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Market Reaction to Local Attention around Earnings Announcements in China: Evidence from Internet Search Activity

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Abstract: The existing literature shows that, due to locality and familiarity, spatial investor–firm adjacency plays a key role in determining stock investor attention, as proxied by the location where investors initiate an Internet search of the ticker symbol. This paper investigates whether Chinese stock markets exhibit the same pattern observed in the U.S. market—demand for a firm's information can exert strong effects on the stock market response during earnings announcements of the firm. Specifically, for each Chinese publicly listed firm, this paper constructs a dynamic local attention ratio that divides the search volume generated within the province where the firm is registered by the contemporaneous nationwide search volume consisting of 31 provinces in total. During 2011–2018 in China's A-share market, it was found that the local attention measure leads the market response around annual earnings announcement dates. For firms with higher local attention, trading is more active before the announcement, and the price changes can better predict incoming earnings news. At the announcement, while trading remains active, the predictivity of price changes for earnings becomes weaker. Furthermore, we only found evidence that supports the local information advantage argument in explaining the locality of Chinese investors' attention.

Keywords: investors' limited attention; local bias; search volume index; earnings announcement; market response

JEL Classification: D83; G12; G14

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1. Introduction

The Chinese A-share market differs from other stock markets in that retail investors not only account for a significant share of trading activities but also hold a sizable proportion of the total market capitalization. As a result, factors that affect individual behaviors play a more important role here in China. Among all these factors, many scholars highlight news reports as they help to mitigate the crucial information asymmetry problem via information dissemination, hence enhancing market response to news shock and reducing mispricing in equity assets (Engelberg and Parsons 2011; Drake et al. 2014). However, Peng and Xiong (2006) argue that only the press articles noticed and properly digested by investors could be incorporated into the latest stock prices. This is because individuals are restricted by their limited attention and are selective when processing information. They just analyze stocks that can draw their attention. In other words, information affects retail investors' decision making on the premise that they need it (Hirshleifer et al. 2009;

Drake et al. 2012). Geography turns out to be a key determinant of investors' demand for information. The previous literature has demonstrated that irrespective of retail or institutional investors in either emerging or mature markets and despite the widely accepted benefit of portfolio diversification, investors still prefer to hold and trade stocks of firms that are located geographically adjacent to themselves, displaying so-called local bias (Coval and Moskowitz 1999; Huberman 2001; Ivković and Weisbenner 2005).

Traditionally, the local bias of institutional investors is reflected in fund portfolio holdings, and that of retail investors can be measured based on order flow data taken from security brokers (Feng and Seasholes 2004). However, this measurement just captures the trading behaviors of locally biased investors. It is inefficient in terms of quantifying local attention and market reactions to it in a timely manner. In the Internet era, the way via which investors access information has changed fundamentally. Search engines have become the most important information distribution centers as well as frequently used entrances to the news. According to the China Internet Network Information Center (CNNIC), there were 989 million Internet users in China by the end of 2020 with a penetration rate of about 70% and a search engine utilization rate of more than 80%. Being China's largest search engine, Baidu.com takes up 76% of the market share as of the October 2020 statistics provided by StatCounter.com, a famous U.S. website traffic monitor website.

A recent CNNIC report states that Internet searches in China are used more intensively in scenarios such as work and study, knowledge, and news when compared to scenarios of entertainment and other life services (See Figure 1). This indicates that the search engine is more of a tool for acquiring professional information. As for investment decisions, Chinese investors can easily obtain information related to listed companies through search engine sites such as Baidu and financial news portals such as Snowball. Moreover, retail investors tend to rely more on search engines to obtain information than institutional investors (Da et al. 2011). Given the fact that the Internet has greatly reduced the cost of information acquisition, this paper first addresses the question of whether geography is still an important factor affecting Chinese investors' interest in a stock by constructing two local bias indicators in a similar fashion as in Huang et al. (2016). If the answer is yes, then the local bias of Chinese retail investors would imply more Internet searches initiated for the A-stock abbreviations of local-province-listed firms than their non-local counterparties. Unlike using posters' IP information on a specific Chinese Internet stock message board—Guba Eastmoney—this paper adopts the search index of Baidu.com, which is publicly available, thus not subject to the potential privacy issue of using web-scraped data as in Huang et al. (2016). In particular, the IP addresses of posters are no longer displayed on either Eastmoney message board webpages or its mobile app; therefore, it is unlikely that such information could be employed for future studies. Moreover, there exists the phenomenon of "thread bumping" and paid posters on discussion boards, both of which may intentionally influence public sentiment. Using the Baidu index could also avoid the hazard of distorted information.

Secondly, this paper closely follows the hypothesis construction of Chi and Shanthikumar (2017) who explore the U.S. sample to investigate whether local Chinese investor attention, as measured by the ratio of local search volume to nationwide search volume, is biased, and more importantly, whether it has an impact on the market response around earnings announcements. The logic behind this exploration lies in the main difference between local and non-local retail investors—the degree of non-public information grasped about and the level of familiarity accumulated with the underlying local-province firm. Since earnings announcements function as a primary channel for listed companies to convey information to investors, in the presence of local bias in attention, the announcing firms' local and non-local investors are more likely to behave differently around earnings announcements. Therefore, earnings announcement is an ideal laboratory to examine how investors allocate their attention will influence their trading behaviors and the subsequent asset pricing in the market.

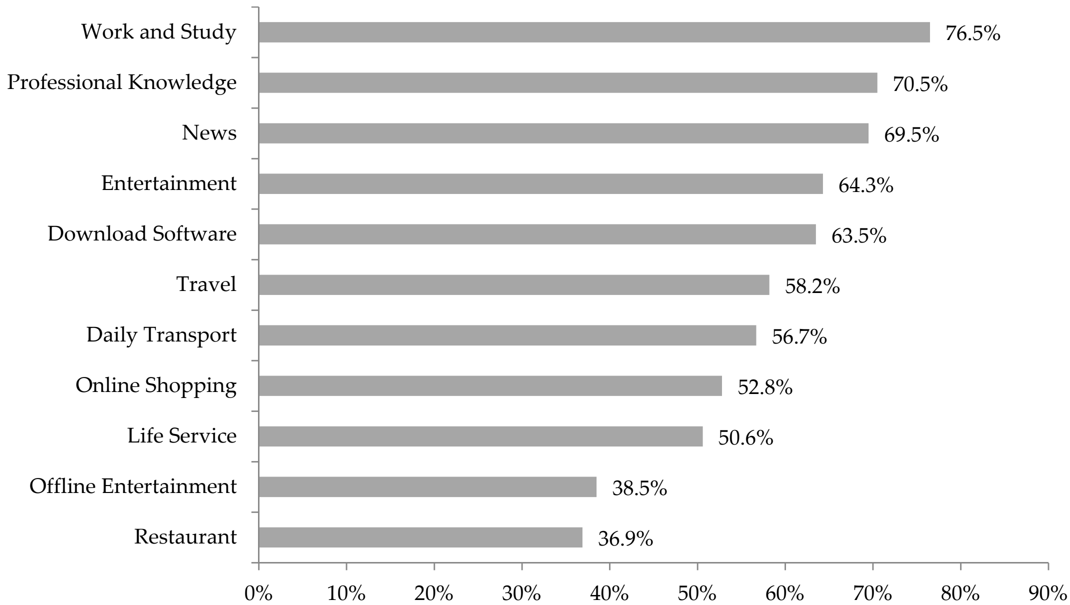

Figure 1. Search Engine Usage under Different Scenarios in China.

Due to the differences in the Internet search volume data between China and the U.S. (Jiang 2016), as well as the difference in demographic features between the two markets, the local attention measurement in this paper is constructed slightly different from that in Chi and Shanthikumar (2017). For example, the local attention ratio is not weighted for the distance between a company's headquarters and the population center of the province, because the provincial capital in a Chinese province is usually the center of population, economy, and administration. In addition, this paper provides clear details concerning sample selection and data screening, which is specifically adapted to Chinese data.

Our empirical results add to the existing literature in two aspects. Regarding the first aspect, this paper facilitates further understanding of the relationship between investor attention and information dissemination in the Chinese emerging market where retail investors prevail. A growing body of research has shown that the demand for information and the associated attention of investors affects the market reaction to earnings figures (Hirshleifer et al. 2009; Drake et al. 2012). This paper proves that province-level adjacency determines the cross-sectional distribution of individuals' attention in the Chinese A-share market. Which investors are paying attention to is more important than the number of interested investors. Further, another research body has found that geography can affect investment decisions and market reactions to news reports (Coval and Moskowitz 1999; Ivković and Weisbenner 2005; Engelberg and Parsons 2011). Utilizing the Chinese data in a similar framework of Chi and Shanthikumar (2017) to investigate the role of local attention in determining the Chinese market response around earnings announcements is meaningful because the Chinese market as an emerging market not only features a more abnormal response before and at the time of earnings announcement on average but also demonstrates much higher mean local attention than in the U.S. stock market. For most measurements of market responses, the effect of local attention is prevailing over the effect of unexpected earnings in the Chinese market, which is opposite to the results in Chi and Shanthikumar (2017).

Concerning the second aspect, we provide new pieces of evidence to understand the cause of individual investors' bias towards local firms. Do investors interested in local-province firms possess local information advantages as described in Ivković et al. (2008)? Or are they just exhibiting familiarity bias, i.e., a tendency to invest in familiar firms, as defined by Huberman (2001)? If the local information advantage explanation dominates, then we should expect informed traders to act in advance. Otherwise, if the familiarity bias explanation dominates, then the expectation is that there will be stronger price drifts for firms with higher local attention due to local investors' underreaction to actual earnings. Thus, we study the impact of local attention on the market response before and after earnings announcements. The conclusion derived based on the China case points to the local information advantage as the main cause.

Another finding reveals the different effect of local attention on market response between the Chinese and the U.S. market is that Chinese firms with more local attention will experience a higher volume of informed trading with more predictive price response to upcoming earnings prior to announcements, compared to higher volume but less price response at earnings announcements. It implies that while informed investors in the U.S. arrange transactions in advance to realize profits before the publicity of the earnings information, leading to less active trading at announcements, the Chinese investors choose to realize the gain as immediately as possible upon the publicity of the earnings information due to the Chinese government's restriction on options trading, while it is a common practice for risk hedging.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature review. Section 3 develops our hypotheses. Section 4 describes data sources and the construction of variables and the sample. Section 5 presents empirical results, followed by Section 6, which includes various robustness tests. Finally, Section 7 concludes.

2. Literature Review

Our paper is related to three strands of the literature. The first strand studies limited investor attention and its measurement. As in the seminal book of Kahneman (1973), attention is a scarce cognitive capacity. Only the information processed can be utilized (Hirshleifer and Teoh 2003). The same is true in the financial market; Fiske and Taylor (1991) argue that retail investors tend to pay more attention to earnings announcements and market shocks. While it is difficult to measure attention directly, the empirical literature adopts two types of indirect proxies constructed from the market performance (Gervais et al. 2001; Seasholes and Wu 2007; Barber and Odean 2008) and news media (Barber and Odean 2008; Grullon et al. 2004; Lou 2014; Chemmanur and Yan 2019) perspective. The validity of indirect proxies depends on the holding of the assumption that stocks with extreme market performance or intensive news coverage will get noticed. However, this assumption is questionable. After all, abnormal returns and trading can be driven by factors unrelated to investor attention. Additionally, for news reports and advertisements to take effect, they must draw attention from investors, which is not guaranteed (Hirshleifer et al. 2009; Drake et al. 2012). Nowadays, with the rapid growth of the Internet and the associated explosion of information, the attention resource becomes even more scarce.

The recent literature hence suggests using Internet search behaviors to measure intention. For example, Ginsberg et al. (2009) analyze search records of 45 influenza-related keywords and successfully predict the doctor visits of patients having similar symptoms a couple of weeks ahead of the Centers for Disease Control reports. Choi and Varian (2012) also succeed in predicting the sales of houses, automobiles, and tourism products with Internet search behaviors. In the field of finance, Da et al. (2011) adopt the Google search volume index (SVI) of the ticker symbol as the proxy for investor attention. They find that the weekly firm-specific Google SVI is positively correlated with the stock's market value, abnormal returns, turnover, and media attention. The study by Bank et al. (2011) on German stocks further confirms that SVI can reflect not only public awareness of the firm but also investor attention in the market. Due to its function of lowering information asymmetry costs, an increase in search volume can foreshadow more cross-border investment (Chen 2017), better M&A performance (Reyes 2018), and a stronger equity market reaction (Bushee et al. 2010; Joseph et al. 2011; Blankespoor et al. 2014) around earnings announcements (Drake et al. 2012, 2014) with subsequent reversal (Bijl et al. 2016). In China, Baidu.com is the most widely used search engine, and the Baidu Index can serve as the Chinese investor attention proxy. In addition, many Chinese scholars also analyze posts from online forums such as Eastmoney.com to study investor attention in China's stock market.

The second strand of the literature involves local bias and its explanation. Local bias in investment refers to the phenomenon that investors allocate too much capital to stocks geographically close to them, resulting in under-diversified portfolios. French and Poterba (1991) are the first to document how U.S. global funds are heavily weighted in the U.S. market. Coval and Moskowitz (1999) find that geographical preference also prevails in the domestic equity market—local firms producing non-traded goods are more preferred by U.S. fund managers. Individual investors around the world also tilt their portfolios toward local firms (Grinblatt and Keloharju 2001; Feng and Seasholes 2004; Ivković and Weisbenner 2005). Moreover, Huang et al. (2016) suggest that local bias is more prominent for firms headquartered in less developed regions, especially those with large market values and low stock turnover.

Two explanations exist for local bias. One relates to the local information advantage, which suggests that local investors and analysts are more likely to know insiders of and read news about local firms (Coval and Moskowitz 1999; Malloy 2005; Ivković and Weisbenner 2005; Massa and Simonov 2006; Engelberg and Parsons 2011; Bernile et al. 2015). Another highlights familiarity bias, which attributes local bias to psychological reasons such as familiarity and overconfidence (Huberman 2001; Grinblatt and Keloharju 2001; Ackert et al. 2005; Barber and Odean 2008; Goetzmann and Kumar 2008; Seasholes and Zhu 2010; Baltzer et al. 2015). Huang et al. (2016) find that local bias in the Chinese A-share market is particularly strong for firms with stock name abbreviations or ticker symbols that can tell their locality.

The third strand of relevant studies investigates stock market activities around earnings announcements (Hirshleifer et al. 2008). We rely on theoretical models from this literature to develop our hypotheses. As for the types of activity, Holthausen and Verrecchia (1990) provide an economic rationale for examining both price and trading volume changes in the market at the release of information. Kim and Verrecchia (1991) distinguish between price and volume movements, letting them represent the average change in traders' beliefs and the sum of all different reactions, respectively. Turning to the time dimension, Kim and Verrecchia (1997) define pre-announcement information as private messages gathered in anticipation of a public disclosure, and event-period information as private information useful only in conjunction with the announcement. They find evidence that trading volume is positively associated with price change in absolute value during pre-announcement periods. At the announcements, they still observe active trades even in the absence of price changes. Ball and Brown (1968) discover the post-earnings announcement drift (PEAD), meaning that stock price will continue to go up after announcements if the actual earnings are unexpectedly positive. On the contrary, if the earnings turn out to be negative, the stock price would drift downward for a while. The existence of PEAD is found in markets all over the world including China, and we would like to test how it is affected by local attention at the provincial level.

Summing up, this paper combines the above three strands of the literature. We use the Chinese stock market as a laboratory to corroborate the impact of geography-induced attention bias on retail investors' behavior and the aggregated market reaction around the event window of annual earnings announcements.

3. Hypothesis Development

Chi and Shanthikumar (2017) have provided solid evidence for investors' local bias in the U.S. stock market in the Internet era when long-distance communication is easier than ever before. In China's A-share market, the local bias of investors is also found by using IP addresses in online forums and search records in Internet search engines. As a result, we also begin by examining the existence of location attention measured by the Baidu search index. Then, we conjecture that the strength of local attention in China varies with firm visibility level. Therefore, the first hypothesis is stated as follows.

Hypothesis 1 (H1): *There exists local attention in the Chinese stock market as evidenced by two facts that (a) firms receive more attention from local investors; and (b) the local attention of a firm is closely related to its visibility.*

Since access to information enhances with increased investor attention and efficient information dissemination, we continue to explore the role of local attention in driving the market response at, before, and after earnings announcements. Given the two possible causes of local attention, we follow Chi and Shanthikumar (2017) and design the two hypotheses below for the Chinese stock markets so that the specific impact of each explanation for market reactions right at and before the earnings announcement can be identified and tested.

Hypothesis 2 (H2): *Higher local attention weakens market response to the earnings announcement on the release day, as measured by (a) lower trading volume; and (b) lower price response to unexpected earnings.*

Hypothesis 3 (H3): *Higher local attention leads to more privately informed anticipatory trading before the earnings announcement, as measured by (a) higher trading volume; and (b) a higher correlation between returns and the unexpected earnings to be disclosed.*

Specifically, let us first discuss the local-information-advantage explanation. On the one hand, according to the theoretical predictions made by Holthausen and Verrecchia (1990) and Kim and Verrecchia (1991, 1997), if more local investors possess private information before the earnings announcement, the announcing event would provide less new information to the market, resulting in lower trading volumes and weaker price changes on and immediately after the announcement day. Following this logic, firms with higher local attention, i.e., firms with a higher proportion of local search volume, should experience smaller market reactions. While this hand of argument is confirmed by Chi and Shanthikumar (2017) with the U.S. data, it does not necessarily hold in the Chinese stock market. On the other hand, based on Kahneman and Tversky (1979), H2a could be rejected because investors tend to sell stocks that have gained value to avoid further risks once the private information becomes public. We refer to such behaviors as "trading to preserve gain", which may lead to higher trading volumes at the announcement. So, in theory, the turnover of stocks with local attention can either go down or up on earnings announcement days.

No contradictory prediction exists for market reaction before the earnings announcement for the local information advantage theory. All existing studies suggest an unambiguous hypothesis H3 that more local investors of a firm are associated with the firm's higher trading volume prior to the announcement (Easley and O'Hara 1992). That is, the trading behavior of local investors should be more predictable with forthcoming earnings (Christophe et al. 2004). Additionally, more information about the upcoming announcement will be impounded into the current stock price (Drake et al. 2012).

Then, we discuss how to test the familiarity-bias explanation. Huberman (2001) suggests that investors driven by familiarity bias tend to be optimistic about things they are familiar with and comfortable with. So, they may choose to buy a particular stock simply because they know the firm well rather than because they learn positive information. Their portfolios are also likely to be static. Since "buy-and-hold" is their common strategy, familiarity will make local investors less responsive to information. Barber and Odean (2008) also point out that investors are more likely to buy rather than sell stocks that attract their attention. This implies that, in the presence of search costs, attention has a greater impact on buying rather than selling decisions, and investors are more optimistic about stocks that they are more familiar with. Therefore, for stocks with high local attention, their market performance should be less responsive to earnings information, i.e., lower trading volume and price sensitivity. If this is true, H2 holds. Moreover, due to the under-reaction in the early stage, price drift towards the direction of unexpected earnings will be more prominent after the earnings announcement, supporting H4 below. Recall that the local information advantage theory cannot lead to this prediction. On the contrary, the local information advantage may lead to a drift in the opposite direction of unexpected earnings due to over-reaction. After the earnings announcement, since investors driven by familiarity bias would underreact to earnings information at the announcement, there will be a stronger drift if there are more local investors in China, similar to the U.S. market reactions described in Chi and Shanthikumar (2017).

Hypothesis 4 (H4): *Higher local attention in a search increases price drift in the same direction as the unexpected earnings after the earnings announcement.*

In summary, H2 tests both the local information advantage and familiarity bias explanations of local investor attention, while H3 is designed for the local information advantage explanation, and H4 is developed to find support for the familiarity bias explanation. If local attention in China can be explained by both explanations, then we expect to find empirical evidence consistent with H3 and H4. Otherwise, if only one explanation drives locality, then only one hypothesis will hold, either H3 or H4.

4. Data Sources

To establish our baseline sample, we start with all non-financial firms initially listed in the Chinese A-share markets before 2018. Secondly, we exclude (i) companies that had been designated as Special Treatment (ST, which is the first step by a Chinese stock exchange in delisting a stock) at least once; (ii) those whose abbreviations of A-Stock have altered once or have not been included in the Baidu search index; and (iii) those with obvious ambiguity in their abbreviations (i.e., retail investors with limited investment experiences may be confused with one another).

Then, we are left with 2070 firms, for which we obtain data on their 2010–2018 annual earnings announcement dates from the China Stock Market & Accounting Research Database (CSMAR). Next, the 14,391 firm-year observations from the above steps are further screened based on the following criteria. First, to avoid the impact of quarterly earnings announcement events on the annual announcement, we delete the observations in which the firm's quarterly earnings disclosure coincides with its annual announcement. Second, to ensure we have sufficient data for each firm to calculate abnormal returns and abnormal trading volumes, stocks traded less than 205 days in the 400 days before the disclosure date of the annual report, firms suspended at their disclosure dates, and stocks traded less than 61 days in the 120 days after the disclosure date of the annual report are further excluded. Third, to avoid the distraction of long holidays on investors' attention to the annual earnings announcement, observations of which firms disclose their earnings before non-weekend holidays are excluded. Fourth, we exclude observations with missing key financial indicators.

For the final step, after the above screening process, 7214 firm-year observations are obtained. Table A1 in Appendix A characterizes the distribution of our sample by industry, year, and province. According to the industry classification of the China Securities Regulatory Commission (CSRC), we categorize our sample firms into different industries and find that the manufacturing industry accounts for 64.8% of observations, followed by wholesale and retail, information technology, real estate, and transportation industry. In the time dimension, sample firms from the fiscal years 2017 and 2018 account for a large proportion. From 2012 to 2016, our sample firms are more evenly distributed. Geographically speaking, Guangdong, Zhejiang, Beijing, and other economically developed regions host more firms in the sample. Sample firms registered in Guangdong province alone account for 14.2% of the total number of observations, while those registered in Zhejiang, Beijing, and Jiangsu account for 11.6%, 10.2%, and 10.1%, respectively. In underdeveloped provinces such as Ningxia, Hainan, Qinghai, and Inner Mongolia, the sample size is much smaller.

It merits a note that data on announcement dates, stock market trading activities, and news reports are all sourced from CSMAR, while data on firm fundamentals such as financial position and number of employees are obtained from The WIND Economic Database. The Baidu search index is available on the website http://index.baidu.com (accessed on 1 February 2021).

After describing the sample, we now are ready to introduce the variables. To test H1, local attention bias is defined by comparing the absolute measure with a benchmark measure of no local bias. We use the event study approach to test H2–4, regarding the impact of local attention on different types of market response at various periods around the earnings announcement. Naturally, the event here is the annual earnings announcement, and its disclosure date is set as the event occurrence time (t = 0). When a firm discloses its annual earnings after the market closing on Friday, we let the event date be next Monday.

First of all, we measure local attention in China with the search volume generated by Internet users of Baidu.com. For each keyword, the Baidu index calculates a weighted sum of volumes from two search types: those initiated from personal computer terminals that start from June 2006 and those initiated from mobile devices that are recorded since January 2011. Da et al. (2011) suggest that, like keywords, ticker symbols (e.g., "MSFT") are less ambiguous than firm names such as "Microsoft", since searching by ticker symbols is highly likely to be investment-related. Following Huang et al. (2016), this paper first aggregates the daily Baidu index for the firm's A-stock abbreviation to the annual level. We then identify local attention by establishing the local version of the index only consisting of searches initiated from the province where the concerned firm is registered. Thus, we construct the following ratio to proxy for the degree of Chinese investors' local attention to a firm.

$$\%Local_{i,t} = \frac{BaiduIndex_{i,t,local}}{BaiduIndex_{i,t,national}} \times 100\%,$$

where $BaiduIndex_{i,t,local}$ is the local Baidu index for firm i in year t generated from the province where the firm is registered, and $BaiduIndex_{i,t,national}$ is the nation-wide Baidu index for firm i in year t generated from all provinces in China.

Next, we compute the standardized unexpected earnings using the same method described in Hirshleifer et al. (2009).

$$UE_{i,t} = AE_{i,t} - FE_{i,t},$$

where $AE_{i,t}$ is firm i's actual earnings per share in year t, and $FE_{i,t}$ is the corresponding expected (forecasted) earnings per share. There are two methods to measure FE: one directly uses analyst forecast and another uses the last-period earnings as forecasts for the current period based on the random walk model. Previous studies (Lee 1992; Bhattacharya 2001; Ke and Petroni 2004; Hirshleifer et al. 2008; Shanthikumar 2012) have shown that, while earnings computed by the former method are more consistent with what institutional investors expect, the latter method gives more appropriate earnings expectations for retail investors. These two expectations may lead to different results when estimating post-earnings drift (Ayers et al. 2011). Since our setup targets individual actions around announcements, we prefer the random-walk expected earnings and scale them by the per-share closing price at the end of the fiscal year. This standardized unexpected earning is thus:

$$SUE_{i,t} = \frac{UE_{i,t}}{P_{i,t}}.$$

Third, we follow Hirshleifer et al. (2009) to calculate the abnormal trading volume and cumulative abnormal return (CAR). In specific, this volume is the sum of the differences between a stock's daily trading volume in natural logarithm and the average log volume over the estimation window [−100, −11]. We also utilize the same formula to calculate the abnormal trading volume for windows [−5, −1] and [0, 1].

$$AbVol[t_1,\ t_2]_i = \sum_{t=t_1}^{t_2} \left[log(Vol_{i,t}) - \frac{1}{90} \sum_{s=-100}^{-11} log(Vol_{i,s}) \right].$$

The CAR of a stock equals its actual return minus a benchmark return. In the relevant empirical literature, the following three methods are commonly adopted to estimate the benchmark return. The mean adjustment method, the risk adjustment method, and the market model use, respectively, the stock's average return, the return of the market portfolio, and the CAPM predictive return during the event window as the benchmark return. This paper chooses the market model and employs the following OLS regression to estimate the CAPM coefficients for stock i.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ and $R_{m,t}$ are the cash dividend reinvestment yield of stock i and the CSI300 market portfolio at t, respectively. The estimation window is [−205, −6], tracing back to 200 trading days before the announcement. The return data are taken from CSMAR. Given the estimated coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$, the abnormal return for stock i at t equals:

$$AR_{i,t} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{m,t}.$$

The cumulative abnormal return for stock i during the event window $[t_1, t_2]$ is hence calculated as follows. We also repeat the CAR calculation for event windows [−5, −1], [0, 1], and [2, 31] in the robustness section.

$$CAR[t_1, t_2]_i = \sum_{t=t_1}^{t_2} AR_{i,t}.$$

Lastly, we introduce a range of control variables that may affect the market response to earnings information. For example, we include announcement density (*R_EA*), as Hirshleifer et al. (2009) found that investors would be distracted by the earnings released by other firms on the same day. In other words, when many firms announce their earnings simultaneously, the immediate market response to the unexpected earnings of our concerned firm becomes weakened and the post-earnings drift becomes greater. We also include the Baidu search volume (*LnSVI*) since Hirshleifer and Teoh (2003) discovered that insufficient attention from overall investors will lead to the neglect of earnings announcements for a specific firm, thus failing to incorporate the earnings information into its stock price in a timely manner. Another control included is earnings sustainability (*EP*): Collins and Kothari (1989) state that the sensitivity of stock price to earnings information is affected by earnings sustainability. We follow this paper by using the first-order autocorrelation coefficient of annual earnings per share in the last four years to measure firm-specific earnings sustainability. Earnings volatility (*EV*) is also important according to Hirshleifer et al. (2009). So, we utilize the standard deviation of annual earnings per share in the last four years to measure *EV*. In addition, we control for the analyst coverage (*LnAF*) because it has been proven to exert an impact on the market response to earnings. Therefore, to measure the analysts' attention to a given firm, we calculate the natural logarithm of the sum of 1 and the number of institutions making forecasts 180 days around the end of the fiscal year. In addition, this paper also controls for the firm size (*LnSize*), institutional ownership (*IO*), and book-to-market ratio (*BM*) in the spirit of Collins and Kothari (1989) and Teoh and Wong (1993). Table A2 in the Appendix A provides a list of the source and definition of our main variables.

As for empirical specifications, recall that we seek answers to three questions. (i) Is there local bias in Chinese retail investors' search behavior? (ii) What is the impact of local attention on the market response to the earnings announcement? (iii) Can the local information advantage or familiarity bias explain such local preference in the A-share market? We develop H1 to approach the first question and H2–4 for the last two questions. In addition, the empirical results of H3–4 can provide evidence for the explanatory power of the two alternative explanations of local attention.

To test H1a, we need a benchmark of no local bias, which is either the percentage of Internet users in a province or the percentage of A-share stock accounts in a province.

$$\%Benchmark_{user,\ i,t} = \frac{InternetUser_{i,local}}{InternetUser_{national}} \times 100\%,$$

where $InternetUser_{i,local}$ and $InternetUser_{national}$ are the number of Internet users in firm i's registration province and China, respectively, according to CNNIC.

$$\%Benchmark_{account,i,t} = \frac{InvestorAccount_{i,local}}{InvestorAccount_{national}} \times 100\%,$$

where $InvestorAccount_{i,local}$ and $InvestorAccount_{national}$ are the numbers of A-share stock accounts in firm i's registration province and all over China, respectively, according to data provided by China Securities Depository and Clearing. Thus, we compare the percentage of local searches with each of these two benchmarks by constructing the following test statistic:

$$LB_{i,t} = \frac{\%Local_{i,t}}{\%Benchmark_{i,t}} - 1.$$

In the absence of local bias, the expected value of LB should have no significant difference from zero. The mean of LB will be larger when the degree of local bias is higher for a given province. A t-test is used for the null and alternative hypotheses of:

$$H_0 : E(LB_{i,t}) = 0;\ H_1 : E(LB_{i,t}) \neq 0.$$

If the expected values of local bias under both benchmarks are significantly different from zero, then we can reject the null hypothesis and believe that retail investors in China display local bias in searching for stock information on the Internet. Next, to test H1b which links local attention with firm visibility, we have the first model:

$$\%Local_{i,t} = \gamma_0 + \gamma_1 LnSVI_{i,t} + \gamma_2 News_{i,t} + \boldsymbol{\gamma_3} \cdot \mathbf{Z}_{i,t} + \gamma_4 Province_i + \gamma_5 Year_i + \varepsilon_{i,t}. \quad (1)$$

In the above equation, $LnSVI_{i,t}$ reflects the change in the visibility of the firm over time to investors who rely on Baidu for stock information (Da et al. 2011; Drake et al. 2012). *News* is the natural logarithm of the count of news pieces about a firm in a year, indicating the media exposure of the firm (Bushee et al. 2010). $\mathbf{Z}$ is a vector consisting of nine control variables: *LnSize*, *AdvExp*, *LnEMP*, *LnSHR*, *LnAF*, *IO*, *BM*, *CSI300*, and *Retail*. *LnSize* is the natural logarithm of the average daily firm market value over the fiscal year. Coval and Moskowitz (1999) have shown that firms with lower market value suffer from stronger bias. Let *AdvExp* be the selling expense as a proportion of the operating revenue. Advertisement relates closely to investor awareness (Grullon et al. 2004; Lou 2014), but advertising expenditure is not a required disclosure item in China. We use selling expenses as a rough approximation. *LnEMP* and *LnSHR* are, respectively, the natural logarithm of the number of employees and the number of shareholders of a firm. Hong et al. (2008) and Bushee et al. (2010) demonstrate that more employees and shareholders raise firm visibility. The above specification also controls for analyst coverage (*LnAF*) and institutional ownership (*IO*), both of which are related to higher visibility in the market. *BM* is the ratio of the book value of net assets to its market value at the end of the reporting period. Firms with low book-to-market ratios may be more favored and cared about by investors (Lakonishok et al. 1994). Ivković and Weisbenner (2005) found that investors have a lower local bias for the S&P 500 stocks. As a result, we also introduce a *CSI300* dummy (which equals 1 if the stock is a CSI300 component stock in the A-share market; it is 0 otherwise). Finally, if a firm sells consumption goods, then it is likely that the firm will be more visible to investors. According to the CSRC industry classification, companies operating in the retail, air transport, accommodation, furniture manufacturing, and food industries are assigned 1 for the dummy *Retail*.

We then establish two models to examine the impact of local bias on the market response around the earnings announcement. Equation (2) is specified to test how local attention in a search affects abnormal trading volume as in H2a and H3a.

$$AbVol[t_1, t_2]_{i,t} = \alpha_0 + \alpha_1 R_{SUE\,i,t} + \alpha_2 R_{\%Local\,i,t-1} + \alpha_3 LnSVI_{i,t-1} + \boldsymbol{\alpha_4}\cdot\boldsymbol{X}_{i,t} + \boldsymbol{\alpha_5}\cdot\boldsymbol{F} + \varepsilon_{i,t}. \quad (2)$$

In the above equation, *R_SUE* is the annual decile rank of standardized unexpected earnings, ranging from 1 to 10; and *R_%Local* is the annual decile rank of lagged local attention, normalized to the range of [−0.5, 0.5]. Besides controlling for factors that may affect trading volumes around the earnings announcement in vector $\boldsymbol{X}$ including *LnSize*, *IO*, *BM*, *EV*, *EP*, *R_EA*, and *LnAF*, we also control for the fixed effects in the province, industry, and year dimensions in the $\boldsymbol{F}$ vector. Equation (3) is established to explore the impact of local attention on cumulative abnormal returns as in H2b, H3b, and H4.

$$CAR[t_1, t_2]_{i,t} = \beta_0 + \beta_1 R_{SUE\,i,t} + \beta_2 R_{\%Local\,i,t-1} + \beta_3 R_{SUE\,i,t} \times R_{\%Local\,i,t-1} + \beta_4 LnSVI_{i,t-1} + \boldsymbol{\beta_5}\cdot\boldsymbol{X_{i,t}} + \boldsymbol{\beta_6}\cdot\boldsymbol{F} + \varepsilon_{i,t}. \quad (3)$$

The estimated coefficient $\hat{\beta_1}$ reflects the average sensitivity level of abnormal returns to the unexpected earnings in the chosen event window. Similarly, the estimated coefficient $\hat{\beta_3}$describes the extent to which local attention affects the incorporation of new earnings information into stock prices. Again, we control for the potential determinants of CAR and the three types of fixed effects as in Equation (2).

5. Empirical Results

Before interpreting the results from formal analyses, let us first present summary statistics in Table 1. For all firm-year observations in the baseline sample, the mean values of abnormal trading volume over the two event windows [−5, −1] and [0, 1] are both positive, suggesting that on average, the trading volume is higher before and at the time of earnings announcement. The abnormal trading volume before the earnings announcement in China is much higher compared to that in the U.S. market, while that on the announcement day is higher with a smaller magnitude than that in the U.S. market. Only the cumulative abnormal return after the earnings announcement in the event window [2, 31] is significantly negative. This implies that our sample displays post-earnings drift characteristics. Focusing on our attention variables, Table 2 demonstrates that the mean value of local attention in the search is 31.85% (19.5% in the U.S. market according to Chi and Shanthikumar 2017), which surpasses both the percentage benchmarks based on local Internet users and local investor accounts, namely 4.97% and 5.88%, respectively. The mean values of the two local bias proxies are also significantly greater than zero at the 1% significance level. At first glance, these observations provide solid evidence for H1a that attention bias, as measured by search behaviors, exists among Chinese investors.

Table 3 presents for each Chinese province the cross-sectional mean of $LB_{account}$, the number of firms included in the sample, and the total number of listed firms as of the last day of our sample period. As can be seen from Table 3, all means of $LB_{account}$ are 1% significantly greater than zero, suggesting the existence of local bias in the search for firms in all Chinese provinces. Firms registered in more developed regions, such as Shanghai, Guangdong, Beijing, Jiangsu, and Zhejiang, exhibit weaker local bias, but those registered in less developed provinces, such as Tibet, Qinghai, Hainan, Ningxia, and Guizhou receive quite high local attention. To get a sense of the magnitude, firms in Shanghai have the weakest local bias in search, with the percentage of the local search only being 2.56 times larger than the percentage of investor accounts opened in Shanghai. In contrast, the percentage of local searches in Tibet is 81 times as large as the percentage of Tibetan investor accounts.

Table 1. Descriptive Statistics for the Base Sample of 7214 Observations.

Variable	Mean	Std. Dev.	Min	P25	P50	P75	Max
AbVol[−5, −1]	1.319	3.413	−8.558	−1.178	0.955	3.501	18.990
AbVol[0, 1]	0.819	1.521	−3.288	−0.290	0.702	1.799	9.460
CAR[−5, −1]	0.006	0.056	−0.249	−0.025	0.002	0.030	0.489
CAR[0, 1]	−0.003	0.042	−0.206	−0.027	−0.005	0.016	0.262
CAR[2, 31]	−0.010	0.136	−0.601	−0.090	−0.021	0.057	1.086
%Local	31.850	12.510	8.333	22.540	30.400	39.920	65.050
SUE	−0.003	0.030	−0.151	−0.010	0	0.008	0.099
LnSVI	6.372	0.717	5.177	5.837	6.262	6.788	8.747
LnSize	13.210	1.043	10.970	12.490	13.110	13.820	16.270
IO	43.500	23.440	0.470	25.460	45.250	61.510	91.050
BM	0.490	0.320	0.0820	0.261	0.410	0.631	1.706
EV	0.204	0.193	0.015	0.075	0.143	0.261	1.065
EP	0.220	0.741	−2.072	−0.184	0.148	0.566	3.001
EA	163.100	155.400	6	58	121	204	896
LnAF	1.336	1.052	0	0	1.386	2.197	3.332
LnNews	3.760	0.929	0.693	3.497	4.190	4.317	5.247
AdvExp	6.940	8.035	0	2.068	4.275	8.505	42.310
LnSHR	1.350	0.903	−0.567	0.712	1.302	1.913	3.897
LnEMP	7.944	1.259	5.011	7.110	7.872	8.653	11.470
HS	0.153	0.360	0	0	0	0	1
Retail	0.143	0.350	0	0	0	0	1

Table 2. Empirical Results of Local Bias.

	Obs.	Mean	Std. Dev.	*t*-Statistic
%Local	7214	31.85	12.51	
$\%\text{Benchmark}_{\text{user}}$	7214	4.97	2.91	
$\%\text{Benchmark}_{\text{account}}$	7214	5.88	3.32	
LB_{user}	7214	7.62	7.47	86.61 ***
LB_{account}	7214	7.44	9.57	66.05 ***

Note: *** $p < 0.01$.

Table 3. Local Bias by Province.

Province	LB_{account}	Firms in Sample	Total Listed Firms	Province	LB_{account}	Firms in Sample	Total Listed Firms
Shanghai	1.56	130	272	Shaanxi	13.97	19	48
Guangdong	3.22	271	562	Jiangxi	14.09	25	41
Beijing	3.60	170	306	Guangxi	16.15	15	36
Jiangsu	3.62	172	376	Xinjiang	16.50	20	52
Zhejiang	4.54	199	416	Tianjin	17.72	25	51
Shandong	4.77	87	192	Jilin	17.93	20	43
Sichuan	6.89	49	113	Chongqing	18.85	22	49
Liaoning	7.20	29	70	Yunnan	20.74	16	33
Hubei	7.27	47	96	Inner Mongolia	21.55	7	25
Fujian	7.65	63	132	Gansu	22.99	13	33
Henan	8.34	45	79	Guizhou	30.20	13	27
Hunan	9.35	51	100	Ningxia	30.63	1	13
Hebei	9.78	25	54	Hainan	44.59	8	31
Anhui	10.96	49	99	Qinghai	65.10	4	12
Heilongjiang	11.46	14	37	Tibet	80.47	8	15
Shanxi	12.21	12	37	Total	7.44	1629	3450

This result is consistent with the estimation of local bias by Huang et al. (2016) using postings on the Eastmoney.com forum and the findings by other studies on the

Chinese geographical differences in local bias using Baidu-index-based measurements alternative to ours. Huang et al. (2016) also state that investor local bias in a Chinese province is negatively correlated with regional economic indicators such as provincial per-capita GDP, Internet penetration, and the total number of listed firms. The imbalanced geographical distribution of local bias in China is twofold. First, the "only-game-in-town" effect (Hong et al. 2008) and the distraction effect (Hirshleifer et al. 2009) reveal that, since there is a large number of publicly listed firms in more developed provinces, local investors normally do not focus on one specific firm. They allocate their attention to many firms, thus having less location bias in richer regions. Second, individuals living in economically developed areas have more access to obtain information on non-local firms. Given this lower information acquisition cost, even in the current Internet era, paying attention to non-local-province firms would be easier for these individuals; hence, relatively fewer attention resources are left for local firms.

Table 4 summarizes the results of using (1) to validate H1b, which proposes the existence of a positive relationship between local attention in search and firm visibility. Column (a) and column (b) differ in that the former controls for retail industry dummies, whereas the latter controls for the industry fixed effect instead. The coefficients of *LnSVI*, *News*, and *LnSHR* are all significantly negative at the 1% level in either column, indicating that higher search volume, wider news coverage, and more shareholders are associated with lower local attention in a search. This conclusion derived from China is similar to what Chi and Shanthikumar (2017) find in the U.S. stock market using Google search data. The coefficient of CSI300 is significantly positive in columns (a)–(b), implying that CSI300 firms have attracted more local attention. In addition, we observe a positive coefficient for *Retail* in column (a), which means that firms producing consumption goods are likely to receive more local attention, different from the insignificant and positive counterpart in the U.S. market. This seems to be counterintuitive, but on second thought, it might be because Chinese retail firms provide more localized products and services, thus attracting more local attention. Regarding column (b), the coefficient of *LnEMP* is significantly positive, which indicates that in China, firms with more employees receive more local attention, opposite to the significantly negative coefficient for the U.S. market. Since most local employees are hired by firms in China, the local attention on larger companies should be enhanced. At last, we discover no significant correlations between local attention and firm asset size, institutional ownership, advertising expenses, or analyst coverage.

Now, we continue to investigate the market response around earnings announcements. Big earnings surprises occurring early in a year will attract more non-local investors' attention. This paper, therefore, employs the lagged local attention and search volume in what follows to study the impact of local attention on how the Chinese stock market responds to earnings announcements. This treatment can also mitigate the potential reverse causality problem. After merging the announcing event dataset and the firm financial position data, we obtain 6606 firm-year observations.

Table 4. Local Attention in Search and Firm Visibility.

	(a)	(b)
	%Local	%Local
LnSVI	−10.3041 ***	−10.3487 ***
	(0.6124)	(0.5563)
News	−1.1278 ***	−1.0046 ***
	(0.2598)	(0.2441)
LnSize	0.4069	0.2765
	(0.2995)	(0.2869)
IO	0.0099	0.0011
	(0.0083)	(0.0079)
BM	1.8646 ***	0.2334
	(0.6293)	(0.5827)
AdvExp	−0.0153	0.0014
	(0.0188)	(0.0174)
LnSHR	−1.9893 ***	−2.1874 ***
	(0.2784)	(0.2745)
LnEMP	0.2932	0.7490 ***
	(0.1927)	(0.1746)
LnAF	0.2259	0.1973
	(0.1631)	(0.1527)
CSI300	2.0557 ***	2.2816 ***
	(0.4622)	(0.4482)
Retail	1.4434 ***	
	(0.4844)	
Province	Yes	Yes
Year	Yes	Yes
Industry	No	Yes
Constant	91.5029 ***	92.5327 ***
	(3.1944)	(3.2696)
Obs.	7214	7214
Adj. R^2	0.7305	0.7483

Note: *** $p < 0.01$; clustered standard errors in parentheses.

The following first set of regressions focuses on the market response right at earnings announcements. The event window of (2) and (3) is both set at $[t_1, t_2] = [0, 1]$ to test H2. Table 5 presents the corresponding regression results. In column (a), the coefficient of *R_%Local* is positive at the 1% significance level—high local attention causes active transactions on the day of the announcement. This result rejects our H2a and contradicts the U.S. market result. However, this is expected due to the "trade to preserve gain" idea prevailing in China's stock market. According to the prospect theory put forward by Kahneman and Tversky (1979), investors will sell stocks that have gained value to avoid bearing risks further once private information becomes public. For firms with high local attention, pre-arrangements of informed local investors may induce "trade to preserve gain" behaviors at the announcement. The results in column (b) show that the coefficient of interaction *R_SUE* × *R_%Local* is negative at the 10% significance level. The immediate price response to earnings announcements decreases with the underlying firm's local attention, which is consistent with our H2b. For both measurements of market response, local attention has a greater effect than the unexpected earnings in China, while the opposite can be observed in Chi and Shanthikumar (2017) for the U.S. market.

Table 5. Local Attention and Market Response at the Earnings Announcement.

	(a)	(b)
	AbVol[0, 1]	CAR[0, 1]
R_SUE	0.0472 ***	0.0002
	(0.0039)	(0.0001)
R_%Local	0.8156 ***	0.0098 ***
	(0.1874)	(0.0020)
R_SUE × R_%Local		−0.0009 *
		(0.0004)
LnSVI	0.2753 ***	0.0030 ***
	(0.0881)	(0.0007)
LnSize	−0.1377 ***	0.0020 *
	(0.0189)	(0.0010)
IO	0.0028 ***	0.0000
	(0.0009)	(0.0000)
BM	0.3493 ***	−0.0022
	(0.0639)	(0.0018)
EV	0.0480	0.0010
	(0.0870)	(0.0025)
EP	−0.0172	0.0006
	(0.0146)	(0.0004)
R_EA	−0.0787 ***	−0.0006 ***
	(0.0077)	(0.0001)
LnAF	0.0061	−0.0007
	(0.0168)	(0.0005)
Province	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Constant	0.3187	−0.0426 ***
	(0.5041)	(0.0112)
Obs.	6606	6606
Adj. R^2	0.2672	0.0214

Note: * $p < 0.1$, *** $p < 0.01$; clustered standard errors in parentheses.

Secondly, to investigate the market response before earnings announcements, we set the event window of (2) and (3) to $[t_1, t_2] = [-1, -5]$ to test H3. Table 6 presents the regression results. In column (a), a 1% significant and positive estimated coefficient of *R_%Local* implies that higher local attention also results in larger trading volumes before the earnings announcement. Turning to column (b), we find that the coefficient of *R_SUE* × *R_%Local* is positive at the 5% significance level, suggesting that the price response possesses stronger predictivity of the upcoming earnings information for firms with higher local attention. The coefficient of *R_SUE* turns out to be positive at the 1% significance level as well. Again, the total effect of *R_SUE* is much smaller than that of *R_%Local*. As a result, before the earnings announcement, local attention is positively associated with abnormal trading volume. Moreover, the correlation between price movements and incoming earnings is higher for firms with higher local attention, supporting H3.

Table 6. Local Attention and Market Response before the Earnings Announcement.

	(a)	**(b)**
	AbVol[−5, −1]	CAR[−5, −1]
R_SUE	0.0294 ***	0.0016 ***
	(0.0062)	(0.0003)
R_%Local	1.2465 ***	0.0099 **
	(0.4173)	(0.0040)
R_SUE × R_%Local		0.0008 **
		(0.0003)
LnSVI	0.6178 ***	0.0033 ***
	(0.1584)	(0.0011)
LnSize	−0.3239 ***	−0.0003
	(0.0258)	(0.0010)
IO	0.0050 **	−0.0000
	(0.0018)	(0.0000)
BM	0.6346 ***	0.0067 ***
	(0.0897)	(0.0014)
EV	−0.3639 *	0.0012
	(0.1736)	(0.0015)
EP	−0.0605	−0.0014 ***
	(0.0643)	(0.0004)
R_EA	−0.1066 ***	−0.0021 ***
	(0.0135)	(0.0002)
LnAF	−0.1756 ***	−0.0011 *
	(0.0357)	(0.0006)
Province	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Constant	1.1983	−0.0161 *
	(1.1175)	(0.0084)
Obs.	6606	6606
Adj. R^2	0.2552	0.0659

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors in parentheses.

Finally, we investigate the price drifting after earnings announcements as market responses. To test H4 designed for post-announcement market response, the event window of (3) takes the value of $[t_1, t_2]$ = [2, 31]. Further, we modify (3) by replacing *R_SUE* with deciles of cumulative abnormal earnings *R_CAR[0, 1]* as an alternative proxy for earnings information disclosed at the announcement window. The corresponding regression results are included in Table 7. In column (a), the coefficient of *R_SUE* is negative at the 1% significance level, contrary to what has been observed in the U.S., as we have previously shown. The implication is that investors over-react to earnings figures and there exists a negative relationship between PEAD and unexpected earnings in the Chinese A-share market. The coefficient of *R_SUE* × *R_%Local* becomes insignificant, suggesting that local attention may not play a role in the pricing of earnings information after the announcement. The results in column (b) show that the negative coefficient of *R_CAR[0, 1]* × *R_%Local* remains significant at the 5% level. Given higher local attention, stock price over-reacts to the earnings information to a higher degree on the day of the earnings announcement. Thus, we are confident in rejecting H4, i.e., the familiarity bias argument fails in explaining the locality problem in the Chinese A-share market.

Table 7. Local Attention and Post-Earnings Drift.

	(a)	(b)
	CAR[2, 31]	CAR[2, 31]
R_SUE	−0.0017 ***	
	(0.0004)	
R_CAR[0, 1]		0.0255
		(0.0297)
R_%Local	0.0484 ***	0.0346 ***
	(0.0108)	(0.0040)
R_SUE × R_%Local	−0.0025	
	(0.0015)	
R_CAR[0, 1] × R_%Local		−0.2622 **
		(0.1191)
LnSVI	0.0116 ***	0.0113 ***
	(0.0032)	(0.0030)
LnSize	−0.0044 ***	−0.0039 **
	(0.0015)	(0.0015)
IO	−0.0002 ***	−0.0002 ***
	(0.0000)	(0.0000)
BM	0.0070	0.0079
	(0.0088)	(0.0086)
EV	−0.0056	−0.0060
	(0.0078)	(0.0077)
EP	0.0030 **	0.0029 **
	(0.0011)	(0.0011)
R_EA	−0.0006	−0.0005
	(0.0005)	(0.0005)
LnAF	0.0024	0.0018
	(0.0018)	(0.0017)
Province	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Constant	0.0050	−0.0093
	(0.0274)	(0.0296)
Obs.	6606	6606
Adj. R^2	0.1297	0.1288

Note: ** $p < 0.05$, *** $p < 0.01$; clustered standard errors in parentheses.

6. Robustness Check

Stocks with abnormal returns or volume may in turn draw local attention, hence driving the effect that we document in a reverse causality. To mitigate this potential endogeneity concern, we resort to the two-stage least squares method and attempt to isolate the part of local attention that is independent of the market reactions around earnings announcements. A *Regional Award* dummy, which indicates whether a firm receives an award of the best firm or the best employer in its region in the previous year, is adopted as the instrument for *%Local* of the concerned firm in the current year. Following the criteria for selecting a valid instrumental variable, our justification is twofold. On the one hand, after one firm wins a regional award, its local visibility is likely to increase (the national visibility will stay the same or improve), drawing more local attention than that from non-locals outside the region. Secondly, award winning is a long-term achievement determined by firm characteristics such as search intensity, firm size, number of employees, shareholding structure, analyst coverage, etc. The correlation coefficients between the chosen IV and *AbVol[−5, −1]*, *AbVol[0, 1]*, *CAR[−5, −1]* and *CAR[0, 1]* are 0.0003, 0.0022, −0.0036, and −0.0388, respectively. It confirms that there is no direct relationship between who wins such an award and short-term market responses around the earnings announcement. If regional award winners do exert an impact on equity market fluctuations, it should function through the channel of visibility within the region, i.e., local attention.

In Table 8, we obtain the first-stage regression results from estimating Equation (1), augmented by the proposed instrumental variable *Regional Award*. This instrument is positively correlated with *%Local* and turns out to be a strong and statistically valid instrument, with its F-statistic exceeding the suggested critical value for the setup with a single instrumental variable of 8.96 (Stock et al. 2002; Larcker and Rusticus 2010). Tables 9 and 10 tabulate the results of the second-stage regression, where $R\_\%Local_{t-1}$ is the annual decile rank of the predicted value of lagged *%Local*. These findings are consistent with those presented in the previous section. Thus, our argument that local attention around earnings announcements causes large responses in the Chinese stock market is unlikely to be driven by the two-causality problem.

Table 8. First-Stage Regression Results.

	%Local
Regional Award	3.9574 ***
	(0.2809)
LnSVI	−10.4925 ***
	(0.5558)
News	−0.8288 ***
	(0.2341)
LnSize	0.8901 ***
	(0.3349)
IO	−0.0001
	(0.0083)
BM	1.5486 **
	(0.6718)
AdvExp	−0.0153
	(0.0181)
LnSHR	−2.2885 ***
	(0.3120)
LnEMP	0.4464 **
	(0.2098)
LnAF	−0.0492
	(0.1662)
HS	2.1175 ***
	(0.5528)
Retail	0.9931 **
	(0.4339)
Province	Yes
Year	Yes
Industry	No
Constant	82.7223 ***
	(4.0872)
Obs.	4658
Adj. R^2	0.7559
F-statistics of the Instrumental Variable	14.09

Note: ** $p < 0.05$, *** $p < 0.01$; clustered standard errors in parentheses.

Table 9. Second-Stage Regression Results of Abnormal Trading Volume.

	(a)	**(b)**
	AbVol[−5, −1]	AbVol[0, 1]
R_SUE	−0.0044	0.0342 ***
	(0.0137)	(0.0065)
R_%Local	1.9654 ***	1.1828 ***
	(0.1604)	(0.1108)

Table 9. *Cont.*

	(a)	(b)
LnSVI	0.9289 ***	0.4332 ***
	(0.1264)	(0.0728)
LnSize	−0.2914 ***	−0.1480 **
	(0.0860)	(0.0538)
IO	−0.0014	0.0003
	(0.0017)	(0.0008)
BM	0.7507 ***	0.3984 ***
	(0.0936)	(0.0958)
EV	−0.4293	−0.0400
	(0.2710)	(0.1372)
EP	−0.0714	−0.0283
	(0.0537)	(0.0172)
R_EA	−0.0786 ***	−0.0746 ***
	(0.0239)	(0.0111)
LnAF	−0.2069 ***	0.0204
	(0.0317)	(0.0252)
Province	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Constant	−1.2497 **	−0.2364
	(0.5830)	(0.3744)
Obs.	2771	2771
Adj. R^2	0.2918	0.3089

Note: ** $p < 0.05$, *** $p < 0.01$; clustered standard errors in parentheses.

Table 10. Second-Stage Regression Results of Cumulative Abnormal Returns.

	(a)	(b)	(c)
	CAR[−5, −1]	CAR[0, 1]	CAR[2, 31]
R_SUE	0.0016 ***	0.0004 *	−0.0018 ***
	(0.0002)	(0.0002)	(0.0005)
R_%Local	0.0163 ***	0.0061	0.1125 ***
	(0.0044)	(0.0072)	(0.0225)
R_SUE × R_%Local	0.0011 **	0.0008	−0.0040 **
	(0.0004)	(0.0006)	(0.0015)
LnSVI	0.0062 *	0.0076 ***	0.0258 ***
	(0.0030)	(0.0023)	(0.0069)
LnSize	−0.0009	0.0005	0.0035
	(0.0015)	(0.0013)	(0.0026)
IO	0.0000	0.0000	−0.0001
	(0.0000)	(0.0000)	(0.0001)
BM	0.0055 *	−0.0039	−0.0030
	(0.0031)	(0.0030)	(0.0068)
EV	−0.0012	0.0047	−0.0213
	(0.0034)	(0.0042)	(0.0167)
EP	−0.0030 ***	0.0011	0.0071 ***
	(0.0005)	(0.0008)	(0.0012)
R_EA	−0.0022 ***	−0.0006 **	−0.0015 ***
	(0.0005)	(0.0003)	(0.0004)
LnAF	−0.0012	−0.0007	−0.0002
	(0.0010)	(0.0008)	(0.0023)
Province	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Constant	−0.0341	−0.0472 ***	−0.2160 ***
	(0.0337)	(0.0113)	(0.0482)

Table 10. *Cont.*

	(a)	(b)	(c)
Obs.	2771	2771	2771
Adj. R^2	0.0555	0.0340	0.1336

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors in parentheses.

We continue to conduct three sensitivity tests. First, an alternative measure of the dependent variable is used to check the robustness of our previous results. Specifically, we re-calculate cumulative abnormal returns based on the Fama-French three-factor model and use them to replace the returns calculated by the previous market model. Table 11 summarizes the results of regressing the three-factor CAR during the event windows [−5, −1], [0, 1], and [2, 31] on our main explanatory variable in the presence of controls. As shown in the table, how prices respond to local attention around earnings announcements stays unchanged. Second, to better understand the influences imposed by local attention on post-earnings drifts over different periods, we change the event window in (3) for the post-announcement to [2, 5], [2, 11], and [2, 61], respectively. The corresponding results are included in Table 12. We find that the coefficient of the interaction *R_SUE* × *R_%Local* is not significant, irrespective of the number of days elapsed since the earnings announcement. In other words, the pricing of earnings shocks seems to be unaffected by the degree of local attention after the announcement. At last, Table 13 illustrates what will happen if we change the estimation window for the benchmark average trading volume in the calculation of the abnormal trading volume from [−100, −11] in Section 5 to [−40, −11] when regressing this volume on unexpected earnings and local attention. By comparing these results with the previous results, we conclude that our event study is robust to such event window manipulations.

Table 11. Empirical Results of CARs of Fama-French model as Dependent Variable.

	(a)	(b)	(c)
	CAR[−5, −1]	CAR[0, 1]	CAR[2, 31]
R_SUE	0.0016 ***	0.0001	−0.0018 ***
	(0.0003)	(0.0001)	(0.0004)
R_%Local	0.0100 ***	0.0085 ***	0.0409 ***
	(0.0032)	(0.0027)	(0.0087)
R_SUE × R_%Local	0.0004 **	−0.0005	−0.0024 *
	(0.0002)	(0.0004)	(0.0012)
LnSVI	0.0010	0.0034 ***	0.0137 ***
	(0.0009)	(0.0007)	(0.0021)
LnSize	0.0001	0.0014	−0.0077 ***
	(0.0008)	(0.0008)	(0.0016)
IO	−0.0000	−0.0000	−0.0001
	(0.0000)	(0.0000)	(0.0001)
BM	0.0055 ***	−0.0025	0.0089 *
	(0.0015)	(0.0018)	(0.0046)
EV	0.0045 ***	0.0012	−0.0021
	(0.0014)	(0.0023)	(0.0070)
EP	−0.0012 **	0.0009 **	0.0028 *
	(0.0004)	(0.0004)	(0.0015)
R_EA	−0.0004 **	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0005)
LnAF	−0.0005	−0.0003	−0.0017
	(0.0005)	(0.0006)	(0.0018)
Province	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Constant	−0.0153 **	−0.0372 ***	0.0373 **
	(0.0069)	(0.0084)	(0.0166)

Table 11. *Cont.*

	(a)	(b)	(c)
Obs.	6606	6606	6606
Adj. R^2	0.0332	0.0175	0.0249

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors in parentheses.

Table 12. Local Attention and Post-Earnings Drift in Different Length of Event Windows.

	(a)	(b)	(c)
	CAR[2, 5]	CAR[2, 11]	CAR[2, 61]
R_SUE	−0.0002	−0.0006 ***	−0.0028 ***
	(0.0002)	(0.0002)	(0.0006)
R_%Local	0.0055	0.0119	0.0241
	(0.0033)	(0.0094)	(0.0143)
R_SUE × R_%Local	−0.0002	−0.0009	0.0004
	(0.0004)	(0.0012)	(0.0025)
LnSVI	0.0005	0.0017	0.0067 *
	(0.0017)	(0.0036)	(0.0036)
LnSize	−0.0013 **	−0.0023 *	−0.0045
	(0.0006)	(0.0012)	(0.0037)
IO	−0.0001 **	−0.0000	−0.0001
	(0.0000)	(0.0000)	(0.0001)
BM	0.0056 ***	0.0127 ***	0.0262 **
	(0.0015)	(0.0021)	(0.0115)
EV	0.0012	0.0019	−0.0018
	(0.0027)	(0.0032)	(0.0109)
EP	0.0019 **	0.0012	0.0044 ***
	(0.0007)	(0.0011)	(0.0013)
R_EA	−0.0007 ***	−0.0010 ***	−0.0019 ***
	(0.0002)	(0.0003)	(0.0005)
LnAF	0.0022 ***	0.0004	0.0067 **
	(0.0004)	(0.0010)	(0.0023)
Province	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Constant	0.0222 **	0.0265	0.0304
	(0.0081)	(0.0176)	(0.0452)
Obs.	6606	6606	6606
Adj. R^2	0.0218	0.0333	0.1294

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors in parentheses.

Table 13. Local Attention and Abnormal Trading Volume.

	(a)	(b)
	AbVol[−5, −1]	AbVol[0, 1]
R_SUE	0.0229 ***	0.0446 ***
	(0.0060)	(0.0045)
R_%Local	0.6631 **	0.5804 ***
	(0.2877)	(0.1309)
LnSVI	0.2613 **	0.1365 **
	(0.0927)	(0.0578)
LnSize	−0.1812 ***	−0.0761 ***
	(0.0238)	(0.0173)
IO	0.0039 ***	0.0022 ***
	(0.0013)	(0.0007)

Table 13. *Cont.*

	(a)	(b)
BM	0.2827 ***	0.2028 ***
	(0.0482)	(0.0653)
EV	−0.1358	0.1379
	(0.1514)	(0.0842)
EP	−0.0312	−0.0107
	(0.0324)	(0.0114)
R_EA	−0.1772 ***	−0.1076 ***
	(0.0171)	(0.0091)
LnAF	−0.1294 ***	0.0208
	(0.0299)	(0.0131)
Province	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Constant	1.1156 *	0.2662
	(0.5787)	(0.2892)
Obs.	6606	6606
Adj. R^2	0.1912	0.2006

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors in parentheses.

7. Conclusions

This paper focuses on the geographical dimension of investor attention. Focusing on the Chinese stock market, we construct a new measure of local attention using the Baidu search index. Specifically, the measure is computed as the ratio of the search volume generated within the province where a publicly listed firm is registered to the nationwide search volume. The aim is to provide answers to the following three research questions: Are individual investors' search behaviors biased toward local companies? What is the exact impact of local attention on the market response to earnings announcement events? If the replies are yes and significantly positive for the first two questions, respectively, then one must be curious about whether a local-information-advantage or a familiarity-bias story can explain the local preference prevailing in China's A-share market.

Based on our empirical design and results, we find several regularities. First, retail investors in China search disproportionately for local firms, and firms with higher visibility experience higher local attention. Second, investors' local attention could significantly affect market responses around earnings announcements. For firms with higher local attention before the announcement, we observe more active trading activities and the stronger predictive power of price response to upcoming earnings information. On earnings announcement days, transactions on those firms' stocks become even more active. The price, however, responds in a weaker way to earnings information. Moreover, firms with higher local attention do not exhibit a stronger positive drift toward unexpected earnings. While most of our results stay in line with what Chi and Shanthikumar (2017) found for the U.S. equity market, our result that intensive trading exists for firms with higher local attention on earnings announcement days constitutes a contradiction. We believe that this contradiction arises because informed local investors in China are limited in realizing their profits and hedging potential risk in the options market so that they execute orders in the stock market immediately after the release of new earnings information. Last but not least, our paper provides evidence that, in the Chinese A-share market, the local information advantage possesses explanatory power to some extent for the trading behaviors of local investors. As for firms, this paper implies that promoting non-local investors' awareness of their stock is more useful in enhancing the firm overall visibility. From the standpoint of regulators, our results suggest that them putting more emphasis on regulating the trading of local investors may better improve the market pricing efficiency.

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Appendix A

Table A1. Sample Distribution by Industry, Year, and Province.

By Industry	**Obs.**	**%**	Real Estate	325	4.5%
Manufacturing	4671	64.8%	Transportation	317	4.4%
Wholesale and Retail	419	5.8%	Others (<4% each)	1074	14.9%
Info. Technology	408	5.7%	Total	7214	100%
By Fiscal Year					
2010	608	8.4%	2015	731	10.1%
2011	612	8.5%	2016	847	11.7%
2012	760	10.5%	2017	965	13.4%
2013	837	11.6%	2018	1152	16.0%
2014	702	9.7%	Total	7214	100%
By Province					
Guangdong	1027	14.2%	Tianjin	121	1.7%
Zhejiang	836	11.6%	Jilin	106	1.5%
Beijing	735	10.2%	Xinjiang	99	1.4%
Jiangsu	725	10.1%	Yunnan	87	1.2%
Shanghai	632	8.8%	Shaanxi	86	1.2%
Shandong	432	6.0%	Guangxi	80	1.1%
Fujian	305	4.2%	Guizhou	61	0.9%
Anhui	271	3.8%	Gansu	54	0.8%
Hunan	219	3.0%	Shanxi	52	0.7%
Henan	216	3.0%	Heilongjiang	47	0.7%
Sichuan	213	3.0%	Tibet	31	0.4%
Hubei	189	2.6%	Inner Mongolia	24	0.3%
Liaoning	136	1.9%	Qinghai	23	0.3%
Jiangxi	130	1.8%	Hainan	22	0.3%
Hebei	126	1.8%	Ningxia	6	0.1%
Chongqing	123	1.7%	Total	7214	100%

Table A2. List of Description and Data Source of Main Variables.

Variable	Description and Data Source
CAR[t_1, t_2]	Firm's cumulative abnormal return during the event window [t_1, t_2] from Wind
Abvol[t_1, t_2]	Firm's cumulative abnormal trading volume during the event window [t_1, t_2] from Wind
R_SUE	Annual decile rank of standardized unexpected earnings from Wind
R_%Local	Local attention as measured by the annual decile rank of the percentage of local search volume from Baidu
LnSVI	Baidu search volume proxied by the natural log of the annual average Baidu index of a firm's security abbreviation from Baidu
LnSize	Firm size proxied by the natural log of average daily market value during the fiscal year from Wind
IO	Institutional ownership proxied by the percentage of shares held by institutions in outstanding shares at the end of the fiscal year from Wind
BM	Book to market ratio at the end of the fiscal year from Wind
EV	Earnings volatility proxied by the standard deviation of annual earnings per share in the recent four years from Wind
EP	Earnings sustainability proxied by the first-order autocorrelation coefficient of annual earnings per share in the last four years from Wind
R_EA	Announcement density proxied by the annual decile rank of the total number of earnings announcement published on the day as the given firm's annual announcements from CSMAR
LnAF	Analyst coverage proxied by the natural log of the sum of 1 and the number of institutions making forecasts 180 days around the end of the fiscal year from Wind

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