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Ning Zhu

Yale School of Management

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Abstract

This study investigates individual investors' bias towards nearby companies. Using data from a large U.S. discount brokerage, we find that individual investors tend to invest in companies closer to them relative to the market portfolio. Unlike Coval and Moskowitz's (1999) findings on institutional investors, however, we find that advantageous information cannot explain individual investors' local bias. Accounting numbers and information asymmetry matter less to individual investors' local bias than to that of institutional investors. Instead, we hypothesize that individuals' non-fundamentally based familiarity with local companies and ready reaction to local information are more plausible explanations. Consistent with this hypothesis, we find that individual investors are more likely to invest in remote companies that spend heavily on advertising. Evidence from investors' reactions to earnings announcements also confirms the hypothesis: local investors do not change their portfolios so as to take advantage of potentially advantageous information before earnings announcements. After earnings announcements, local investors change their portfolios more than remote investors in the direction opposite to the same earnings surprises.

JEL Classification: G11 G14 G15

Keywords: Local Bias, Individual Behavior, Asset Pricing, Asymmetric Information, Overreaction, Familiarity.

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Abstract

This study investigates individual investors' bias towards nearby companies. Using data from a large U.S. discount brokerage, we find that individual investors tend to invest in companies closer to them relative to the market portfolio. Unlike Coval and Moskowitz's (1999) findings on institutional investors, however, we find that advantageous information cannot explain individual investors' local bias. Accounting numbers and information asymmetry matter less to individual investors' local bias than to that of institutional investors. Instead, we hypothesize that individuals' non-fundamentally based familiarity with local companies and ready reaction to local information are more plausible explanations. Consistent with this hypothesis, we find that individual investors are more likely to invest in remote companies that spend heavily on advertising. Evidence from investors' reactions to earnings announcements also confirms the hypothesis: local investors do not change their portfolios so as to take advantage of potentially advantageous information before earnings announcements. After earnings announcements, local investors change their portfolios more than remote investors in the direction opposite to the same earnings surprises.

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1 Introduction

Recent studies have shown that local bias is prevalent among institutional investors' investments.[1] Coval and Moskowitz (1999) use U.S. mutual fund holdings to reveal U.S. mutual fund managers' bias towards holding locally headquartered companies in their domestic portfolios. Hiraki et al. (2001) find a similar local bias pattern in Japanese institutional investors. Given the potential impact on asset pricing (Brennan and Cao, 1997; Coval, 2002), it is important to further understand why local bias exists.

Despite Coval and Moskowitz's (1999) findings that advantageous information motivates fund managers' local bias, little effort has been made to understand individual investors' local bias. Some theoretical studies (Fama, 1980; Modigliani and Pogue, 1975) have shown that agency problems, compensation schemes, and career concerns can cause mutual fund managers' objectives to differ from those of their investors. Empirically, Chevalier and Ellison (1997, 1999) and Roston (1997) show that both incentives and career concerns affect mutual fund managers' risk taking. In addition, individual portfolios are typically less diversified (Goetzmann and Kumar, 2002) and more susceptible to the impact of tax filing (Constantinides, 1984; Odean, 1998). Individuals are also different in that they devote a smaller fraction of their time and energy to their investments, compared to institutional investors (Mamaysky and Spiegel, 2002).

All these reasons distinguish individuals from mutual fund managers and motivate us to explore individual investors' local bias. Now that about one half of the equity investments in the United States are held directly by households,[2] it has become increasingly important to understand whether individual investors exhibit local bias and, if so, what drives it.

This study focuses on the individual investor preference for nearby investments. Using data on 27,189 investors and their account activities with a large U.S. brokerage firm, I find that individual equity investors exhibit a significant bias towards local firms. The results indicate that the average individual investor's portfolio is between 139.4 and 160.8 miles, or 12.42% and 14.65%, closer to home than the universe of domestic common stocks. I also show that a preference for local domestic firms is correlated to a preference for domestic investment over foreign investment, supporting that

[1] The finance literature has documented that investors have a strong preference for domestic investments over international counterparts (French and Porterba, 1991; Kang and Stulz, 1997; and Tesar and Werner, 1995).

[2] Securities Industry Fact Book, 1999.

the local bais and home country bias may be a function of the same underlying driving factor.

These results are consistent with Grinblatt and Keloharju (2001) who use a Finnish dataset to show that both institutional and individual investors tend to hold the stocks of companies with nearby headquarters. My study differs from theirs in that I am able to differentiate this effect within investor class and test hypotheses about the cause of the local preference using cross-sectioinal differences in local bias. In particular, I test whetehr the local bias may be due to informational advantage, suggested by Coval and Moskowitz (1999), or to a familiarity bias, consistent with Huberman (2001). I find more support for the familiarity hypothesis as opposed to the information advantage hypothesis. Their research, however, does not addresses the local bias within the individual investor class, nor the range of possible factors contributing to the local bias. The findings on U.S investors also extend their findings on Finnish investors, due to Finland's limited size of the territory, economy, and capital market.[3]

The present study relates U.S. individual investor local bias to the tendency to hold foreign assets. It finds that investors holding foreign assets exhibit smaller domestic local bias than other investors, which confirms that domestic local bias and international home bias are related. The correlation between these two types of local biases is nevertheless low, suggesting that "the relationship is rather complicated" (Coval and Moskowitz, 1999) when one extrapolates the impact of distance into the international investment arena. Investors from California, where many high-technology growth companies are headquartered, show stronger local bias than individuals from the rest of the country. Investors living in New York City, where many finance companies are headquartered, have smaller local bias than the rest of the country.

The second part of this article explains why individual investors favor nearby investment. Coval and Moskowitz (1999) show that U.S. mutual fund managers prefer local companies, because they gain advantageous information on such investments. Although information could be a reason why institutional investors tilt towards nearby companies, it may not play an equally important role in individual investors' local bias. First, individual investors are presumably less sophisticated than fund managers. Fund managers typically receive education in business-related fields and have

[3]Finland's GNP is approximately U.S. $100 billion compared to U.S.'s GNP of more than U.S. $9 trillion in 2000 (World Bank Annual Report, 2000). About 100 companies' stocks trade at Helsinki Stock Exchange, while more than 8,000 stocks trade at New York Stock Exchange (NYSE) and NASDAQ.

accumulated considerable experience in asset management, whereas individual investors have typically less understanding about their investments. Second, unlike mutual fund managers, ordinary individuals have their own careers and devote limited time and effort to their investments. Finally, mutual funds' local bias may be attributed to self-selection, as some funds locate themselves close to their investments to maintain a close relationship with the management and to obtain advantageous information. Coval and Moskowitz (1999) report that sector funds and regional funds have the highest local bias among all types of mutual funds. These differences suggest that information may not drive individual investors' local bias.

Alternatively, individual investors' tendency to invest locally may be driven by familiarity which is unrelated to fundamental information. Huberman (2001) finds that investors are much more likely to invest in a Regional Bell Operation Company (RBOC) that operates in their areas than in any other RBOC and, furthering that finding, argues that familiarity induces investors to hold stocks of local companies. He also points out that such familiarity may not reflect advantageous information.

Many individual investors are employed by local companies and know many people in the community with similar career profiles and concerns. Although individuals can obtain more information from familiarity, not all information associated with such familiarity is relevant to investment. This study compares gross and risk-adjusted portfolio returns of individual investors with different levels of local bias and finds that investors with greater local bias do not outperform those with weaker local bias under different risk measurements. Indeed, the results suggest that, though familiarity is responsible for individuals' local bias, it does not help individual investors obtain higher return.

This study also shows that individual investors care less about the financial distress and other accounting ratios than institutional investors reported elsewhere (Kang and Stulz, 1997; Coval and Moskowitz, 1999). This further suggests that individual investors invest locally for reasons other than information asymmetry. Rather, companies' advertising intensity significantly reduces individual investors' local bias, suggesting that investors may invest in non local companies because of a higher level of awareness of, or a stronger reaction to, more salient information in advertising. Advertising and the resulting familiarity do not necessarily help investors attain higher returns. This casts further doubt on the advantageous information explanation and lends support to the familiarity explanation.

This study also finds that investor sophistication within individual investor group influences the magnitude of individuals' local bias. Consistent with previous findings (Dhar and Zhu, 2002), more sophisticated individuals, in particular those who are wealthy and work in professional occupations, show significantly smaller local bias.

Evidence from investor response to earnings announcements also support the hypothesis that factors other than advantageous information are responsible for individual investor local bias. Before earnings announcements, investors living close to companies making earnings announcements cannot predict actual earnings better than investors living far away from those companies. This fact again undermines the explanation that local individuals possess an information advantage.

Local individual investors do, however, exhibit stronger responses to earnings surprises than remote investors do right after earnings announcement. In reaction to both positive and negative earnings surprises, local investors tend to move their portfolios more in the direction opposite to earnings surprises than remote investors do. Awareness and attention to local firms and media, can potentially explain this discrepancy.

The rest of the paper is organized as follows: section 2 describes the dataset and outlines the methodology; section 3 tests the local bias of individual investors and links the domestic local bias to the home bias in international investment; section 4 examines the factors that contribute to individual investors' local bias; section 5 presents additional evidence that behavioral factors drive individuals' local bias; and section 6 concludes.

2 Data and Methodology

The primary data were obtained from a large U.S. discount brokerage firm on more than 50,000 households. There are three files in the data. The positions file records the end-of-month portfolio positions of all investors between January, 1991 and November, 1996. The trade file contains all transactions that these investors have made during the same period. The demographic file contains key demographic information, such as age, income, and geographical location (zip code) of investors. Such information is available on only a subset of investors. Descriptive statistics of the data are presented in Table 1.

(Please insert Table 1 here)

In an average month households in our sample hold more than 2 billion dollars of securities in their portfolios. They trade a wide variety of securities, including domestic equities, fixed income securities, mutual funds, and foreign assets. Out of about 3 million trades executed by all households, this study focuses on the 1,854,776 trades in U.S. common stocks.[4]

Geographical data are obtained on 27,189 households whose residence zip codes are available. The investors are located throughout the 50 United States. Of the sampled investors, 42% are from the West; 19% from the East; 24% from the South and 15% from the Midwest. The geographical distribution of the investors in our sample is illustrated in Figure 1.

(Please insert Figure 1 here)

The locations of public company headquarters are obtained through Compustat Research Insight, which reports the 5-digit zip codes of company headquarters. Headquarter locations of 5,707 companies were collected during the period of study. Because a disproportionably large number of companies are incorporated in Delaware, I use the location of headquarters as the location of the companies.[5] 17% of sample companies are located in the West.; 44% in the East; 26% in the South; and 13% in the Midwest. The geographical distribution of company headquarters appears in Figure 2.[6]

(Please insert Figure 2 here)

Since only the information on the zip codes of households and company headquarters is available, the exact distances between companies and households cannot be calculated. Instead, I calculate the distance between the centroid of a company's zip code and an investor's zip code area as the

[4] I exclude the trades on ADRs (American Depositary Receipts) because they are foreign companies and it is ambiguous to define their locations.

[5] An alternative way is to measure the locations where companies have business presence. Such an approach would offer a better definition of the company locations. This approach is however complicated, because it is hard to collect information on where companies do business. Even with such information, it would be difficult to define the nature and scope of the business and determine the exact location of a company.

[6] Corporate headquarters in many cases are close to corporate core businesses. For further detail, please see Young et al. (2000), which extensively studied the impact of corporate headquarter.

distance between the firm and the household. Because the centroids of many nearby 5-digit zip code areas are often within miles, 5-digit zip codes do not offer particularly useful information. Instead, I use 3-digit zip codes, which also facilitate the calculation of distances between investors and companies.[7] Using Archview Packages, one can calculate the distance between any two 3-digit zip codes in the data. To avoid outliers that would bias the result, I focus only on the investors and companies within the continental U.S. by excluding all investors and companies in Alaska, Hawaii, and Puerto Rico.

I measure the individual investor local bias by the following 3 steps:

Step 1 Calculate the distance between an investor and the market portfolio. Following Coval and Moskowitz (1999), I calculate the distance between an investor and the market portfolio. The location of the market portfolio is calculated as the value-weighted average of the location of all stocks in the market. Specifically, I obtain the latitude and longitude of the centroids of all 3-digit zip codes. I then calculate the total market value of companies headquartered in each 3-digit zip code.[8] The latitude and longitude of the market portfolio is the average of the latitude and longitude of all 3-digit zip codes weighted by the total value of public companies headquartered in each particular zip code area. The distance between a particular investor and the market portfolio is then calculated as the distance between the zip codes of the investor and the market portfolio.

Step 2 Calculate the distance between an investor and her own portfolio. I study the stocks that investors have chosen to invest during the studied period. We focus on investors' purchase transactions instead of their positions since it is the trades that change investors' portfolios. Also, the data contain information on investors' accounts only for the six-year period from 1991 to 1996. Roughly half of the households opened their accounts before 1987, and the rest opened their

[7]We truncate the last two digits of 5-digit zip codes to get 3-digit zip codes. For example, 00101 and 00115 will bear the same 3-digit zip code of 001. This procedure puts nearby 5-digit zip code areas into fewer and bigger areas identified with particular 3-digit zip codes. This procedure has been widely used in ecology literature (Shelly, 1997). One particular benefit of this procedure is that, instead of having to deal with 30010*30010 matrix of distances between 5-digit zip codes, one only needs a 878*878 matrix to compute distances between 3-digit zip codes.

[8]I weigh the location of companies with the companies' market value at January, 1991. As a robustness check, I also weigh the location of companies with the companies' market value as of December, 1996, and the results are similar.

accounts between 1987 and 1991.[9] The data contain only a fraction of the entire investment that individual investors have made after they opened accounts. Because investors' investment objectives and styles may change over time (Duffie, 2002), the position information may not reflect precisely the investors' decisions during the studied period. I focus on only buy transactions because short selling (borrowing securities first and then selling them) is very limited.[10] The sample investors sell stocks largely to liquidate their long positions by definition.

For each buy transaction, the distance between the investor and his or her particular investment is measured as the distance between the zip code of his or her home and that of the company's headquarter. I calculate the distance between investor and personal portfolio as the average of the distances between investor and his or her investments, weighted by the value of each transaction as follows:

$$Dist_{i,own} = \sum_{j=1}^{n_{i,j}} w_{i,j} Dist_{i,j} \tag{1}$$

where $Dist_{i,own}$ is the distance between investor i and her own portfolio. Additionally, $w_{i,j}$ is the value of jth buy transaction divided by the total value of investor i's buy transactions during the entire sample period, $n_{i,j}$ is the number of buy transactions that investor i has made during the studied period, and $Dist_{i,j}$ is the distance between investor i's home and the headquarters of the company of her jth's buy.

Step 3 Calculate value-weighted and equally weighted local bias. I measure the local bias of an investor in two ways. The absolute local bias LB^{abs} is calculated as the difference between an investor's distance to the market portfolio and the distance to his or her own portfolio:

$$LB_i^{abs} = Dist_{i,market} - Dist_{i,own} \tag{2}$$

where $Dist_{i,market}$is the distance between investor i and the market portfolio and $Dist_{i,own}$ is the distance between investor i and her own portfolio as already defined. This absolute local bias can be either positive or negative. A positive (negative) absolute local bias indicates that the investors' own portfolio is closer to (farther from) her than the market portfolio (for greater detail, see Coval and Moskowitz, 1999).

[9] Barber and Odean (2000)

[10] Less than 1 percent of trades short sell shares.

To accommodate the heterogeneity in investors' locations, I use an alternative normalized measurement of local bias. It is defined as the absolute local bias normalized by the distance between the investor and the market portfolio:

$$LB_i^{norm} = \frac{LB_i^{abs}}{Dist_{i,market}} \tag{3}$$

where $LB_i^{norm}$is the normalized local bias of investor i. As the sample size gets larger, the normalized measurement will approximately follow a normal distribution. This will facilitate future statistical analysis of local bias. In particular, if there is no local bias in individual investors' investments, the normalized local bias will have the mean of 0.

The average distance between investors and the market portfolio is measured as both an equally weighted and as a value-weighted average of all investors' distances to the market portfolio. Formally, they can be expressed as

$$Dist_{avg,market}^{equal} = \frac{1}{27,189} \sum_{i=1}^{27,189} Dist_{i,market} \tag{4}$$

$$Dist_{avg,market}^{value} = \sum_{i=1}^{27,189} (\frac{Value_i}{\sum_{i=1}^{27,189} Value_i}) * Dist_{i,market} \tag{5}$$

where $Dist_{avg,market}^{equal}$ is the equally weighted average of the distances between investors and the market portfolio and $Dist_{avg,market}^{value}$ is the value-weighted average of the distance between investors and the market portfolio. $Valu_i$ is the total value of all buy transactions that investor i has made during the sample period.

The equally weighted and value-weighted average distance between investors and their own portfolios are similarly defined as:

$$Dist_{avg,own}^{equal} = \frac{1}{27,189} \sum_{i=1}^{27,189} Dist_{i,own} \tag{6}$$

$$Dist_{avg,own}^{value} = \sum_{i=1}^{27,189} (\frac{Value_i}{\sum_{i=1}^{27,189} Value_i}) * Dist_{i,own} \tag{7}$$

I calculate average absolute and normalized local biases as equally weighted and value-weighted averages of all investors' absolute and normalized local bias:

$$LB^{abs}_{avg,equal} = \frac{1}{27,189}\sum_{i=1}^{27,189} LB^{abs}_i \text{ and } LB^{abs}_{avg,value} = \sum_{i=1}^{27,189}(\frac{Value_i}{\sum_{i=1}^{27,189} Value_i}) * LB^{abs}_i \quad (8)$$

$$LB^{norm}_{avg,equal} = \frac{1}{27,189}\sum_{i=1}^{27,189} LB^{norm}_i \text{ and } LB^{norm}_{avg,value} = \sum_{i=1}^{27,189}(\frac{Value_i}{\sum_{i=1}^{27,189} Value_i}) * LB^{norm}_i \quad (9)$$

where $LB^{abs}_{avg,equal}$, $LB^{abs}_{avg,equal}$, $LB^{norm}_{avg,equal}$ and $LB^{norm}_{avg,value}$ are the equally weighted and the value-weighted average of the absolute and normalized local bias.

Calculating the local bias in absolute distance and the normalized percentage allows us to compare the empirical results with the benchmark of no local bias. If individuals do not exhibit local bias, we expect the mean of the normalized local bias to be 0, as the noise contributed by each investor will cancel out. If the difference between these two distances is instead significantly greater than 0, we then have to reject the null hypothesis that there is no local bias in individual investment decision. Formally, we can test Hypothesis 1.

Hypothesis 1: The normalized home bias is not different from zero.

We make the following simplifying assumptions when testing Hypothesis 1. First, we can assume that individual investors consider all securities in the U.S. market portfolio when making investment decisions. This assumption is consistent with the prediction of the Capital Asset Pricing Model (CAPM), that investors consider the whole universe of stocks when making investment decisions. Although individuals obviously do not have the necessary time or capability to consider all securities, they can invest in mutual funds instead of a few particular stocks to hold a portfolio similar to the market portfolio. [11]As a result, if distance does not influence individuals' investment decisions, we should observe a distance to their own portfolio similar to that to the market portfolio.

Second, we implicitly assume that investors are consistent in their investment decisions during the sample period. As investors need to hedge against supply shocks or unexpected demands, it is possible that an investor changes his or her investment objective and strategy during the studied period. Since no relevant information is available, I do not consider such changes in the current research.

[11] Since we focus on only equity trades in this study, one caveat of this assumption is that investors may be holding mutual funds which are more diversified. In a separate study, Ivkovich, Weisbenner and Zhu (2002) study how individual investors choose mutual funds relative to their equity portfolio holdings.

Finally, we assume that investors do not change their residence during the sample period. Even though I have stated that the change in the market portfolio location does not change the results, the results would be less reliable if investors moved during the sample period. We shall therefore assume investors stayed where they lived and use the location of the market portfolio during 1991 to keep both data consistent.

3 Individual Investors' Local Equity Bias

3.1 Individual Investor's Local Equity Bias

If individual investors invest as predicted by the CAPM, they will choose to invest in a wide universe of stocks. Because investors have different investment objectives (i.e., risk aversion and desired level of expected return), it is not surprising that a particular investor chooses to invest in securities located away from the market portfolio. On average, however, we expect investors' portfolios to include stocks similar to the market portfolio. As a result, the distances between investors and their portfolios should be similar to the distances between investors and the market portfolio.

However, both absolute and normalized measurements report significant bias in individual investors' stock selections. The result appears in Table 2. The equally weighted and value-weighted average distance between investors and the market portfolio is 1185.1 and 1171.2 miles, respectively. On the other hand, the equally weighted and the value-weighted average distances between investors and their own portfolios are 1024.3 and 1031.8 miles, respectively. The absolute local bias is 160.8 and 139.4 miles, respectively, measured with the two different weighting methods, and is significantly greater than 0 at the 1 percent level. The normalized measurement of local bias generates similar results. Investors' portfolios are 12.42% and 14.65% closer to investors' residences than the market portfolio. These results are also significantly greater than 0 at the 1 percent level.

(Please insert Table 2 here)

The local bias documented in this research is greater than the home bias of mutual fund managers reported in Coval and Moskowitz (1999). This challenges the notion that advantageous information is the major reason for individuals' local bias. Professional money managers collect information on a wide range of companies. They also enjoy direct contact with company management and, thus, have better opportunities to understand their investments. Hence, it is a common presumption that institutional investors possess more information on their investments than do individual investors. If this assumption and the advantageous information explanation both hold, we would expect individual investors to exhibit weaker local bias than institutional investors. This is, however, opposite to what we find. Since the time period and sample selection are quite different, comparability between these results and those of Coval and Moskowitz (1999) could be low. Still, the discrepancy leads us to ponder other factors that could contribute to individual investors' local bias.

As a matter of fact, the comparison between these results and Coval and Moskowitz (1999) is consistent with the findings of Grinblatt and Keloharju (2000), who find that individual investors exhibit stronger local bias in their equity investments than institutional investors. The difference between institutional and individual investors' local bias is, however, much smaller in the U.S. than in the Finnish stock market. This suggests that individual investors from different countries can have different tendencies to invest locally. This empirical study with the U.S. data is more generalized because Finland is very unusual in its population density and the public company location.[12]

3.2 Local Bias of individual investors from California and New York City

Californian investors are particularly interesting for two reasons. First, a large fraction of Californian companies are in high-technology industries such as biochemistry, electronics, and information technology. Such growth companies are typically hard to value. Many local investors work in related areas and feel optimistic about these companies' prospects. They may also favor local companies because they believe they possess advantageous information.

Second, about 20% of our sample investors live in California. If Californian investors behave differently from other investors, they may bias the results for the entire nation. Separating Californian investors will therefore test the robustness of our results.

[12] About 20 % of Finland's population lives in Helsinki metropolitan areas while 35.7 % of public companies are located there. (http://www.lysator.liu.se/nordic/scn/faq45.html#4.5.1, http://www.stat.fi/tk/tp/tasku/taskue_vaesto.html#region). Grinblatt and Keloharju (2000) use the same data to show that, in addition to geographical reason, culture and language also influence investors' decisions. The U.S. data allow us to avoid such complications.

The results are presented in Table 3. The equally weighted and value-weighted average of Californian investors' absolute local bias is 172.8 and 156.9 miles, respectively. The normalized local bias is 14.63% and 15.27%, respectively. Both measurements are significantly greater than the rest of the country at the 1 percent level. This confirms our hypothesis that Californian investors exhibit stronger local bias.[13]

(Please insert Table 3 here)

New York is unique in that the New York City is the financial center of the world. A higher fraction of residents work in finance-related companies (such as banks, insurance companies, and investment companies). It is interesting to explore whether such a high density of finance-related professionals might help individual investors from New York reduce their bias towards local companies. Reported in Table 3, the equally weighted average distances between New York investors and their portfolios and New York investors and the market portfolio are 1044.4 and 1193.7 miles, respectively. The local bias defined in both measurements is 149.3 miles and 12.75%, respectively, which are marginally weaker local biases as compared to the rest of the sample. [14]

3.3 Local Bias of Investors Holding Foreign Securities

Coval and Moskowitz (1999) link international home bias to domestic local bias and report that distance can explain about one-third of the home bias in international investment. If distance plays a role in local bias both domestically and internationally, we would expect domestic local bias and international local bias to be correlated. To test this hypothesis, I compare the domestic local bias of investors with and without foreign- related assets in their portfolios.

With the aid of information on type of securities held in investors' portfolios in our sample, we can first identify 5,023 investors who held at least one foreign-related asset in their portfolios. For the purpose of this analysis, we regard foreign equities, foreign fixed income products, foreign exchanges, and international mutual funds as foreign-related securities.

[13]We also perform non-parametric rank-sum test comparing the sample medians when comparing California and New York investors, respectively. The results are almost the same and not reported.

[14]Since investors from East coast are under-represented in the sample, our results on New York investors may be less representative than Californian investors of the entire population.

The home biases of investors with and without foreign-related assets in their portfolios are compared and the results reported in Table 4. According to the equal- and value-weighted measures, the portfolios of investors holding foreign assets are 131.0 and 120.6 miles closer to investors than the market portfolios, respectively. The normalized home bias is 6.36% and 8.45%, respectively. On the other hand, the portfolios of investors not holding foreign assets are 164.8 and 144.2 miles closer to the investors than the market portfolio and their equal- and value-weighted normalized local biases are 14.83% and 15.61%, respectively. Both measures are significantly greater than those of investors with foreign assets.[15] One possible reason for such a positive correlation is that investors who are more sophisticated follow a wider spectrum of securities both internationally and domestically. Such investors are better aware of the benefits of holding remote assets and therefore tend to invest remotely both within a country and across borders.

(Please insert Table 4 here)

3.4 Biases in the Distance Metrics

Several considerations have to be taken into account when we interpret the local bias using the measure outlined above, as was used in Coval and Moskowitz (1999).

One potential caveat of the relative measure is that it is asymmetrically distributed. Note from the definition of the normalized local bias that the highest possible measure of local bias is 1, when an investor buys a company headquartered in the same 3-digit zip code area as the investor's home. On the other hand, if an investor lives in the same 3-digit zip code area as the hypothetical location of the market portfolio, it is possible for the measure to take a value of negative infinity. To address this problem, we have excluded investors who are located in the same area as the market portfolio. However, investors close to that zip code can still have a large negative effect on sample mean.

Two reasons suggest that this does not pose a serious problem. First, the distribution of the sample data of individual investors' local bias is not dramatically skewed – the means and medians do not differ dramatically. In Section 3.1, we tested the results with non-parametric ranksum test in addition to t-test. The results are highly significant under this non-parametric test. Second, even

[15] We also perform non-parametric rank-sum test comparing the sample medians. The results are almost the same and not reported.

if negative observations do shift the entire sample mean towards the left, it should bias our results against finding local bias. Therefore, this potential bias actually works against finding positive local bias.

Another issue we have to keep in mind is that there is no guarantee the local bias measure will equal zero under the null hypothesis of no local bias. This is because the market portfolio is geographically tilted toward the East, and the individual investor sample is tilted toward the West. Consequently, the local bias may not follow the normal distribution even as the sample size gets large. This is a potential challenge to our results as well as those of Coval and Moskowitz (1999). It would be preferable to have a bias measure for which the null hypothesis is centered on zero, rather than dependent upon the geographical distribution of investors and firms in each country to which the test is applied.

To explore the magnitude of this problem, we bootstrap the empirical distribution of the current measure under the null hypothesis that there is no local bias in individual investments. Within each iteration, we assign each investor to a randomly selected 3-digit zip code area with equal probability. We then compute the local bias of each investor as defined in Section 2. The local bias of the entire sample is defined as the equally weighted average of the local bias of all sample investors. We then iterate this procedure 1,000 times, obtain the empirical distribution, and summarize the mean and the standard deviation of the bootstrapping distribution in Figure 3. Ideally, the mean of the distribution should not be significantly different from 0. The mean of the empirical distribution is actually 24.68, which is significantly greater than 0 at the 1 percent significance level. However, the absolute value of this deviation is significantly smaller than the local bias reported previously at 1 percent level. This indicates that we can reject the null hypothesis that individual investors exhibit no local bias robustly. Thus, although it does not affect our inference in this paper, it is of potential concern to future researchers seeking to use this metric.

(Please insert Figure 3 here)

Another approach is to form a null hypothesis that corresponds to each individual in the sample having an equal probability of purchasing shares in a given firm. To do this, we compute two distance measures for each of the 500 most frequently traded companies in our sample.[16] We first

[16] I thank William Goetzmann and Jon Ingersoll for pointing out this alternative measurement.

compute the distance between the company and all investors within the sample as the equally weighted average of distance between the firm and each investor.[17] Next, we compute the distance between the company and investors who have bought this particular company. This distance is similarly defined as the equally weighted average of distance between the firm and each investor who has bought this company. This new measure is independent from the location of each particular investor and instead more closely related to the location of public companies. Since we picked the 500 most frequently traded companies, we believe this generates representative results for the entire sample. The results are presented in Table 5 and Figure 3 and 4. It is obvious that the distance between companies and their shareholders is significantly smaller than the distance between the companies and all sample investors. Thus, we are able to reject the null that, on average across the top 500 firms, the investors that purchase their shares are drawn randomly from the population. We therefore conclude that our results are robust and not driven by a particular set of measurements

(Please insert Table 5 here)

(Please insert Figure 4 and 5 here)

4 Factors Contributing to Individual Local Bias

Having observed that individual investors exhibit local bias, we take a step further to ask whether they exhibit local bias for the same reasons as institutional investors do. Kang and Stulz (1997) and Coval and Moskowitz (1999) suggest that institutional investors' local bias in international and domestic investments is driven by information asymmetry. The present findings on individual local bias undermine this explanation since it is implausible that on average, individual investors possess more advantageous information than fund managers.

Familiarity with companies could be one factor. Huberman (2001) finds that investors are more likely to invest in a RBOC that operates in their areas, presenting evidence that "familiarity breeds investment". Familiarity is complicated because it brings out information that is both

[17] We also compute this measure as the weighted average of distance to all investors by trade size and the results remain large unchanged and not reported.

relevant and irrelevant to investments. Investors can gain familiarity with companies by examining the companies' annual and quarterly reports or by seeking a better understanding of their business models, both of which can provide valuation-relevant information. On the other hand, investors can become familiar with a company by consuming its products or being exposed to its advertisements. As the popularity of a company's products is not necessarily related to its stock performance and idiosyncratic risk, familiarity generated in this manner does not necessarily provide investors with the information relevant to investment.

One way to evaluate the information content of such familiarity is to investigate investor portfolio returns. If investors with higher local bias possess advantageous information, their portfolios should outperform those who are less locally biased. The rationale is that investors with advantageous information will utilize such information and trade on mispriced stocks. In the next section, I perform cross-sectional tests to see whether investors who are more locally biased enjoy higher returns.

4.1 Portfolio Returns of Individual Investors

We calculate the gross monthly return on the household's portfolio[18]

$$R_{i,t} = \sum_{j=1}^{s_{j,t}} p_{ij,t} R_{j,t} \tag{10}$$

where $p_{ij,t}$ is the beginning-of-month market value for the holding of stock j by investor i in month t divided by the beginning-of-month market value of all stocks held by investor i; $R_{j,t}$ is the gross monthly return for stock j in month t; and $s_{i,j}$ is the number of stocks held by investor i in month t (for greater detail, see Barber and Odean, 2000).

The gross monthly return earned by the average household during month t is calculated as

$$R_t^{avg} = \frac{1}{n_t} \sum_{i=1}^{n_t} R_{i,t} \tag{11}$$

where n_t is the number of investors with common stock investment in month t.

[18] An alternative way is to measure investors' portfolio return net of transaction costs. I do not pursue this measurement since I am interested in the cross-sectional difference of portfolio returns for investors with different levels of local bias. Barber and Odean (2001) report that the transaction costs are about 1 % of total transaction value.

We divide investors into quintiles based on their local bias and calculate the gross monthly portfolio return for each quintile. If biasing towards local companies helps individuals better understand their investments, investors with greater local bias should record higher portfolio returns than those who invest more in remote companies. However, the empirical results in Table 6 do not support such predictions. The portfolio return of the first quintile (smallest local bias) is not significantly different from that of the last quintile (largest local bias). This result lends support to the hypothesis that advantageous information is not a major factor for individual investors' local bias.

(Please insert Table 6 here)

Next, we calculate the risk-adjusted return of investors' portfolios. We estimate the risk-adjusted return by following the framework of the CAPM and the three-factor model by Fama and French (1993). For the CAPM model estimation, we estimate Jensen's alpha by regressing the individual investor's monthly excess return on the monthly market excess return.

$$(R_t^{avg} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_{it} \tag{12}$$

where R_{ft} is the monthly return on Treasury bill, R_{mt} is the monthly return on a value-weighted market index, α_i is the CAPM intercept (Jensen's alpha), and β_i is the market beta.

For the Fama-French three factor model, we regress:

$$(R_t^{avg} - R_{ft}) = \alpha_j + \beta_j(R_{mt} - R_{ft}) + s_j SMB_t + h_j HML_j + \varepsilon_{jt} \tag{13}$$

where SMB_t is the return on a value-weighted portfolio of small stocks minus the return on a value-weighted portfolio of large stocks, and HML_t is the return on a value-weighted portfolio of high book-to-market stocks minus the return on a value-weighted portfolio of low book-to-market stocks. The regression yields parameter estimates of α_j, β_j, s_j, and h_j.

Regression results in Table 5 show that the risk-adjusted portfolio return is not significantly different for investors with high or low local bias. This confirms findings that investors with greater local bias do not outperform investors with smaller local bias. In addition, the coefficients for SMB_t and HML_t are both significantly positive, indicating that individuals tilt towards small and value stocks. Such tendency is similar across all quintiles.

4.2 Local Bias and Investor Sophistication

Grinblatt and Keloharju (2000) show that different classes of investors are quite different in their local biases. Dhar and Zhu (2002) find that investor sophistication varies even within individual investor class. They argue that income and profession can proxy for investor sophistication, because wealthy and professional investors have better analytical skills and better access to business-related information. Consistent with their hypothesis, sophisticated investors exhibit a weaker disposition effect than less sophisticated investors. The current research is particularly concerned with learning whether different demographic groups exhibit different levels of local bias.

Experimental economists have documented that experience helps individuals perform better (Wegener and Petty, 1995). Dhar and Zhu (2002) find the same pattern in individual investors' trading that more experienced investors exhibit significantly weaker disposition effect. Likewise, this study posits that investors with more trades understand the financial markets better and therefore exhibit weaker local bias.

We carry out the following regression to understand the impact of demographics and trading experience on local bias:

$$LB = X\beta + \varepsilon \tag{14}$$

where LB is a vector of normalized local bias of each trade; X is a matrix of investor characteristic variables. The local bias of each individual transaction is defined according to the same principle as the normalized local bias measurement. We measure the local bias of each investor as the equally weighted average of the local bias of all investments that the investor has made during the six-year period.[19] Investor characteristics variables include investor occupation dummies, investor income dummies, investor age, and the number of trades that each investor has executed.

The "professional" dummy is set to 1 if the investor's job is in the "professional/technical" or "administrative/managerial" professions, and 0 otherwise. The "non professional" dummy is set to 1 if an investor's job is in the "clerical/white collar," "craftsman/blue collar," or "sales/service" professions, and 0 otherwise. The "high income" dummy is set to 1 if the investor's annual income is greater than $100,000. The "low income" dummy is set to 1 if the investor's annual income is

[19] We also calculated the local bias of each investor as the value-weighted average of local bias of all investments that the investor has made. The regressions generate very similar results that are not reported here.

lower than \$40,000. An investor's trading experience is the total number of trades that he or she has executed within the sample period. We use the logarithm of the number of trades, because the distribution of the number of trades is positively skewed.

The empirical results are reported in Table 7. The coefficient for "non professional" is significantly positive (1.26), indicating that "Non professional" investors exhibit significantly stronger local bias than other investors. The coefficient for "high income" investors is significantly negative (-1.24), indicating that they exhibit significantly less local bias than other investors. In line with Grinblatt and Keloharju's (2000) findings, that more sophisticated investor classes show weaker local bias, this study finds investor sophistication matters within the individual investor class. The more sophisticated investors, such as wealthy and professional individuals, have significantly smaller local bias than less sophisticated ones. Different from Dhar and Zhu (2002)'s findings on the disposition effect, the present study finds that age and trading experience do not have meaningful impact on investors' local bias.

(Please insert Table 7 here)

4.3 Individual Local Bias and Investment Characteristics

The existing literature (Kang and Stulz, 1997; Coval and Moskowitz, 2002) argues that institutional investors favor remote companies that are large in size and financially healthy. Since information on large and healthy companies is generally more available, their findings support that advantageous information in part motivates fund managers' local bias. This study explores whether individual investors also possess such discerning ability and the impact of firm-specific characteristics on individual's local bias.

We calculate the normalized local bias of each trade according to equation (3). There are two ways to perceive trades within the portfolio of the same investor. Each investment can be regarded as part of an investor's entire portfolio and, therefore, related to other investments. Alternatively, it is also conceivable that an investor made independent decisions regarding different investments because of stochastic information flow or hedging demand. We make the latter assumption and adopt OLS regression in this study. Investors in our sample do not trade frequently, and the median investor makes about 3 trades every year. The long intervals between transactions tend to attenuate the potential correlation between trades.[20]

(Please insert Table 8 here)

I next consider several firm characteristics that could influence investor's home bias: size, leverage, current ratio, book-to-market ratio, the number of employees, and advertising intensity. Results are reported in Table 8. In regression (A) we regress home bias on the log of firm market value. The coefficient is negative and significant, implying that investors choose large companies when investing remotely. This is consistent with previous research (Kang and Stulz, 1997), which suggests that investors avoid remote companies whose information is hard to obtain. Because large companies provide better investor relationship and are followed by more research analysts, individual investors favor large companies when they invest remotely.

We include leverage and current ratio in regression (B) as proxies for company financial distress. Leverage, defined as the ratio of total liabilities to total assets, measures the overall likelihood of company distress. Current ratio, defined as the ratio of current assets to current liabilities, measures the short-term financial health of a company. If individual investors' local bias is driven by advantageous information, local bias will be negatively correlated with financial distress. Investors are more likely to invest in risky projects locally because they have more information on local companies. When investors decide in which non-local companies to invest, they will invest in non-local companies that have safer accounting numbers (Kang and Stulz, 1997). The coefficients of both variables are significant and have the expected signs. The absolute values of both coefficients are much smaller than those documented in Coval and Moskowitz (1999), indicating that financial distress matters far less to individual investors than it does to institutional investors.

We include the market-to-book ratio in regression (C). The coefficient of market-to- book ratio is negative, suggesting that investors exhibit greater local bias towards growth companies, although the impact is economically marginal and statistically insignificant. This indicates that leverage and current ratio have greater explanatory power than the market-to-book ratio in explaining local bias. In regression (D), the number of employees does not have much impact on the magnitude of the local bias.

[20] We also model correlation between trades in an explicit way similar to that in Coval and Moskowitz (1999). The results remain largely unchanged and therefore are not reported here.

Overall, regression coefficients suggest that the impact of common factors representing company risk on the individual investors' local bias is economically limited, suggesting that individual investors care less about financial distress or information asymmetry. Since it is clear that investors with high local bias do not have higher returns, I conclude that individuals' local bias is not driven primarily by information asymmetry.

4.4 Awareness, Advertising, and Investment

Huberman (2001) shows that investors tend to invest in companies with which they are familiar. An implication of this is that individuals' local bias is potentially influenced by advertising. Nelson (1974) points out that one important role of advertising is to communicate information. A company uses advertising to make the public aware of its product, brand, or image. The more an individual is exposed to a company's advertising, the more familiar he or she becomes with the company. Investors can decide to invest in a company because they are familiar with the brands or products of the company. The information contained in advertising, however, pertains to product and branding rather than investments. Hence, it is hard to determine how much individuals, as investors, would benefit from advertising.

Several studies report that advertising is effective in attracting investment. Sirri and Tufano (1998) argue that advertising can reduce investors' searching costs and attract investments to mutual funds. Jain and Wu (2001) confirm this and show that mutual funds advertising past outstanding performance do not show superior performance during the period following their advertisements, implying that such advertisements do not necessarily contain investment-relevant information.

Three particular reasons explain how advertising attracts investment. First, advertising increases investors' awareness of certain companies. Part of the reason why investors do not invest in some companies or economies is that they are not aware of the existence of such companies or economies. Advertising brings such information to light for investors.

Second, advertising can perhaps help reduce the set of considered opportunities and increase the likelihood of investors' considering investing in a particular company. Because information search is costly, individuals simplify their choices by first predetermining a small set of candidates, from which they will make their final choices (Hauser and Wernerfelt, 1990). Given that individual portfolios are far from being mean-variance efficient (Benartzi and Thaler, 2001; Goetzmann and Kumar, 2002), individuals may use a similar heuristic in their investment decisions. If so, advertising can increase the likelihood of a company's being included into the choice set. As Nelson (1974) shows empirically, individuals are more likely to gain exposure to advertising of local companies than to that of remote companies and local advertising can be more effective than national advertising because it bears more consumption-relevant information.

Finally, advertising can make investors more familiar with a particular company by facilitating investors to retrieve such companies from their memory. Since more retrievable information is also more available, individuals tend to bias toward such information (Tversky and Kahneman, 1974). More recently, Nedungadi (1990) shows with experiments that advertising helps individuals retrieve particular products from their memories and makes investors more aware of certain companies than of others. This awareness can be independent from individuals' evaluation of different objects, and the most easily retrievable items are not necessarily those with the highest utility to individuals. In the context of investment, a company's advertisement can make the company easily accessible to an investor as a potential investment candidate even though the particular stock is not the best choice for the investor's portfolio.

To test whether advertising impacts local bias, I include the advertising intensity as a proxy for familiarity into regression specified in equation (13) and report the results in regression (E) of Table 8. Advertising intensity is defined as the total advertising expenditures divided by the total sales of a company. The total advertising expenditures are not used because of the possible collinearity problem between the total advertising expenditures and the market capitalization variables. It is assumed that advertising by different companies generates a homogeneous effect among all investors, because it is not feasible to control for variations in advertising's reach and effectiveness (Guadagni and Little, 1983).

The coefficient of advertising intensity is negative and significant, which suggests that individual investors exhibit less local bias in their investment in companies that advertise more. Consistent with Huberman (2001), we find that familiarity indeed induces individuals' investments. Advertising is shown to be effective in attracting individuals' investments to certain equities. Given that portfolio returns are not significantly different for investors with different local biases, advertising does not seem to reward investors with excess return.

It is also interesting to note that after one includes advertising intensity, the coefficient of market value becomes much smaller and less significant. Collinearity does not seem to be an explanation, because the correlation coefficient between these two variables is small. This could imply that the impact of firm size on local bias is actually twofold. First, as Fama and French (1993) suggest, firm size is a proxy for cross-sectional risk of companies. Second, as the current regression indicates, size is also a proxy for familiarity. As larger companies advertise more nationwide, individual investors are more familiar with them and therefore exhibit less local bias when investing in large companies.

5 Investors' Responses to Local Earnings Announcements

Another potential way to separate information- and non-information-based factors behind individual investors' local bias is event study. If local individual investors possess advantageous information, they should take advantage of it by trading before events. This would differentiate them from remote investors, who do not have advantageous information. Alternatively, even though local investors do not possess advantageous information, they react more than remote investors to the same information, a tendency which can also generate local bias. If this is true, local investors are expected to behave differently after events, when important information is revealed.

Earnings announcement, as an information-related event, allows us to explicitly study individual investors' responses to information. Earnings announcement is important to common stock investment because it offers firm-specific information to investors. Firms with positive earnings surprises outperform firms with negative earnings surprises in the six-month period following announcement (Chan, Jegadeesh, and Lakonishok, 1996). The timing of an earnings announcement is usually scheduled several weeks in advance so that investors have expectation of it. However, investors do not know whether companies can beat the earnings forecast consensus.

As discussed, if individual investors can predict the earnings announcement better than remote investors, they should increase/decrease their positions in stocks with positive/negative earnings surprises before the earnings announcements for higher portfolio returns. Such trading patterns would significantly distinguish them from remote investors who do not possess such information. Hence, we may expect local investors to change their portfolios more than remote investors relative to average week trading volume (AWTV) before earnings announcement. We can formally test this expectation as Hypothesis 2.

Hypothesis 2a: Before positive earnings surprises, local investors do not increase their position in such stocks more than remote investors do.

Hypothesis 2b: Before negative earnings surprises, local investors do not decrease their position in such stocks more than remote investors do.

An alternative explanation is overreaction to local information. Tversky and Kaheman (1974) show that individuals exhibit an "availability heuristic," meanings that they are more responsive to more readily available information. Following studies (Borgida and Nisbett, 1977) also show that information salience and personal communications make information more readily available. Since local information is more salient and can be conveyed through personal interaction, investors will therefore be more responsive to local information. If individual investors indeed respond asymmetrically to local and remote company information, local investors will change their positions more than remote investors do in response to the same earnings surprises. More active reaction to information on local companies can in part explain why individual investors favor local stocks. We may formally test this as Hypothesis 3:

Hypotheses 3a: After positive earnings surprises, local investors do not change their positions of local stocks more than remote investors do.

Hypotheses 3b: After negative earnings surprises, local investors do not change their positions of local stocks more than remote investors do.

5.1 Earning Announcement Data and Methodology

The earnings announcement dataset comes from I/B/E/S and contains 82,291 quarterly announcement events covering 6,224 stocks between 1991 and 1996. I exclude companies for which forecast and actual earnings data are unavailable as well as companies whose return data are not available from CRSP. The final summary forecast matching the earnings announcement is available for 71,577 announcement covering 5,384 stocks.

Because individual investors trade infrequently, the control event window is set to be 24 weeks before and after the earnings announcement to obtain enough observation for calculating the average weekly trading volume (AWTV). To prevent outliers from contaminating the analysis, we exclude observations outside three standard deviations from the mean of earnings surprises. We exclude forecasts made by fewer than three analysts to ensure the forecast is consensus rather than distinctive opinions by few analysts. This criterion is not set higher because fewer analysts follow small companies. A more stringent criterion may bias the sample toward large companies.[21] Earnings surprises are defined as the differences between realized earnings levels minus the consensus of earnings forecast. A positive earnings surprise means that the company beats the forecast consensus, whereas a negative one indicates that the company misses the forecast consensus. Since we intend to study only investors' responses to earnings surprises, cases in which there are no earnings surprises, i.e., the actual earnings announcement is the same as the earnings forecast, are excluded.

To test Hypotheses 2 and 3, we define the key statistics of Buy-Sell Imbalance (BSI) as:

$$BSI_i^t = \frac{VB_t^i - VS_t^i}{AWTV_i} \tag{15}$$

where

VB_i^t = Dollar value of stocks i purchased during week t before or after its earnings announcement;

VS_i^t = Dollar value of stocks i sold during week t before or after its earnings announcement;

$AWTV_i$ = Average weekly dollar value of trading on stock i during the 48 weeks around earnings announcement (for details, see Hong and Kumar, 2002).

To estimate $AWTV_i$, I first compute the trading volume generated by all investors during a particular week and then take the average of trading volume of all 48 weeks to obtain $AWTV_i$. Since individual investors trade infrequently in the sample, we include only those weeks when there is trade on stock i.[22]

This measurement reflects investors' relative tendency to buy or sell a particular stock during a particular week. The bigger/smaller the absolute value of BSI_i^t, the stronger/weaker the investors' tendency to buy stock i in week t. Positive/negative BSI_i^t indicates individual investors are net buyers/sellers of stock i during week t. If local investors are more responsive to earnings surprises from local companies than remote investors during the studied period, the absolute value of BSI_i^t for local investors should be larger than that for remote investors.

[21] Separately, we use the median of earnings forecast as the consensus of the earnings forecast and the results remain unchanged.

[22] We also experimented the results when we include the weeks with no trade and the current results are robust.

To obtain enough trade observations by both local and remote investors, we focus on stocks on which sample investors have made at least 10 trades. This filtering rule leaves us 713,041 trades and 22,640 investors from 309 unique 3-digit zip code areas. Local investors of each area are defined as investors who live within 50 miles of the centroid of each 3-digit zip code area. Remote investors are defined as investors living more than 1,000 miles away from the centroid of each 3-digit zip code area.[23] BSI_i^t for local and remote investors is computed following definition outlined in equation (14). Our final earning surprise data comprises of 15,769 earnings announcement events for 1,230 companies, 8,621 of which are positive earnings surprises and 7,148 of which are negative earnings surprises. For each zip code area, the BSI_i^t during week t for local/remote investors is computed as average of BSI_i^t of all stocks traded during week t by local/remote investors from that area. The BSI_i^t for all local/remote investors during week t of the entire sample is defined as the equal average of BSI_i^t of all stocks traded by all local/remote investors during week t.

5.2 Empirical Results

5.2.1 BSI Movement before Earnings Announcements

The BSI movement before earnings announcement for local and remote investors appears in Figure 6 and 7. I also formally test whether the BSI is significantly different from 0 for each period and report results in Table 9 and 10. For most periods, the BSI is significantly different from 0 for local and remote investors. Also tested is whether the BSI of local investors is significantly greater/smaller than that of remote investors for positive/negative earnings surprises in column 4 of Table 9 and 10, respectively. For more than half of the periods, the BSI s of local and remote investors are not significantly different for both positive and negative earnings surprises. This is not surprising since there is possibly little directional information during most periods and individual investors move their portfolios in a "noisy" way, given their heterogeneous expectations or hedging demands.

(Please insert Figure 6 and 7 here)

[23] I tried several definition of local and remote investors. Investors are defined as investors living within 25, 50, and 75 miles of the centroid of the 3-digit zip code area. Remote investors are defined as investors living more than 500, 750, and 1,000 miles away from the centroif of the 3-digit zip code area. The results remain largely unchanged.

(Please insert Table 9 and 10 here)

The last 4-week period before the earnings announcement period is particularly relevant to this research because the earnings announcement should become the most important factor that influences investors' decisions regarding these particular stocks. For positive earnings surprises, the BSI of both local and remote investors are significantly different during the 2 weeks just before earnings announcement (t-statistics equal to -1.984 and -3.814, respectively). However, it is the local investors who reduce their positions in these stocks more than remote investors (-0.321 vs. –0.244 and –0.333 vs –0.238). This is opposite to Hypothesis 2 that local investors make better predictions of earnings surprises. Instead, it implies that local investors react more to upcoming events, disregarding its information content.

The BSI from T-3 to T-4 weeks are not significantly different for local and remote investors. It is interesting that both local and remote individual investors decrease their positions significantly before positive earnings surprises. It seems that individual investors, on average, have wrong expectations about earnings for stocks with positive earnings surprises.

The results are mixed for BSI movement before negative earnings surprises. The BSI of local and remote investors are not significantly different during three of the four weeks right before earnings announcement (t-statistics equal to –1.056, 1.342, and 1.303, respectively). During T-2 week, local investors decrease their portfolios more than remote investors do, which rejects Hypothesis 2b.

Even though individual investors move their portfolios in the correct direction before earnings announcements with negative surprises in one week, one has to be careful in concluding that individual investors can predict earnings. There is a fifty percent likelihood that individual investors move their portfolios in the correct direction for either positive or negative earnings surprises by pure chance. Also, if individual investors can really predict earnings surprises, we should observe them demonstrate similar ability for positive earnings surprises. A more plausible explanation is that, regardless of the direction of earnings surprises, individual investors tend to decrease their positions in such stocks to reduce risk exposures before earnings announcements.

In sum, for both positive and negative earnings announcements, Hypothesis 2a and 2b cannot be rejected for the month before earnings announcements. This leads us to conclude that, compared with remote investors, local investors do not possess better ability to forecast earnings surprises. This offers additional support to the previous findings that local investors do not possess a greater amount of advantageous information about local companies than their remote counterparts.

5.2.2 BSI Movement after Earnings Announcements

Now that information has already been made public at the earnings announcement, investors' portfolio changes shortly after the earnings announcement should not be attributable to advantageous information but to investor behavior instead.

It appears in Table 11 that, investors decrease their positions in stocks after positive earnings surprises. This result is consistent with findings of Hong and Kumar (2002), who attribute such movement to individuals' responses to price trends. In this research, I focus only on comparing the BSIs between local and remote investors and do not investigate the rationale behind such behavior. Local investors' BSI is greater than that of remote investors in absolute value for every week during the first four weeks after earnings announcement and the overall portfolio decrease in the stocks during the four weeks is significantly greater for local than remote investors. Both results indicate that local investors respond more to positive earnings surprises.

The results in Table 12 shows that, local investors increase their positions in stocks after negative earnings surprises during the 3-week period after the earnings announcement (p-values are 0.604, 0.000, and 0.000, respectively). This is consistent with previous finding (Hong and Kumar, 2002, Goetzmann and Massa, 2000) that investors are contrarians in the short run. On the other hand, there is no clear direction in remote investors' portfolio change after negative earning surprises (BSI equals to –0.017, 0.004, and –0.064 with corresponding p-values of 0.364, 0.874, and 0.000, respectively.). For week T+2 and T+3, the BSI of local investors are significantly greater than that of remote investors, indicating that local investors exhibit stronger contrarian buying intensity than remote investors do. The BSIs of local and remote investors become largely similar during most weeks after week T+4.

(Please insert Figure 8 and 9 here)

(Please insert Table 11 and 12 here)

In sum, for the four-week period after earnings announcement, both Hypothesis 3a and 3b are rejected, making me conclude that investors indeed respond more to local company earnings surprises than to those of remote companies. Since information is virtually the same to local and remote investors after the earnings announcement, I conclude that this contrast is not due to local and remote investors' differential information but to their differential responses to the same information.

5.2.3 Discussion

One possible reason that investors respond more to local earnings surprises is that it takes time for information to reach remote investors and, therefore, the up-to-date earnings surprise is not readily available to them. This explanation is however problematic since an earnings announcement typically takes place after the stock market closes. Until the next morning when the market opens, the earnings announcement will be published and broadcast throughout the country. As a result, exactly the same earnings announcement should be available to both local and remote investors by the next day's market opening. Additionally, I study the BSI of the first week instead of the first day after earnings announcement. This should significantly alleviate the potential impact of information delay on remote investors' responses.

Another explanation is that local and remote investors respond differently to the same piece of information. Psychology literature has documented that individuals do not respond to information in the same way. Tversky and Kahneman (1974) show in their pioneering work that individuals are more responsive to salient information and information that is more easily available for the mind to process.

It is conceivable that earnings surprises are more salient to local than to remote investors. Individuals generally have two channels through which they obtain information, mass media and personal interaction. Remote investors typically obtain their information through the media, namely newspaper or television broadcasting.

In addition to mass media, investors learn about local companies through personal information exchange (i.e., from their friends or relatives, who may be holding the same stock or working for the company that just issued earnings announcement). Personal descriptions of business prospects can make the earnings announcement more salient than those obtained through media (Borgida and Nisbett, 1977). Such salience can make investors bias toward local information and induce investors to move their portfolios more than remote investors.

Yet another possibility is that personal interactions make local information more available to investors. This will also prompt individual investors to follow local news more closely and pay more attention to local companies' earnings forecasts and announcements than to those of remote companies. This, too, can make investors more responsive to local stock earnings announcements. Such active response, in part, can also explain individual investors' tendency to favor local stocks.

Assuming individuals process earnings announcements similarly to the way they would process other types of information, our results can be generalized: individual investors are more responsive to information about local companies. This will lead investors to invest more in local companies.

6 Conclusions

In this article, I investigate individual investors' bias towards local companies in their domestic equity investment. Various measurements show that individual investors exhibit significant bias towards the companies that are close to their residences. Our sample individuals exhibit a stronger home bias than the mutual fund managers in Coval and Moskowitz (1999). Investors holding foreign securities exhibit significantly weaker local bias than those not holding foreign securities, suggesting that international home bias and domestic home bias are correlated.

Unlike institutional investors' choices, individual investors' local bias is less related to advantageous information. Investors with stronger local bias do not outperform those with weaker local bias. Information such as accounting number has less impact on the individual investors' local bias than on that of institutional investors. Instead, individual investors' local bias is negatively related to the advertising intensity of companies. These findings cast doubts on the hypothesis that advantageous information drives individual investors' local bias. Instead, they support that investors tend to invest in companies with which they are familiar even though such familiarity is not particularly helpful to their equity investment. Behavioral theory on decision heuristics and the mechanism of advertising can explain part of the puzzle.

Evidence from investors' responses to earnings announcements offers additional support to the behavioral hypotheses. Local investors cannot predict earnings surprises better than remote investors, which contradicts the advantageous information explanation. Rather, local investors are more responsive than remote investors to the same earnings surprises after earnings announcement. Investors' overreaction to information on local companies can, in part, explain their tendency to invest locally.

Results in this study show that investor behavior varies significantly across investor classes, which motivates future research on the impact of investor clientele upon asset prices (Barberis, Shleifer and Wurgler, 2002). It is also important to examine whether investors respond differently to the same information under other circumstances and to incorporate such phenomena into future theoretical frameworks.

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Table 1. Data Description

The primary dataset contains individual investor data from a large U.S. discount brokerage firm between 1991 and 1996. The dataset contains three files: (1) Trades file contains buy and sell transactions executed by all investors; (2) Demographics file contains key demographic information, such as income, occupation, age, and geographical location (5-digit zip code) for a subset of investors; (3) Positions file contains the end-of-month portfolios of all investors.

Panel A: Trades	
Total number of trades	2,886,912
Total number of trades in stocks	1,854,776
Average number of trades	41 (Median = 19)
Average holding period	187 days (Median = 95)
Panel B: Households	
Number of households	79,995
Number of households trading equities	62,387
Number of households with location information	27,189
Panel C: Demographics	
Average income	$59,097 (Median = $50,000)
Average age	50 (Median = 48)
Panel D: Positions	
Average account size	$35,629 (Median = $13,869)
Average number of stocks in the portfolios	4 (Median = 3)
Average monthly portfolio turnover	7.59% (Median = 2.53%)

Table 2. Local Bias of Individual investors

$Dist_{avg,market}$, the average distance between investors and the market portfolio, is in Column 2. $Dist_{avg,own}$, the average distance between investors and their own investment portfolios, is in Column 3. The absolute home bias measured in miles is in Column 4. The normalized home bias measured in percentage is in Column 5. There are a total of 27,189 investors in the full sample, 20,509 investors in the ex-CA sub-sample, and 24,591 investors in the ex-NYC sub-sample. In Panel A, $Dist_{avg,market}$ and $Dist_{avg,own}$ are the equally weighted average of investors' distances to the market portfolio and their own portfolios. In Panel B, $Dist_{avg,market}$ and $Dist_{avg,own}$ are the value-weighted average of investors' distances to the market portfolio and their own portfolios. Absolute and normalized local bias is equal- and value-weighted average of absolute and normalized local bias of corresponding investors in Panel A and B, respectively.

	$Dist_{avg,market}$	$Dist_{avg,own}$	LB^{abs}_{avg}	LB^{norm}_{avg}	$p-value$
Panel A: Equal-Equal					
Equal-Equal	1185.1	1024.3	160.8	12.42***	0.000
Equal-Equal(ex-CA)	1186.5	1029.6	156.9	12.00***	0.000
Equal-Equal(ex-NYC)	1182.2	1020.6	161.6	12.49***	0.000
Panel B: Value-Value					
Value-Value	1171.2	1031.8	139.4	14.65***	0.000
Value-Value(ex-CA)	1104.8	971.1	133.6	14.44***	0.000
Value-Value(ex-NYC)	1184.4	1043.6	140.8	14.75***	0.000

*** indicates significant at 1 percent level (two tailed)

Table 3. Home Bias of New York Metropolitan and Californian Investors

$Dist_{avg,market}$, the average distance between investors and the market portfolio, is in column 2. $Dist_{avg,own}$, the average distance between investors and their own investment portfolios, is in column 3. The absolute home bias measured in miles is in column 4. The normalized home bias measured in percentage is in column 5. There are 6,680 investors living in California, and 2,598 investors living in the metropolitan areas of New York City. Absolute and normalized local bias is equal- and value-weighted average of absolute and normalized local bias of corresponding investors in Panel A and B, respectively. In Panel A, $Dist_{avg,market}$ and $Dist_{avg,own}$ are the equally weighted average of investors' distances to the market portfolio and their own portfolios. In Panel B, $Dist_{avg,market}$ and $Dist_{avg,own}$ are the value-weighted average of investors' distances to the market portfolio and their own portfolios.

	$Dist_{avg,market}$	$Dist_{avg,own}$	LB^{abs}_{avg}	LB^{norm}_{avg}	$p-value$
Panel A: Equal-Equal					
California	1180.8	1008.1	172.8	14.63***	0.000
New York City	1193.7	1044.4	149.3	11.69***	0.000
Panel B: Value-Value					
California	1370.6	1213.8	156.9	15.27***	0.000
New York City	1048.9	922.2	126.6	13.73***	0.000

*** significant at 1 percent level (two tailed)

Table 4. Local Bias of Investors Holding and Not Holding Foreign Assets

$Dist_{avg,market}$, the average distance between investors and the market portfolio, is in column 2. $Dist_{avg,own}$, the average distance between investors and their own investment portfolios, is in column 3. The absolute home bias measured in miles is in Column 4. The home bias measured in percentage is in column 5. There are 5,023 investors holding foreign related assets and 22,166 investors not holding foreign related assets. Absolute and normalized local bias is equal- and value-weighted average of absolute and normalized local bias of corresponding investors in Panel A and B, respectively.In Panel A, $Dist_{avg,market}$ and $Dist_{avg,own}$ are the equally weighted average of investors' distances to the market portfolio and their own portfolios. In Panel B, $Dist_{avg,market}$ and $Dist_{avg,own}$ are the value-weighted average of investors' distances to the market portfolio and their own portfolios.

	$Dist_{avg,market}$	$Dist_{avg,own}$	LB^{abs}_{avg}	LB^{norm}_{avg}
Panel A: Equal-Equal				
Foreign	1166.4	1035.5	131.0	6.36
No foreign	1187.5	1022.7	164.8	14.83
Foreign-No Foreign			-33.8 ***	-8.47***
Panel B: Value-Value				
Foreign	1157.6	1037.0	120.6	8.45
No foreign	1171.4	1027.1	144.2	15.61
Foreign-No Foreign			-23.6***	-7.16***

*** Significant at 1 percent level (two tailed)

Table 5. The distance between firms and all sample investors and the distance between firms and investors who traded the focal stocks.

We select 500 most frequently traded stocks by sample indivdual investors. For each company, the distance between the company and all sample investors is defined as the equal average of the distance between the company and each individual investor. The distance between the company and investors who have invested in this stock is defined as the equal average of the distance between the company and each individual investor who has traded this stock. Signifiance from t-test and wilcoxon ranksum test are provided in parentheses.

	Distance between Companies and Investors		
	All Sample Investors	Investors who Invested in Focal Stocks	Difference
Mean	1295.7	1184.8	110.9
			(4.88)***
Median	1260.5	973.4	287.1
			(7.48)***

*** indicates significant at 1 percent level (two tailed).

Table 6. Portfolio Return for Investor Quintile Formed on Local Bias

The sample is account records for 27,189 households at a large U.S. discount brokerage firm from January 1991 to November 1996. Households are sorted into quintile based on the local bias they exhibit in the entire period. The local bias of each household is defined as the value-weighted average of the local bias of all of its trades. Formally, the local bias of each household is defined as $LB_i^{norm} = \frac{LB_i^{abs}}{Dist_{i,market}}$. CAPM intercept is the estimated intercept from a time series regression of the household excess return on the market excess return ($R_{mt} - R_{ft}$). Fama-French intercept is the estimated intercept from time series regressions of household excess return on the market excess return, a zero-investment size portfolio (SMB_t) and a zero-investment book-to-market portfolio (HML_t). p-values are presented in the parentheses.

	Quintile					
	1	2	3	4	5	Difference
	(Low)				(High)	High-Low
Panel A: Descriptive Statistics						
Local Bias	-0.210	0.043	0.145	0.240	0.397	0.607***
						(0.000)
Raw return	1.531	1.501	1.506	1.468	1.482	-0.049
						(0.351)
CAPM Intercept	-0.044	-0.090	-0.089	-0.060	-0.084	-0.040
	(0.918)	(0.589)	0.250	0.575	0.384	(0.449)
Fama-French Intercept	-0.096	-0.128	-0.127*	-0.136**	-0.128*	-0.032
	(0.900)	(0.144)	(0.059)	(0.040)	(0.055)	(0.604)
Panel B: Fama-French Three Factor Model						
Fama-French Intercept	-0.096	-0.128	-0.127*	-0.136*	-0.128*	-0.032
	(0.124)	(0.144)	(0.059)	(0.040)	(0.055)	
$(R_{mt} - R_{ft})$	1.051	1.160***	1.112**	1.120***	1.120***	0.069
	(0.141)	(0.000)	(0.020)	(0.000)	(0.000)	
SMB_t	0.512***	0.592**	0.534**	0.531**	0.736***	0.224
	(0.000)	(0.014)	(0.022)	(0.029)	(0.000)	
HML_t	0.099**	0.167**	0.162**	0.163***	0.177***	0.078
	(0.014)	(0.003)	(0.014)	(0.000)	(0.000)	
$R-square$	87.2	82.4	85.7	77.2	84.0	

***, ** and * indicate significant at 1,5, and 10 percent levels (two-tailed).The null hypothesis for the coefficient estimates on the market excess return is $H_0 : \beta = 1$, and in the difference column the null hypothesis is $H_0 : \beta = 1$

Table 7. Local Bias and Investor Characteristics

The dependent variable is the local bias of each investor. The normalized local bias of each trade is defined as $LB_i^{norm} = \frac{LB_i^{abs}}{Dist_{i,market}}$. The local bias of each household is defined as the weighted average of the loca bias of all her trade by trade amount. The "professional" dummy variable is 1 if an investor reports to work in "professional/technical" or "administrative/managerial" professions and 0 otherwise. The "non professional" dummy variable is 1 if an investor reports to work in "clerical/white collar", "craftsman/blue collar" or "sales/service" professions and 0 otherwise. "High income" dummy variable is 1 if an investor's annul income is greater than \$100,000, and 0 otherwise. "Low income" dummy variable is 1 if an investor' s annual income is smaller than \$40,000, and 0 otherwise. Ln(Number of trades) is the logarithm of the number of trades that an investor executed during the 6-year studied period. t-statistics are reported in parentheses.

	Dependent Variable: LB_i^{norm}			
	(A)	(B)	(C)	(D)
Constant	12.38	12.52	12.18	13.62
Professional	-0.0030	-0.0030	-0.0039	-0.0026
	(-1.51)	(-1.52)	(-1.43)	(-0.91)
Non professional	1.39**	1.38**	1.38**	1.26*
	(2.02)	(2.00)	(2.01)	(1.79)
High income		-0.62	-0.62*	-1.24***
		(-1.59)	(-1.66)	(-2.99)
Low income		0.089	0.089	0.054
		(0.20)	(0.20)	(1.11)
Ln(numtrade)			0.12	0.034
			(0.49)	(0.13)
Age				-0.015
				(-1.08)
R-square	0.02	0.03	0.04	0.04

***, **, * indicate significant at 1,5, and 10 percent level, respectively (two tailed).

Table 8. Local Bias and Firm Characteristics

The dependent variable is the local bias of each trade executed by investors. The normalized local bias of the jth trade of investor i is defined as $LB_{i,j}^{norm} = \frac{LB_{i,j}^{abs}}{Dist_{i,market}}$. $Ln(MV)$ is the logarithm of the market value of each firm. The leverage is the ratio of a firm's total liabilities to its assets. The current ratio is the ratio of a firm's current assets to its current liabilities. The market-to-book ratio is the ratio of a company's market value to its book value. Advertising intensity is a company's total advertising expenses in millions of dollars, normalized by its total sales in millions of dollars in percentage. t-statistics are reported in parentheses.

	Dependent Variable: LB_i^{norm}				
	(A)	(B)	(C)	(D)	(E)
Constant	15.15	16.44	16.92	18.46	15.81
Ln(MV)	-0.52***	-0.61***	-0.69***	-0.54***	-0.19*
	(-6.84)	(-7.96)	(-8.74)	(-3.14)	(-1.85)
Leverage		0.030***	0.030***	0.077***	0.083***
		(2.81)	(3.01)	(2.74)	(3.06)
Current Ratio		-0.17***	-0.17***	-0.18***	-0.20***
		(-5.13)	(-5.03)	(-4.50)	(-1.83)
Market to Book Ratio			-0.004	-0.052	-0.017**
			(-0.86)	(-1.33)	(-2.63)
Employee (thousand)				-0.0008	-0.001
				(-0.25)	(-0.28)
Advertising Intersity (%)					-0.29**
					(-2.15)
R-square	0.01	0.01	0.02	0.02	0.03

***, ** and * indicate significance at the 1, 5, and 10 percent levels, respectively (two tailed).

Table 9. BSI of Local and Remote Investors before Positive Earnings Surprises

Buy-sell imbalance (BSI) is defined as $BSI_i^t = \frac{VB_t^i - VS_t^i}{AWTV_i}$, the dollar value of buying trades minus the dollar value of selling trades, divided by the average weekly trading volume ($AWTV$) during the event window. For each event, local investors are defined as investors living within 50 miles of the centroid of the 3-digit zip code area where the company is located. Remote investors are defined as investors living more than 1,000 miles away from the centroid of the same area. BSI for local and remote investors is the average of BSI of all events for local and remote investors during an event week. In column 2 and 3, p-values for for t-test of BSIs being different from 0 are provided in parentheses. In column 4, t-statistics for remote investors' BSIs being greater than that of remote investors are provided in parentheses.

	BSI		
Week	Local Investors	Remote Investors	Difference
T-1	-0.321 (0.000)	-0.244 (0.000)	-0.076 (-1.984)**
T-2	-0.333 (0.000)	-0.238 (0.000)	-0.095 (-3.814)***
T-3	0.080 (0.001)	0.076 (0.000)	0.003 (0.478)
T-4	-0.255 (0.000)	-0.189 (0.000)	-0.066 (-1.637)
T-5	-0.273 (0.000)	-0.209 (0.000)	-0.065 (-2.552)**
T-6	-0.131 (0.000)	-0.141 (0.000)	0.010 (0.380)
T-7	0.121 (0.000)	0.187 (0.000)	-0.066 (2.476)**
T-8	0.292 (0.000)	0.281 (0.000)	0.010 (0.410)
T-9	-0.165 (0.000)	-0.212 (0.000)	0.047 (2.047)**
T-10	0.022 (0.344)	0.048 (0.028)	-0.026 (-1.103)
T-11	-0.243 (0.000)	-0.199 (0.000)	-0.045 (-1.167)
T-12	-0.212 (0.000)	-0.189 (0.000)	-0.024 (-0.965)
T-13	0.087 (0.020)	0.083 (0.664)	0.004 (0.148)
T-14	0.079 (0.110)	-0.058 (0.017)	0.137 (0.911)
T-15	-0.261 (0.000)	-0.216 (0.000)	-0.045 (-1.848)*
T-16	-0.247 (0.000)	-0.197 (0.000)	-0.05 (-1.928)**
T-17	0.086 (0.003)	0.098 (0.000)	-0.013 (-0.477)
T-18	-0.207 (0.000)	-0.223 (0.000)	0.016 (0.626)
T-19	-0.258 (0.000)	-0.194 (0.000)	-0.064 (-2.364)**
T-20	0.147 (0.000)	0.107 (0.000)	0.040 (1.629)
T-21	-0.226 (0.000)	-0.099 (0.000)	-0.128 (-5.079)***
T-22	0.313 (0.000)	0.196 (0.000)	0.116 (0.436)
T-23	-0.282 (0.000)	-0.212 (0.000)	-0.070 (-1.523)
T-24	0.052 (0.008)	-0.003 (0.366)	0.055 (1.690)*

***, ** and * indicate significance at the 1, 5, and 10 percent levels, respectively (two tailed).

Table 10. BSI of Local and Remote Investors before Negative Earnings Surprises

Buy-sell imbalance (BSI) is defined as $BSI_i^t = \frac{VB_t^i - VS_t^i}{AWTV_i}$, the dollar value of buying trades minus the dollar value of selling trades, divided by the average weekly trading volume ($AWTV$) during the event window. For each event, local investors are defined as investors living within 50 miles of the centroid of the 3-digit zip code area where the company is located. Remote investors are defined as investors living more than 1,000 miles away from the centroid of the same area. BSI for local and remote investors is average of BSI of all events for local and remote investors during an event week. In column 2 and 3, p-values for t-test of BSIs being different from 0 are provided in parentheses. In column 4, t-statistics for remote investors' BSIs being greater than that of remote investors are provided in parentheses.

	BSI		
Week	Local Investors	Remote Investors	Difference
T-1	-0.234 (0.000)	-0.228 (0.000)	-0.006 (-1.056)
T-2	-0.301 (0.000)	-0.246 (0.000)	-0.056 (-2.188)**
T-3	0.088 (0.000)	0.065 (0.000)	0.023 (1.342)
T-4	-0.232 (0.000)	-0.196 (0.000)	-0.037 (-1.303)
T-5	-0.261 (0.000)	-0.204 (0.000)	-0.057 (-2.060)**
T-6	0.133 (0.000)	0.147 (0.000)	-0.014 (-0.483)
T-7	0.015 (0.613)	0.012 (0.256)	0.002 (0.079)
T-8	-0.311 (0.000)	-0.234 (0.000)	-0.077 (-2.647)***
T-9	0.179 (0.001)	0.176 (0.000)	0.003 (0.119)
T-10	0.046 (0.239)	0.100 (0.028)	-0.054 (-1.987)**
T-11	-0.223 (0.000)	-0.170 (0.000)	-0.053 (-1.871)*
T-12	0.168 (0.000)	0.172 (0.000)	-0.004 (-0.137)
T-13	-0.024 (0.410)	-0.028 (0.664)	0.004 (0.131)
T-14	-0.044 (0.121)	0.007 (0.245)	0.137 (0.911)
T-15	-0.227 (0.000)	-0.274 (0.000)	-0.051 (-1.401)
T-16	-0.171 (0.000)	-0.249 (0.000)	0.047 (-1.729)*
T-17	0.088 (0.000)	0.135 (0.000)	-0.047 (1.655)*
T-18	-0.169 (0.000)	-0.177 (0.000)	0.008 (0.277)
T-19	0.159 (0.000)	-0.225 (0.000)	-0.065 (-2.194)**
T-20	0.167 (0.000)	0.079 (0.064)	0.088 (3.297)***
T-21	-0.018 (0.104)	0.052 (0.031)	-0.071 (-4.555)***
T-22	-0.155 (0.000)	-0.223 (0.000)	0.068 (2.366)**
T-23	-0.137 (0.000)	-0.183 (0.000)	0.046 (1.868)*
T-24	-0.028 (0.300)	0.050 (0.004)	-0.078 (-2.389)**

***, ** and * indicate significance at the 1, 5, and 10 percent levels, respectively (two tailed).

Table 11. BSI of Local and Remote Investors after Positive Earnings Surprises

Buy-sell imbalance (BSI) is defined as $BSI_i^t = \frac{VB_t^i - VS_t^i}{AWTV_i}$, the dollar value of buying trades minus the dollar value of selling trades, divided by the average weekly trading volume ($AWTV$) during the event window. For each event, local investors are defined as investors living within 50 miles of the centroid of the 3-digit zip code area where the company is located. Remote investors are defined as investors living more than 1,000 miles away from the centroid of the same area. BSI for local and remote investors is the average of BSI of all events for local and remote investors during an event week. In column 2 and 3, p-values for t-test of BSIs being different from 0 are provided in parentheses. In column 4, t-statistics for remote investors' BSIs being greater than that of remote investors are provided in parentheses.

	BSI		
Week	Local Investors	Remote Investors	Difference
T+1	-0.065 (0.000)	-0.017 (0.110)	-0.048 (-1.693)*
T+2	-0.059 (0.000)	-0.039 (0.020)	-0.019 (-0.807)
T+3	-0.101 (0.001)	-0.064 (0.000)	-0.036 (-1.365)
T+4	-0.058 (0.000)	0.039 (0.001)	-0.098 (-3.094)***
T+5	-0.016 (0.214)	0.009 (0.373)	-0.025 (-0.992)**
T+6	0.028 (0.190)	-0.011 (0.405)	0.038 (1.479)
T+7	-0.060 (0.004)	0.019 (0.259)	-0.079 (-3.026)***
T+8	-0.015 (0.366)	-0.023 (0.174)	0.008 (0.226)
T+9	-0.074 (0.000)	-0.021 (0.128)	-0.053 (-2.271)**
T+10	0.040 (0.089)	0.001 (0.850)	0.039 (0.047)
T+11	-0.018 (0.369)	-0.021 (0.088)	0.003 (0.129)
T+12	-0.003 (0.682)	0.020 (0.285)	-0.022 (0.902)
T+13	0.005 (0.665)	-0.039 (0.250)	0.044 (1.594)
T+14	-0.052 (0.001)	-0.032 (0.014)	-0.021 (0.779)
T+15	-0.079 (0.000)	-0.112 (0.000)	0.033 (2.790)***
T+16	-0.059 (0.000)	-0.006 (0.732)	-0.053 (-2.177)**
T+17	-0.004 (0.036)	0.046 (0.054)	-0.049 (-1.83)
T+18	-0.107 (0.000)	0.019 (0.051)	-0.126 (-4.739)***
T+19	0.045 (0.000)	0.019 (0.346)	0.026 (0.432)
T+20	0.023 (0.011)	0.004 (0.777)	0.019 (0.734)
T+21	-0.065 (0.000)	0.019 (0.069)	-0.084 (-3.185)***
T+22	0.028 (0.094)	0.033 (0.034)	-0.005 (-0.503)
T+23	0.005 (0.044)	-0.054 (0.000)	0.059 (2.366)**
T+24	-0.008 (0.017)	0.080 (0.000)	-0.088 (-2.949)***

***, ** and * indicate significance at the 1, 5, and 10 percent levels, respectively (two tailed).

Table 12. BSI of Local and Remote Investors after Negative Earnings Surprises

Buy-sell imbalance (BSI) is defined as $BSI_i^t = \frac{VB_t^i - VS_t^i}{AWTV_i}$, the dollar value of buying trades minus the dollar value of selling trades, divided by the average weekly trading volume ($AWTV$) during the event window. For each event, local investors are defined as investors living within 50 miles of the centroid of the 3-digit zip code area where the company is located. Remote investors are defined as investors living more than 1,000 miles away from the centroid of the same area. BSI for local and remote investors is average of BSI of all events for local and remote investors during an event week. In column 2 and 3, p-values for t-test of BSIs being different from 0 are provided in parentheses. In column 4, t-statistics for remote investors' BSIs being greater than that of remote investors are provided in parentheses.

	BSI		
Week	Local Investors	Remote Investors	Difference
T+1	0.013 (0.604)	-0.017 (0.364)	0.030 (1.287)
T+2	0.091 (0.000)	0.004 (0.874)	0.087 (2.195)**
T+3	0.103 (0.001)	-0.064 (0.000)	0.167 (2.372)**
T+4	-0.034 (0.137)	-0.039 (0.101)	0.005 (0.208)
T+5	-0.017 (0.465)	0.009 (0.525)	-0.026 (-0.989)
T+6	0.0002 (0.995)	-0.011 (0.221)	0.011 (0.713)
T+7	-0.002 (0.933)	0.019 (0.315)	-0.021 (-0.6416)
T+8	-0.026 (0.256)	-0.023 (0.802)	-0.003 (-0.084)
T+9	-0.042 (0.055)	-0.021 (0.636)	-0.021 (-1.955)*
T+10	0.052 (0.027)	0.001 (0.953)	0.051 (0.278)
T+11	0.019 (0.446)	-0.021 (0.118)	0.040 (0.150)
T+12	0.010 (0.661)	0.020 (0.908)	-0.010 (-0.436)
T+13	0.021 (0.429)	-0.039 (0.275)	0.060 (1.316)
T+14	-0.031 (0.102)	-0.032 (0.080)	0.001 (0.012)
T+15	-0.098 (0.000)	-0.012 (0.523)	-0.086 (-3.309)***
T+16	-0.104 (0.000)	-0.006 (0.764)	-0.098 (-3.599)***
T+17	0.016 (0.516)	0.046 (0.003)	-0.030 (-1.151)
T+18	0.106 (0.000)	0.019 (0.345)	0.087 (1.711)*
T+19	-0.015 (0.541)	0.019 (0.240)	-0.034 (-1.193)
T+20	-0.022 (0.378)	0.004 (0.438)	-0.025 (-0.341)
T+21	-0.064 (0.012)	0.019 (0.489)	-0.084 (-2.585)**
T+22	0.003 (0.905)	0.033 (0.073)	-0.036 (-1.594)
T+23	0.064 (0.001)	0.034 (0.008)	0.030 (1.815)
T+24	0.059 (0.020)	0.080 (0.000)	-0.021 (-1.334)

***, ** and * indicate significance at the 1, 5, and 10 percent levels, respectively (two tailed).

Figure 1. Geographical Distribution of Individual Investors

The number of investors in each 3-digit zip code area is calculated. Different 3-digit zip code areas are divided into quartiles based on the number of investors within each area. The first quartile has the smallest number of investors (less or equal to 4), and the fourth quartile has the largest number of investors (more than 47). No investor in our sample lives in the blank area.

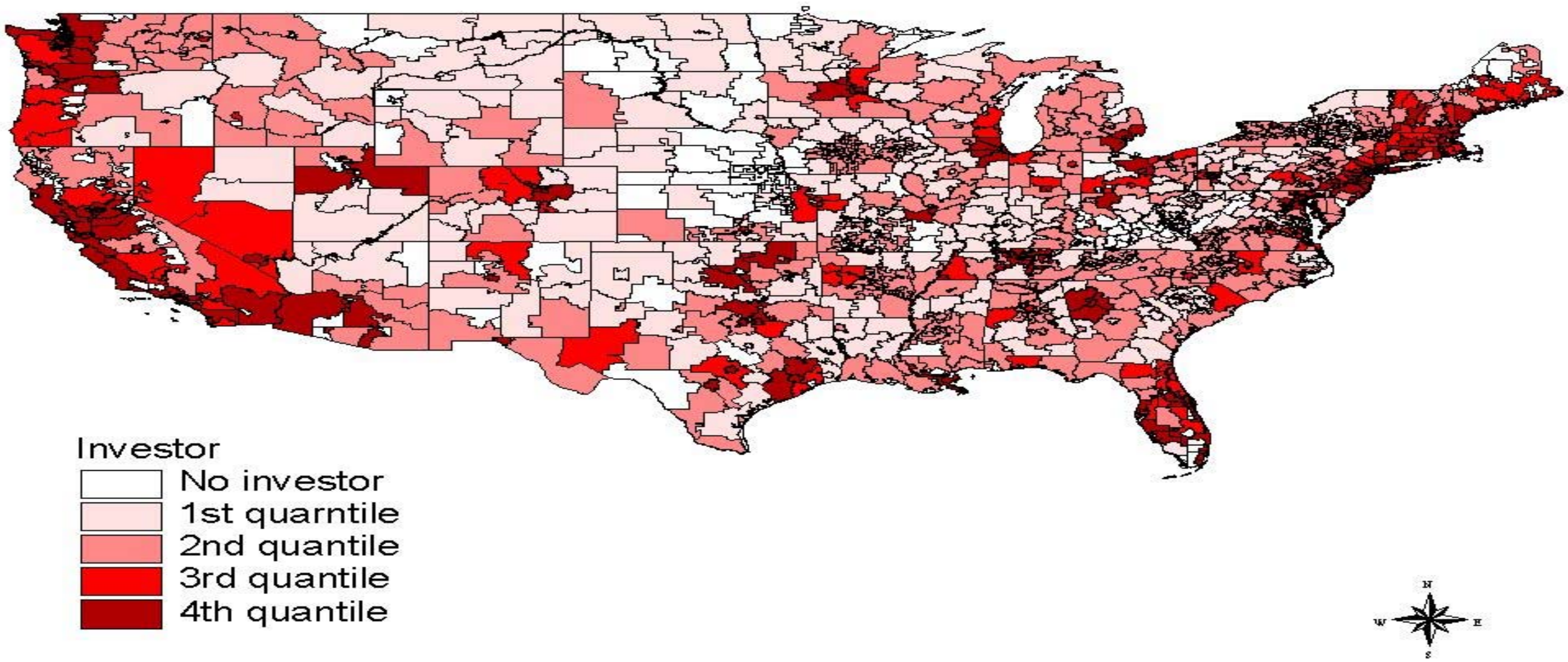

Figure 2. Geographical Distribution of Public Companies

The number of public companies in each 3-digit zip code area in the data is calculated. Different 3-digit zip code areas are divided into quartiles based on the number of public companies within each area. The first quartile (lightest) has the smallest number of public companies (less or equal to 5) and the fourth quartile (darkest) has the largest number of public companies (more than 50). No public company locates in the blank area.

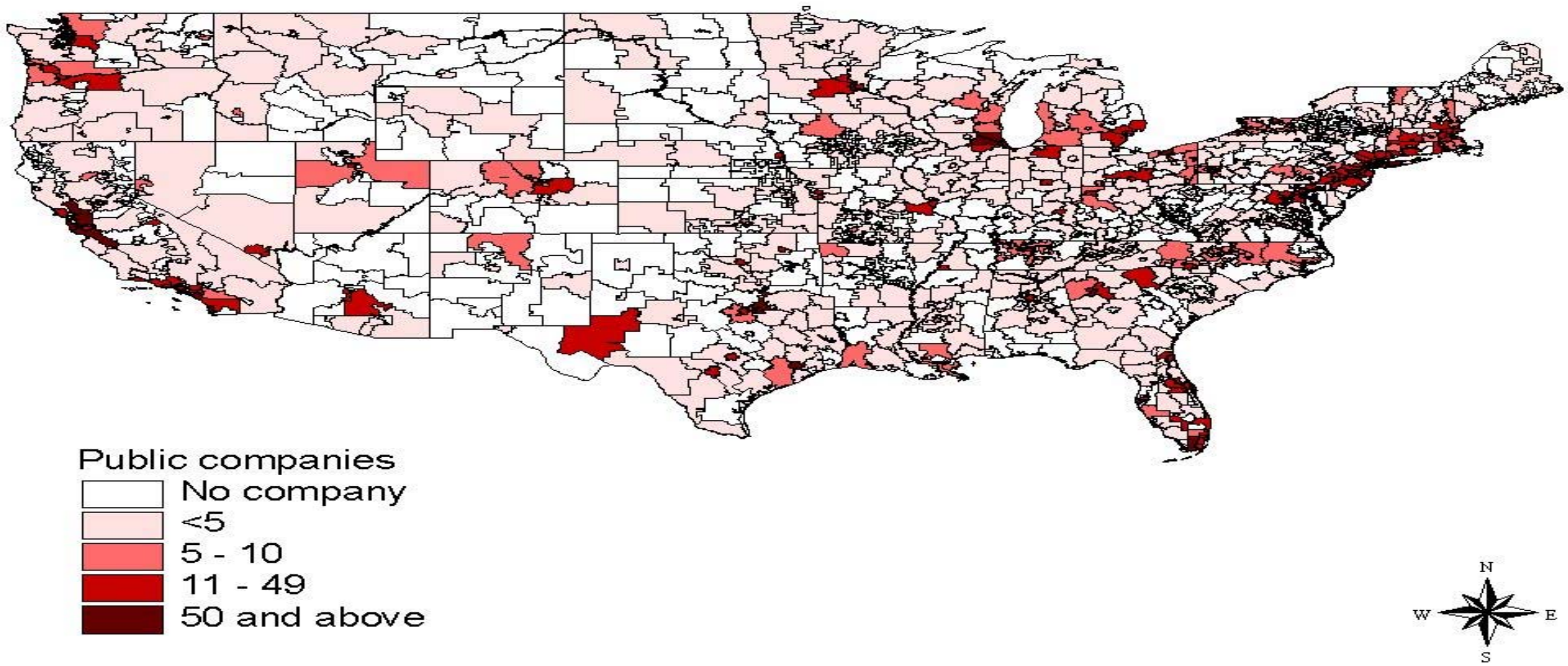

Figure 1. The Histogram of Local Bias under Null Hypothesis

We bootstrap the local bias of sample investors under the null hypothesis by randomly assigning investors to a 3-digit zip code area and compute the local bias of all sample investors. The empirical distribution has a mean of 24.68 and standard deviation of 3.55. The local bias reported in Section 3 is significantly greater than 24.68 at 1-percent significance level.

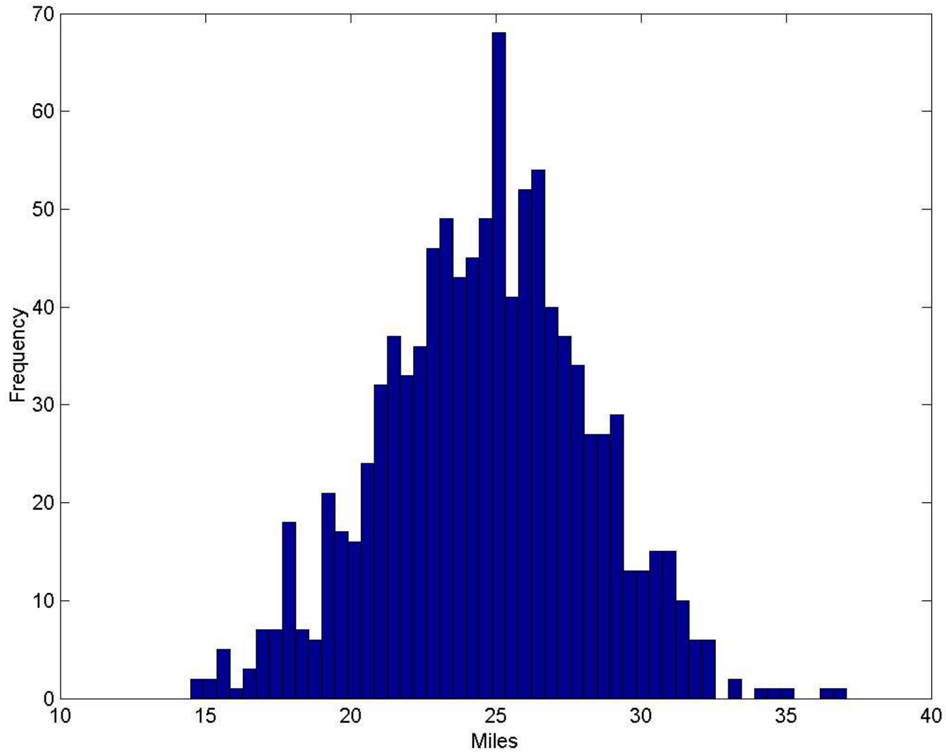

Figure 2. The histogram of distance between firms and all investors

We compute the distance between a firm and all sample investors as the equally weighted average of the distance between the firm and each investor. The mean and median distance between firms and all investors is 1295.7 miles and 1260.5 miles, respectively.

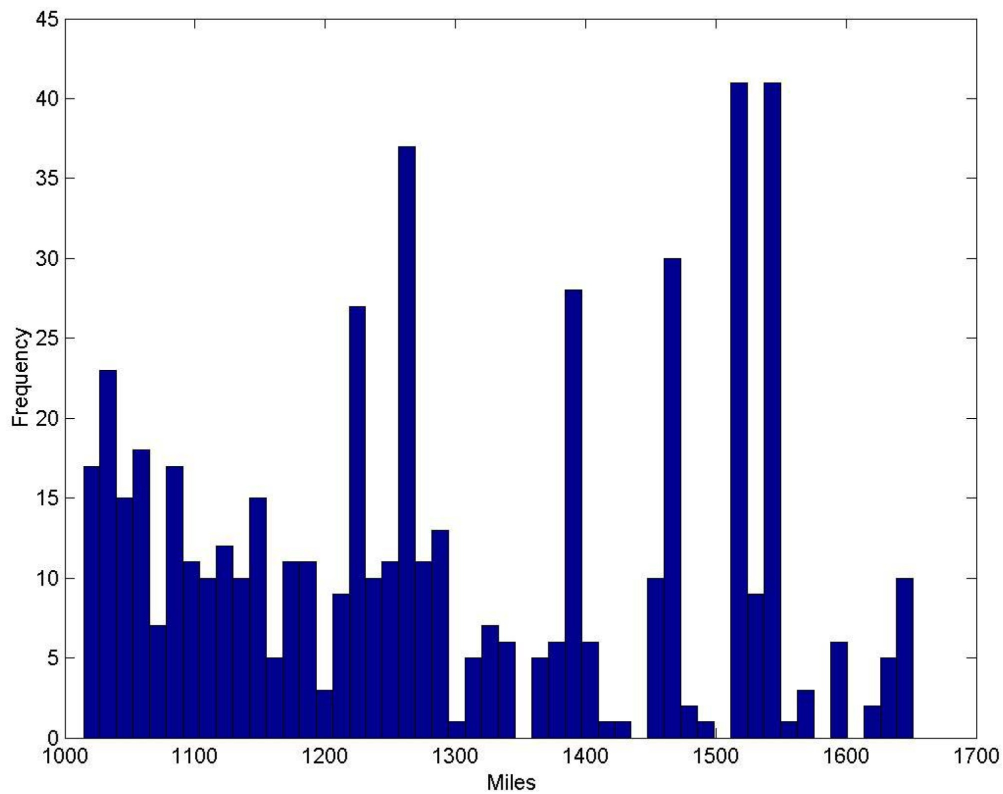

Figure 3. The histogram of distance between firms and investors who invested in focal firms

We compute the distance between a firm and all investors who invested in the firm as the equally weighted average of the distance between the firm and each investor who invested in the stock. The mean and median distance between firms and all investors is 1184.8 miles and 973.4 miles, respectively.

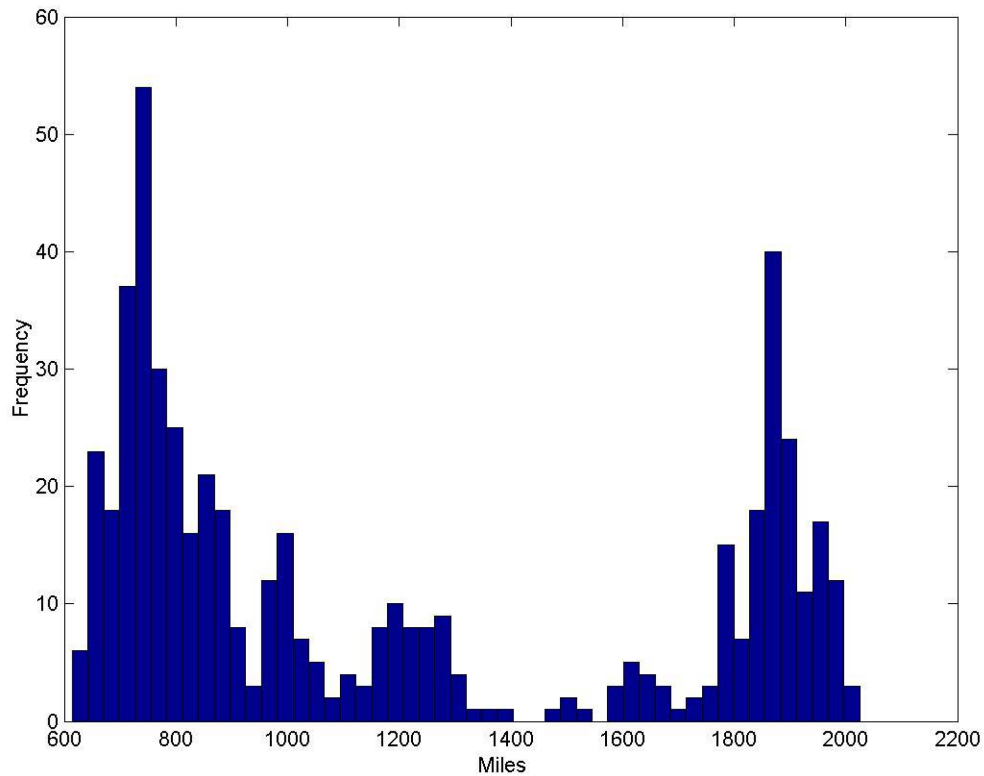

Figure 3. BSI Movement before Positive Earnings Surprises

Buy-sell imbalance (BSI) is defined as the dollar value of buying trades minus the dollar value of selling trades divided by the average weekly trade volume (AWTV) during the event window. The horizontal axis is the number of weeks before earnings announcement. The front row is the BSI for local investors, and the back row is the BSI for remote investors.

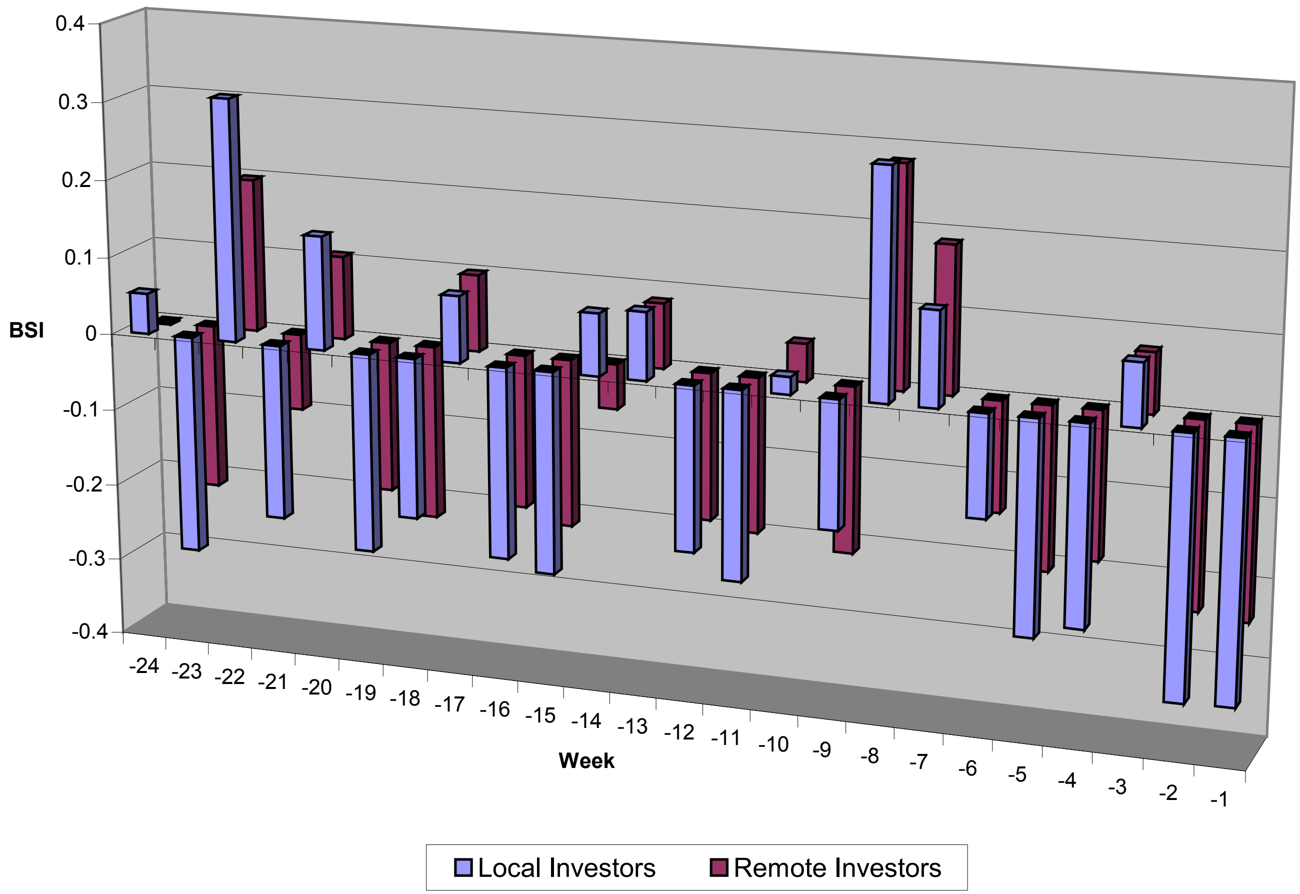

Figure 4. BSI Movement before Negative Earnings Surprises

Buy-sell imbalance (BSI) is defined as the dollar value of buying trades minus the dollar value of selling trades divided by the average weekly trade volume (AWTV) during the event window. The horizontal axis is the number of weeks before earnings announcement. The front row is the BSI for local investors, and the back row is the BSI for remote investors.

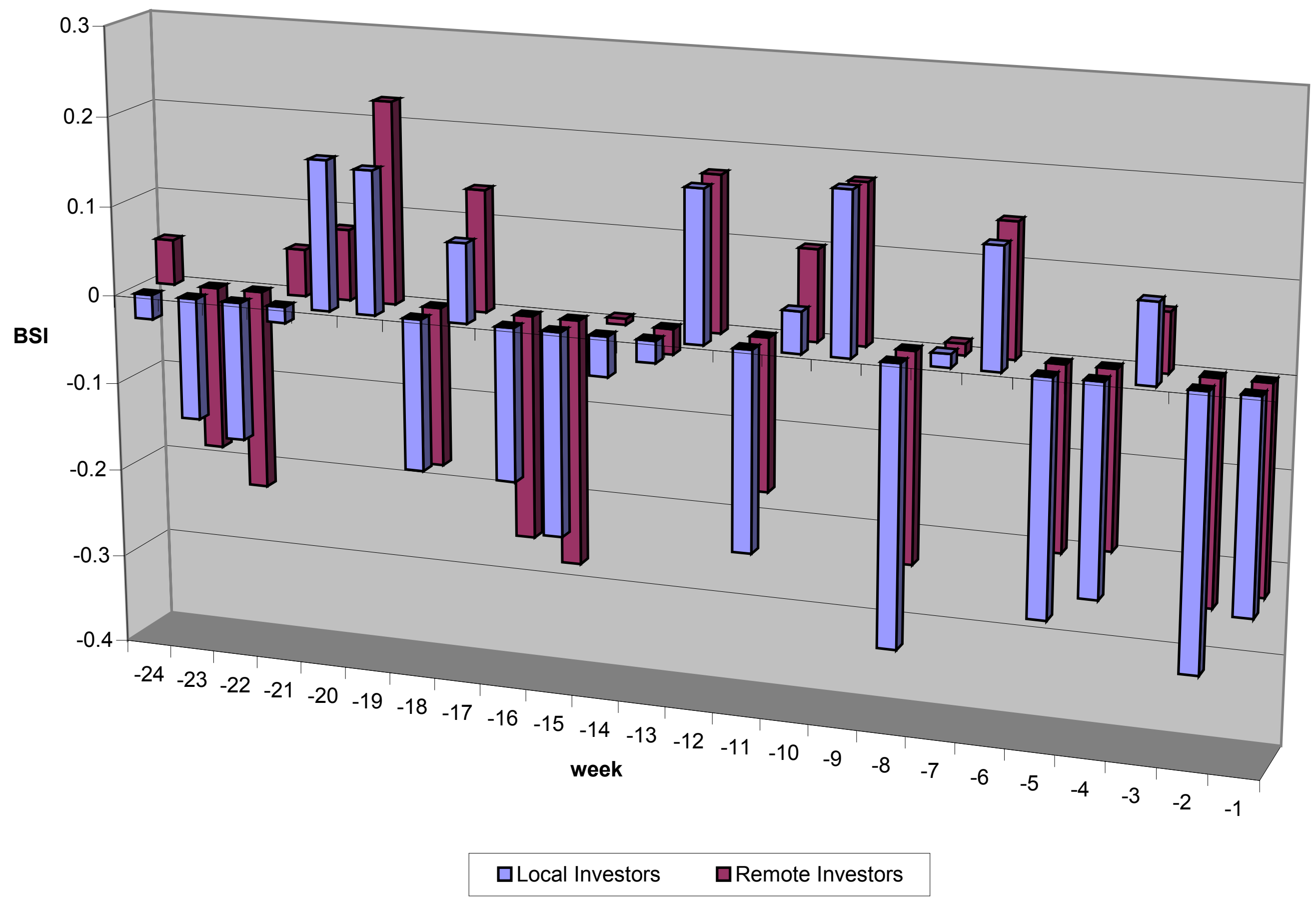

Figure 5. BSI Movement after Positive Earnings Surprises

Buy-sell imbalance (BSI) is defined as the dollar value of buying trades minus the dollar value of selling trades divided by the average weekly trade volume (AWTV) during the event window. The horizontal axis is the number of weeks after earnings announcement. The front row is the BSI for local investors, and the back row is the BSI for remote investors.

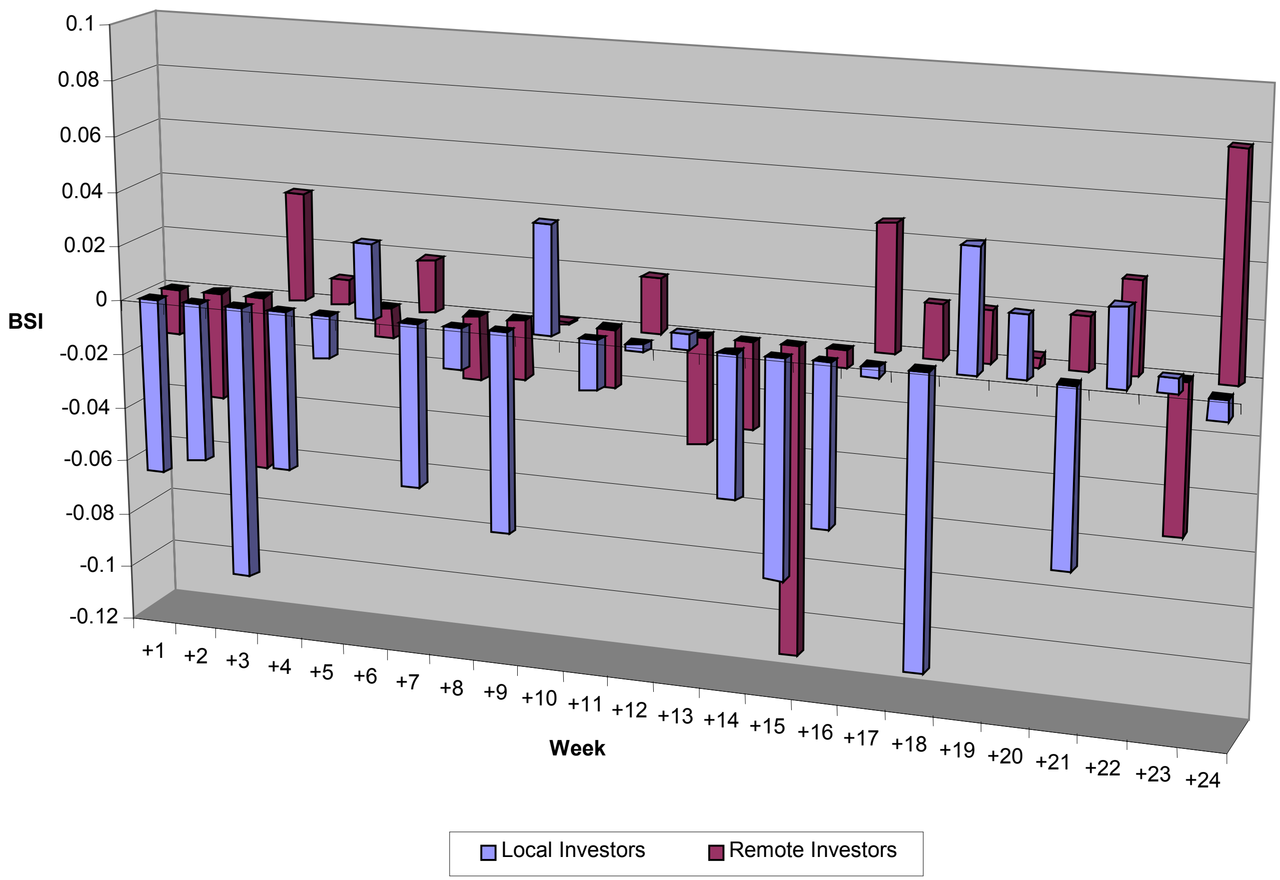

Figure 6. BSI Movement after Negative Earnings Surprises

Buy-sell imbalance (BSI) is defined as the dollar value of buying trades minus the dollar value of selling trades divided by the average weekly trade volume (AWTV) during the event window. The horizontal axis is the number of weeks after earnings announcement. The front row is the BSI for local investors, and the back row is the BSI for remote investors.