(-10.01)	(17.89)	(16.08)

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

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****
Earnings	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**
Earnings 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 Shareholding proportion change

This table presents the change of shareholding proportion before events among investors with various holding size. 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 holding proportion change among investors with various holding size, such as holding less than or equal to 1000 shares, between 1000 and 10,000 shares, etc. We report the estimated means with cluster-corrected t-statistics (cluster at monthly level, testing the hypothesis of zero holding change).

Quintile	≤1000		1000~10000		10000~50000		50000~100000		100000~500000		500000~1000000		1000000~5000000		5000000~10000000		>10000000	
	mean	t	mean	t	mean	t	mean	t	mean	t	mean	t	mean	t	mean	t	mean	t
1	0.00285	7.88***	0.01405	12.69***	0.00764	9.21***	0.00061	1.67*	-0.00310	-5.16***	-0.00252	-5.88***	-0.01028	-6.81***	-0.00636	-6.36***	-0.00288	-3.20***
2	0.00041	2.94***	0.00314	12.76***	0.00161	4.49***	-0.00026	-1.20	-0.00204	-8.40***	-0.00104	-5.12***	-0.00247	-7.12***	-0.00112	-3.46***	0.00178	2.90***
3	-0.00020	-1.54	-0.00119	-3.56***	-0.00066	-1.88*	-0.00026	-2.31**	-0.00044	-1.60	-0.00002	-0.13	-0.00036	-1.41	0.00066	2.07**	0.00248	3.68***
4	-0.00053	-4.39***	-0.00442	-9.58***	-0.00223	-11.74***	-0.00006	-0.39	0.00144	4.10***	0.00063	3.49***	0.00205	6.34***	0.00020	0.57	0.00292	5.27***
5	-0.00176	-14.82***	-0.01706	-9.59***	-0.00849	-18.24***	-0.00051	-1.52	0.00466	4.27***	0.00393	8.94***	0.00919	8.89***	0.00344	4.80***	0.00660	8.25***

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

Table 7 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
Earnings	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
Earnings 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 8 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
Earnings	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

	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
Earnings	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
	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***
Earnings Forecast	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
	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
M&A	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
	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
Bank Loan	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 9 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 Bank Loan 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 10 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

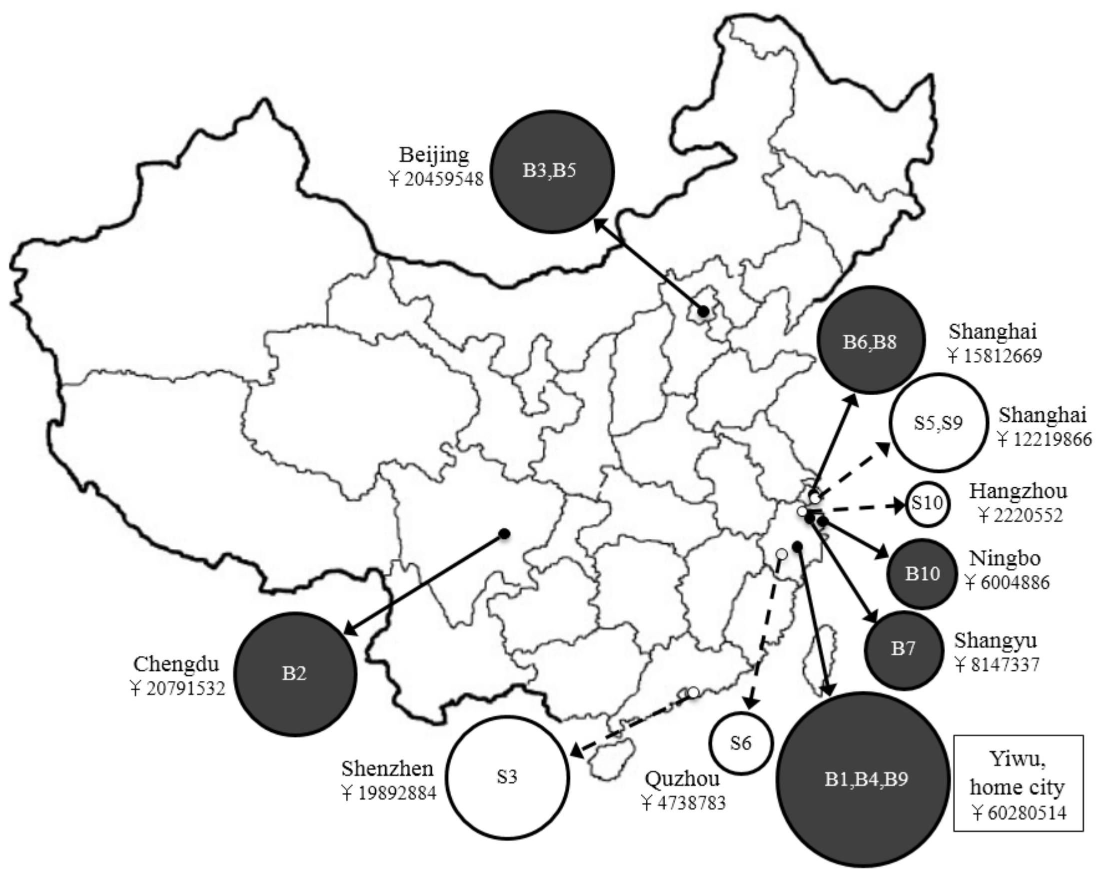
Panel C: Private Firms

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.

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 buyers		*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

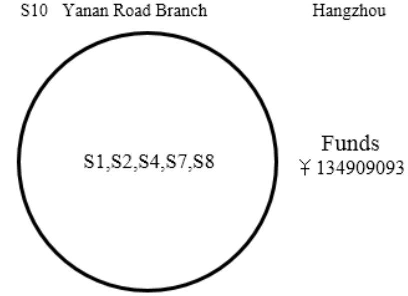


Figure 2. The average rate of appearing among the top ten investors.

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.

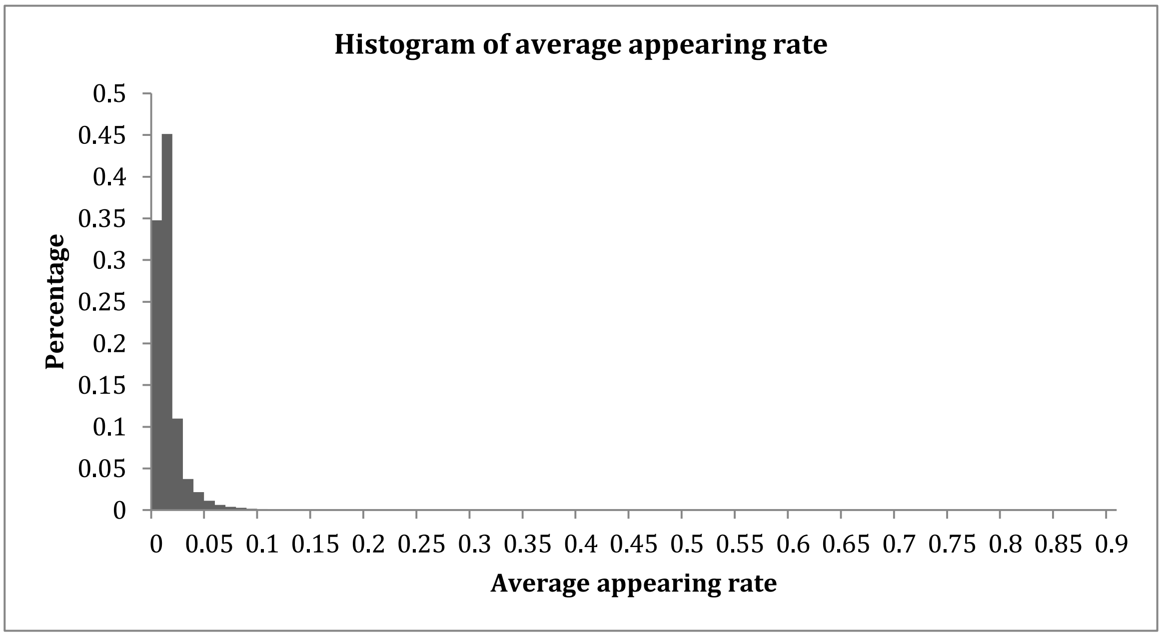


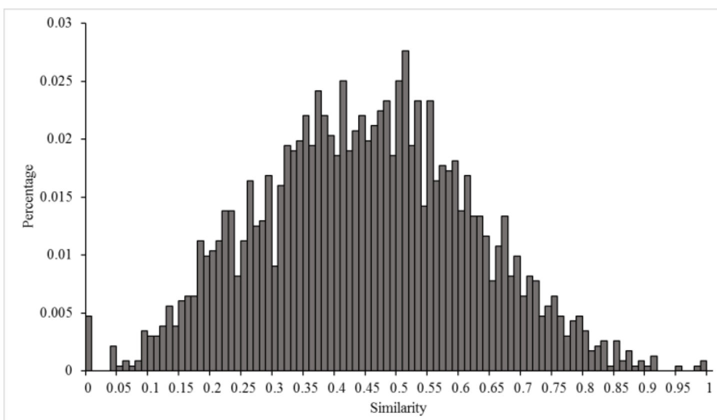
Figure 3. Distribution of branch appearance

Figure 3 plots the histogram of the standard_cosine similarity measure of branches, which is calculated as

$$standard\_cosine = \frac{\text{cosine\_similarity(home, benchmark)} - \text{cosine\_similarity(insider, benchmark)}}{1 - \text{cosine\_similarity(insider, benchmark)}}$$

Where *home* refers to the vector of the actual appearance frequency of the branches, while *benchmark* (*insider*) refers to the vector of the appearance frequency of hypothetical benign (insider). Panel A plots the histogram for branches in home city stocks' appearance, while Panel B plots the histogram for branched in a randomly drawn city stocks' appearance.

Panel A. Home city



Panel B. A randomly drawn city