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Local Bias in Google Search and the Market Response around Earnings Announcements

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ABSTRACT: We examine the impact of distance on internet search, and the effect of the "local bias" in search on the stock market response around earnings announcements. We find significant local bias in search behavior. Motivated by theories explaining local bias, *local information advantage,* and *familiarity bias,* we predict and find that firms with higher local bias in search experience higher bid-ask spreads, lower trading volumes, and lower earnings response coefficients at the time of earnings announcements, consistent with non-local investors relying more than locals on public information announcements. Consistent with local information advantage, we find that in the week prior to the announcement, firms with higher local bias have higher bid-ask spreads, higher trading volumes, and returns that are more predictive of the coming earnings surprise. Consistent with familiarity bias, firms with higher local bias in search experience stronger post-earnings announcement drift. We use unique predictions, propensity score matching, and two-stage least squares to identify the effects of local bias separately from the effects of overall visibility. Overall, we show there is significant local bias in search, and that this local bias has a significant impact on the market response around earnings announcements.

Keywords: geography; local bias; Google; investor attention; information asymmetry; earnings response coefficient; post-earnings announcement drift; investor psychology.

I. INTRODUCTION

The ways in which investors obtain information have changed dramatically over the last 20 years. Today, an investor can quickly, easily, and inexpensively access firm-related information (e.g., Securities and Exchange Commission [SEC] filings, press releases, and analyst earnings forecasts) through websites like Yahoo! and Google Finance. In this paper, we suggest that while the internet has lowered information acquisition costs substantially, geography is still important in the internet era. In particular, we suggest that the same factors that drove investors to disproportionately invest in local stocks 20 years ago will continue to affect their interest in stocks today. This will manifest in investors searching the internet disproportionately for information about the stocks of local firms. The literature on local bias in investing suggests that local and non-local investors differ in terms of their private information and the extent to which their investing is based on familiarity. Based on this literature, we predict and find that local bias, measured by the proportion of internet searches for a firm's stock ticker that originate from within a local radius, impacts the market response around earnings announcements, specifically, information asymmetry, trading volume, and the incorporation of information into stock price.

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A growing body of research examines the effects of information dissemination and finds that press coverage reduces information asymmetry, increases investor response to information, and reduces mispricing of information (Bushee, Core, Guay, and Hamm 2010; Soltes 2010; Engelberg and Parsons 2011; Drake, Guest, and Twedt 2014). However, in order for information to have an impact, investors need to pay attention to, or demand, the information (Hirshleifer, Lim, and Teoh 2009; Drake, Roulstone, and Thornock 2012). We focus on a specific dimension of investors' information demand: geography. We use state-level search information from Google's Search Volume Index to create a measure of local bias in search, based on the proportion of U.S. investors searching for a given firm's stock ticker who are located near the firm's headquarters, for the years 2005 through 2011. Prior literature (e.g., Coval and Moskowitz 1999; Ivkovic and Weisbenner 2005) has established that investors have a preference for owning and trading stock of firms headquartered nearby (referred to as "local bias"). We find that for 81 percent of firm-years in our sample, the firm's headquarters state has a higher level of search than expected. In addition, average firm-searcher distances are similar to firm-investor distances documented in prior literature on local bias (Ivkovic and Weisbenner 2005). Thus, local bias persists in the internet era, as measured by internet search.

We ask whether this local bias in internet search behavior impacts the market's reaction to information. Prior literature has posited two main reasons for local bias in investing: *local information advantage* (e.g., Ivkovic and Weisbenner 2005; Ivkovic, Sialm, and Weisbenner 2008) and *familiarity bias,* the tendency to invest in firms with which we are familiar (Huberman 2001). Based on existing theories, we develop hypotheses for how investors will react around earnings announcements. Both explanations for local bias imply that local investors are likely to react more weakly than non-locals to public information such as earnings announcements, although due to pre-event information in the case of local information advantage and due to behavioral biases in the case of familiarity bias. Thus, we predict that for firms with more local bias in search, the market reaction to earnings announcements will be more muted. Specifically, we expect higher abnormal bid-ask spreads, lower abnormal trading volumes, and lower earnings response coefficients at the time of earnings announcements.

We find strong evidence consistent with these predictions. Announcement window abnormal bid-ask spreads are positively related to the local bias in search, while abnormal trading volumes and earnings response coefficients are negatively related to local bias. These results hold when (1) examining the relation cross-sectionally, including controls for firm characteristics; (2) when examining propensity score matched pairs based on a large set of firm characteristics, including measures of firm visibility; (3) using an instrumental variable two-stage least squares approach; or (4) examining changes. The magnitudes are also economically significant when compared to the effects of other dimensions of visibility. While the increases in abnormal bid-ask spreads and drops in abnormal trading volume are small, the magnitudes are similar to, or larger than, the effects observed for press coverage and level of search. The decrease in earnings response coefficients is large: Firms with high local bias in search experience over 30 percent lower earnings response coefficients than propensity score matched firms with low local bias. Overall, the results are consistent with higher local bias in search significantly decreasing the market response to earnings announcements. Put another way, a broader, more geographically dispersed investor base is associated with a higher market response to earnings announcements.

In addition to the predictions described above, which do not distinguish the local information advantage and familiarity bias explanations of local bias, we conduct additional tests to discern which of these two explanations is descriptive of investor behavior. However, it may be the case that local information advantage is the primary driver of local bias for some firms, while familiarity bias is the primary driver for others. It is also plausible that for a given firm, some local investors may invest due to their information advantage, while other local investors invest due to their familiarity bias. Thus, in aggregate, we may find evidence of both.

Local information advantage is likely to have a significant impact on trading *before* the public earnings announcement. Local investors are more likely to anticipate the news in the coming announcement through their private information. Thus, if there is a higher concentration of local investors, then we would expect higher information asymmetry across investors and higher trading volumes before the earnings announcement due to pre-announcement private information (e.g., following Copeland and Galai 1983; Easley and O'Hara 1992; Glosten and Milgrom 1985; Krinsky and Lee 1996), as well as pre-announcement returns that anticipate the earnings news to a greater degree (e.g., Christophe, Ferri, and Angel 2004; Drake et al. 2012). As with the event window market response, we use four methods to analyze pre-announcement spreads, volume, and returns: cross-sectional analysis, propensity score matched pairs, an instrumental variable approach, and an analysis of changes. We find evidence consistent with local investors trading on more private information about the upcoming earnings announcement than non-locals.

Huberman (2001) provides evidence that not all local-investor behavior can be explained by information advantage—familiarity bias must play some role. Under the familiarity bias explanation, local investors trade local stocks due to the behavioral bias of wanting to own stocks with which they are familiar. Therefore, their trade is based less on information. Consistent with this notion, we expect familiarity bias-driven local investors to underreact to earnings news. Thus, we expect higher post-earnings announcement drift when there is higher local bias, to the extent that the local bias is driven by behavioral biases. In contrast, the local information advantage explanation does not lead to clear predictions for post-earnings announcement drift. If anything, we might expect lower drift when there are more local investors and, thus, more private information incorporated into price before and during the earnings announcement window. We find that post-earnings announcement drift is significantly higher for firms with higher local bias. High local bias firms experience 10–12 percent higher post-earnings announcement drift than matched firms. Thus, our evidence is consistent with at least some local bias in search being driven by familiarity bias, and with familiarity bias affecting market responses. Together, our evidence suggests that local information advantage drives a portion of local bias, while familiarity bias drives a portion, as well.

Our study contributes to the literatures on local bias, information dissemination, and investor attention. Prior research has shown that geography matters to investors in their investing choices and their responses to newspaper articles (Coval and Moskowitz 1999; Ivkovic and Weisbenner 2005; Engelberg and Parsons 2011; Miller and Shanthikumar 2012). We show that the local bias of investor interest, even in the internet era, affects the incorporation of earnings information into stock price. We document previously unexamined effects of local bias on stock trading: Local bias is related to more pre-announcement informed trading, to a lower response at the time of the earnings announcement, and to higher post-earnings announcement drift. These results also speak to the underlying explanations for local bias, suggesting that *both* local information advantage and familiarity bias play a role in local bias, and in the impact that local bias has on the market's response to information.[1]

Prior research has shown that investor attention and information demand are generally important for the market's response to earnings information (Hirshleifer et al. 2009; Drake et al. 2012). We show that geography is an important dimension of investor interest: It is not simply a question of how many investors are paying attention, but rather *who* is paying attention. Are the investors who are following the firm more privately informed, or more biased? Our study suggests that these are important questions that have a significant impact on the effects of investor following. These results contribute to our understanding of investor attention and the effects of information demand.

II. PRIOR LITERATURE AND EMPIRICAL PREDICTIONS

Several recent papers suggest that the extent to which investors access information, which increases both with broader dissemination and increased investor attention, is related to lower information asymmetry, such as lower bid-ask spreads, higher trading volumes (Bushee et al. 2010; Soltes 2010; Blankespoor, Miller, and White 2014), and better pricing of accounting information (Hirshleifer et al. 2009; Drake et al. 2012; Drake et al. 2014). Building on this literature, we aim to better understand the role that geography plays in the market response to earnings announcements, given that geography is likely to impact investors' access to information and their information demand.

Prior literature has proposed two explanations for investors' local bias: *local information advantage* and *familiarity bias*. Even in the internet era, these two factors are likely to drive investor interest, and we verify that investors search disproportionately for local firms. Each of these explanations leads to predictions regarding how local investors will react to information, such as an earnings announcement. The significant variation in the local bias in search across firms implies a significant impact of local bias on the market's response around firms' earnings announcements. In the remainder of this section, we discuss the specific implications of each explanation for the market response around earnings announcements and develop hypotheses.

Local Information Advantage and the Market Response around Earnings Announcements

Several studies of local bias suggest that local investors and analysts are better informed than non-locals (e.g., Coval and Moskowitz 2001; Ivkovic and Weisbenner 2005; Malloy 2005; Engelberg and Parsons 2011; Miller and Shanthikumar 2012). If more local investors gather more private information about the firm before the earnings announcement, then the earnings announcement should provide less new information, resulting in lower volume and price reactions to the announcement (for relevant analytical models, see Holthausen and Verrecchia [1990], Kim and Verrecchia [1991], and Kim and Verrecchia [1997]). Thus, firms with proportionally more local investors, that is, higher local bias in search, should experience weaker volume and price reactions to the earnings announcement.

[1] Our results do not imply that a single individual trades a particular local stock due to both local information advantage and familiarity bias. It is unlikely that the same individual who has private information and trades in an informed way before the earnings announcement also underreacts overall and contributes to higher post-earnings announcement drift. The fact that we find evidence of both local information advantage and familiarity bias suggests that each explanation contributes to some local bias and, thus, impacts the aggregate market response around earnings announcements. For example, it may be that a subset of investors trades in local stocks due to local information advantage, while other investors trade in local stocks due to familiarity bias. Local internet search, as a proxy for overall local bias, captures both.

In addition, prior literature suggests that broader information dissemination leads to lower abnormal bid-ask spreads around earnings announcements (Bushee et al. 2010; Blankespoor et al. 2014). Since firms with more non-local investors are expected to have proportionally more investors who would pay attention to and react to the earnings announcement, we expect a similar effect: Higher local bias in search should lead to higher abnormal bid-ask spreads around earnings announcements.[2]

Finally, the local information advantage explanation leads to additional (unique) predictions regarding pre-announcement information asymmetry, trading volume, and returns. Specifically, because local investors have more private information about the forthcoming earnings announcement, the adverse selection component of the bid-ask spread will be larger if there are proportionally more local investors (Copeland and Galai 1983; Glosten and Milgrom 1985; Krinsky and Lee 1996), and trading volume should be higher during the pre-announcement window as local investors acquire private information and trade on it (Easley and O'Hara 1992). In addition, given their private information, we would expect local investors' trading to be more predictive of the upcoming earnings announcement (Christophe et al. 2004) and, thus, we expect that more information about the forthcoming earnings announcement will be incorporated into price during the pre-announcement window (as in Drake et al. 2012). Overall, we expect that for firms with higher local bias in search, bid-ask spreads and trading volumes will be higher in the pre-announcement window, and returns in the pre-announcement window will be more predictive of the upcoming earnings announcement.[3]

Familiarity Bias and the Market Response around Earnings Announcements

Huberman (2001) develops the idea of familiarity bias, in which investors tend to invest in familiar stocks not because they have superior information, but because they tend to be optimistic about stocks they are familiar with. It is possible that the familiarity bias phenomenon drives a portion of local bias, while local information advantage drives another portion of local bias, or that one or the other of these two explanations dominates.

Huberman (2001) discusses and documents empirical regularities consistent with familiarity bias. Evidence that local investors fail to earn positive abnormal returns (Seasholes and Zhu 2010) supports the idea that they invest locally due to familiarity rather than information advantage. Huberman (2001, 675–676) also argues that the empirical and experimental evidence suggests that familiarity bias investors have a general optimism about the stocks they invest in that drives them to buy and not sell. Because of this, Huberman (2001) writes about investors who put their money in familiar stocks: "Investors in the familiar seem to have static, 'buy-and-hold' portfolios." This suggests that familiarity bias-driven local investors will react more weakly to information events. Overall, Huberman (2001) suggests that these investors choose a stock simply because they know the company and are optimistic about it, not because of specific information that comes out. Thus, a stock with more locally concentrated investor interest, i.e., higher local bias in search, would experience weaker market responses to earnings announcements, all else being equal. As a result, we expect that firms with higher local bias will have lower trading volume, lower earnings response coefficients, and higher bid-ask spreads at the time of the announcement, as well as higher post-earnings announcement drift. It may seem counterintuitive that firms with more local investors would have higher post-earnings announcement drift, but it is important to emphasize that this is a unique prediction of *behavioral bias-driven* local bias. Local bias based on information advantage would not lead to the same prediction.

Hypotheses

Both local information advantage and familiarity bias suggest that firms with more local bias in search will have a smaller proportion of their investors trading based on public information such as earnings announcements, as locals use this information less than non-locals. As such, higher local bias will have roughly the inverse impact on market responses to earnings news as higher investor attention or broader dissemination of information: higher bid-ask spreads, lower trading volumes, and lower earnings response coefficients.

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[2] Based upon existing theory, the predictions for event window abnormal bid-ask spreads are ambiguous. In particular, the existence of privately informed investors in the pre-announcement period may increase pre-announcement information asymmetry and lead to a larger drop in bid-ask spreads at the time of the announcement, while the existence of privately informed investors at the time of the announcement, who can use their private information in interpreting the earnings announcement, may lead to an increase in bid-ask spreads around the announcement (Kim and Verrecchia 1997; Krinsky and Lee 1996). Thus, we rely on relevant empirical evidence (Bushee et al. 2010; Blankespoor et al. 2014) to derive this prediction.

[3] We follow Christophe et al. (2004) and Drake et al. (2012) by focusing on a five-trading-day window prior to the earnings announcement date, [–5,–1].

FIGURE 1
Summary of Hypotheses and Associated Explanations of Local Bias
The Effects of Higher Local Bias

	Announcement Period	**Pre-Announcement Period**	**Post-Announcement Period**
Local Information Advantage →	A weaker reaction to new public information: • Higher bid-ask spreads • Lower trading volume • Lower ERC	More privately informed anticipatory trading: • Higher bid-ask spreads • Higher trading volume • Higher ERC	No formal prediction
Familiarity Bias →	A weaker reaction to new public information: • Higher bid-ask spreads • Lower trading volume • Lower ERC	No formal predictions	More biased reaction to the earnings announcement: • Higher PEAD

For the pre-announcement window, local information advantage leads to specific predictions, while familiarity bias does not lead to any specific predictions for this period. In contrast, familiarity bias leads to the prediction of lower post-earnings announcement drift, while local information advantage does not lead to any specific predictions for drift.[4] We summarize the predictions in Figure 1. Stated in alternative form, the hypotheses we test are:

H1: Higher local bias in search decreases the market response to earnings announcements, as measured by (a) higher bid-ask spreads, (b) lower trading volumes, and (c) lower earnings response coefficients, around the earnings announcement, based upon both the local information advantage and familiarity bias explanations of local bias.

H2: Higher local bias in search increases privately informed trading before the earnings announcement, as measured by (a) higher bid-ask spreads, (b) higher trading volumes before the earnings announcement, and (c) a higher relation between pre-announcement returns and the upcoming news, based upon the local information advantage explanation of local bias.

H3: Higher local bias in search increases post-earnings announcement drift, based upon the familiarity bias explanation of local bias.

Note that H2 is based upon the local information advantage explanation of local bias, while H3 is based upon the familiarity bias explanation. To the extent that both explanations coexist and drive a portion of local bias, we may find evidence consistent with both H2 and H3. If only one explanation dominates and the other is insignificant, then we may find support for only one of these hypotheses. Thus, in addition to providing direct evidence of the impact of local bias on the market response to earnings-related information, tests of H2 and H3 also provide insight into the underlying drivers of observed local bias.

[4] Under the local information advantage explanation of local bias, regardless of the level of private information in the market, the market should react, on average, correctly to the public earnings announcement, leading to, on average, no drift. However, one could envision that in a world with post-earnings announcement drift, it could be lower with more local bias. Given that the market should react *at least as completely* with more private information, drift would be no higher. If the market reacted *more completely* to the earnings information with more private information, then drift would be lower. Given that this story is not derived from theory, we do not state it as a formal hypothesis; however, it contrasts with the prediction derived from familiarity bias.

III. DATA AND VARIABLE MEASUREMENT

The sample consists of stocks listed on the NYSE, AMEX, and NASDAQ from 2005 through 2011,[5] with CRSP and Compustat data and with state-level annual Google search data. To identify firms in Google Trends, we use ticker symbols, as in Da, Engelberg, and Gao (2011). There are 1,529 distinct tickers in the initial sample. We remove tickers with alternate meanings, such as "LAKE," "MAIN," and "RENT"; require non-missing data for key variables; and eliminate penny stocks. The final sample contains 945 distinct firms and 21,597 firm-quarter observations. Table 1, Panel A outlines the sample selection process.

Measuring the Local Bias in Google Search

We collect state search data from Google Trends (see: http://www.google.com/trends), which tracks Google users' search volume by search term. Google uses Internet Protocol (IP) addresses to identify the location of a computer used for a search. Google aggregates search data for each of the 50 states and the District of Columbia (hereafter, state), and then identifies the state with the most searches for a given term (the top state). It defines the search volume index (SVI) for each state as the ratio of searches from that state to searches from the top state.

For a given firm-year, we calculate the proportion of searches for the firm that originate from within 250 miles of the firm. We use a 250-mile cutoff following Ivkovic and Weisbenner (2005); however, we also replicate all tests using alternate cutoffs of 50 and 500 miles (see Section IV, subsection "Sensitivity Analyses"). For each state, X, we calculate the population center of the state by population-weighted latitudes and longitudes based on all zip codes within a state, using data from the Census Bureau's 2010 Gazetteer. We then calculate the distance between corporate headquarters and the population center of the state X as $distance_{firm\ headquarters,\ state\ X}$. If that distance is less than or equal to (more than) 250 miles, then that state's search for the firm is categorized as local (non-local). The precise formula for our primary local bias variable is as follows, excluding Hawaii and Alaska to avoid skewing the measure (Ivkovic and Weisbenner 2005):[6]

$$\%Local = \frac{\sum_{X=1}^{49}(SVI\ for\ state\ X)*I\left((distance_{firm\ headquarters,\ state\ X}) \leq 250\ miles\right)}{\sum_{X=1}^{49}(SVI\ for\ state\ X)}. \tag{1}$$

Earnings Surprises

We follow prior literature (e.g., Bernard and Thomas 1990; Livnat and Mendenhall 2006; Hirshleifer et al. 2009) to compute standardized unexpected earnings, SUE. Unexpected earnings is defined as $UE_{jq} = AE_{jq} - FE_{jq}$, where AE_{jq} is the announced quarterly earnings per share (EPS) and FE_{jq} is expected earnings. We use two pairs of AE and FE: (1) EPS before extraordinary items for the given quarter and for the prior year's same quarter, and (2) the "actual" value of earnings from I/B/E/S and the consensus analyst earnings forecast calculated from I/B/E/S detail data.[7] The consensus analyst forecast is defined as the median of analysts' final forecasts over 60 trading days before the announcement date, with at least three analysts covering the firm. SUE is defined as UE_{jq} scaled by price per share at the end of quarter q.

Market Response Measures

We examine several aspects of the market response: announcement period and pre-announcement abnormal bid-ask spreads, abnormal trading volume, earnings response coefficient (ERC), and post-earnings announcement drift (PEAD). Abnormal spreads, $AbSpreads[x,y]$, are calculated as average daily bid-ask spreads over trading days x through y relative to the

[5] The sample ends after 2011 for two reasons. First, although Google Search Volume Index (SVI) data are publicly available and continuously updated, the download and cleaning of the data is fairly time-consuming. Google currently limits any given user and IP address to 800 downloads per day, but that limit was 50 until very recently. For each ticker in our sample, we conduct a separate download for each year to gather state-level data for that year. This data download, and the associated cleaning of the data, was completed during 2012. Second, Google has more recently changed their normalization process, making new/updated state-level data downloads less appropriate for calculating local bias. While our measure can be adapted to use current Google SVI state-level normalization, it requires an additional step that would add noise to the measure. Further details are available upon request.

[6] To gauge the level of noise added by having only state-level location data, we estimated the ideal local bias measure using exact zip code data from discount brokerage account data for 1991–1996, as well as Equation (1), using state-level data for investor locations. The correlation between the two measures is 84.5 percent. For 1,214 out of 1,229 firms (98.8 percent), the rank of the two measures is the same.

[7] Prior literature has shown that small individual investors are more likely to use a random walk-based earnings expectation model and react naively to earnings announcements, while analyst forecasts are more representative of institutional investor expectations (e.g., Lee 1992; Bhattacharya 2001; Ke and Petroni 2004; Hirshleifer, J. Myers, L. Myers, and Teoh 2008; Shanthikumar 2012). This results in two post-earnings-announcement drifts—one for each type of earnings expectation model (Ayers, Li, and Yeung 2011). We use both models to ensure that our results are not driven by using the expectations model of only one type of investor, particularly given that individuals may be more likely to use Google search (Da et al. 2011).

TABLE 1

Sample Selection and Distribution

Panel A: Sample Selection Process

	Firm-Quarter	Firm
NYSE, AMEX, and NASDAQ observations with state Google Search Volume Index	36,024	1,601
Ambiguous tickers	(6,835)	(319)
Insufficient Compustat and CRSP data	(6,640)	(291)
Price per share < $1	(952)	(46)
Baseline observations (2005–2011)	21,597	945

Panel B: Sample Distribution by Year

Year	# of Observations	Percent
2005	2,632	12.19%
2006	2,842	13.16%
2007	3,036	14.06%
2008	3,094	14.32%
2009	3,202	14.82%
2010	3,424	15.86%
2011	3,367	15.59%
Total	21,597	100.00%

Panel C: Sample Distribution by Headquarter State

State	# of Observations	Percent
California	2,855	13.22%
Texas	2,461	11.40%
New York	1,866	8.64%
Illinois	1,192	5.52%
Ohio	1,160	5.37%
Others (< 5% each)	12,063	55.85%
Total	21,597	100.00%

Panel D: Sample Distribution by Industry

Industry	# of Observations	Percent
Retail	2,808	13.00%
Business Services	2,302	10.66%
Electronic Equipment	1,125	5.21%
Others (< 5% each)	15,362	71.13%
Total	21,597	100.00%

earnings announcement date minus the average daily bid-ask spreads over trading days [−41,−11]. Daily spreads are the difference between the quoted offer and bid prices, divided by the midpoint, multiplied by 100 (e.g., Bushee et al. 2010; Soltes 2010). Following Hirshleifer et al. (2009), we compute *AbVol*[*x*,*y*] similarly, as the stock's average of daily trading volume over trading days *x* through *y* minus the average over trading days [−41,−11], where daily trading volume is the log of dollar trading volume, calculated using the product of the closing price and the number of shares traded. Finally, to estimate ERCs and PEAD, we compute abnormal stock returns, *CAR*[*x*,*y*], as the sum of the cumulative abnormal return over days *x* through *y*, where abnormal returns are the difference between the raw return from CRSP and the return on a portfolio of firms matched on size and book-to-market ratio (following Fama and French [1993] to construct 25 June-end portfolios). We calculate all three

TABLE 2

Descriptive Statistics

	n	Mean	Std. Dev.	Q1	Median	Q3
Primary Variables of Interest						
AbSpreads[0,1]	21,597	0.023	0.386	−0.042	−0.003	0.044
AbSpreads[−5,−1]	21,597	0.007	0.162	−0.027	−0.003	0.016
AbVol[0,1]	21,597	0.637	0.590	0.269	0.623	0.992
AbVol[−5,−1]	21,597	0.048	0.302	−0.189	0.035	0.266
AF_SUE	17,842	0.000	0.019	0.000	0.001	0.002
CAR[0,1]	21,597	0.002	0.077	−0.035	0.000	0.040
CAR[−5,−1]	21,597	0.002	0.062	−0.023	0.001	0.026
CAR[2,61]	21,597	0.000	0.160	−0.083	0.002	0.083
%Local	21,597	0.195	0.258	0.009	0.095	0.261
RW_SUE	21,597	0.001	0.054	−0.004	0.002	0.007
Additional Variables						
AF (Analyst Following)	21,597	9.834	10.790	2	6	14
EA (# of Earnings Announcements)	21,597	193.255	114.351	100	200	278
# of News	11,604	0.095	0.382	0	0	4
# of Revision	21,597	7.010	6.801	2	5	11
AbsCAR[0,1]	21,597	0.055	0.057	0.016	0.038	0.075
AbsCAR[−5,−1]	21,597	0.033	0.038	0.010	0.022	0.043
Adv Exp	21,597	0.010	0.023	0.000	0.000	0.010
BM	21,597	0.611	0.456	0.315	0.506	0.774
chSVI	21,597	1.502	1.070	0.693	1.504	2.251
EMP	21,597	20.783	48.422	0.960	4.290	15.181
EP	21,597	0.607	0.299	−0.082	0.291	0.613
EV	21,597	0.081	0.124	0.022	0.043	0.084
IO	21,597	0.462	0.365	0	0.553	0.800
MF	21,597	0.323	0.468	0	0	1
MKVol	21,597	78.600	57.264	29.442	119.326	258.505
RECPRC	21,597	0.089	0.128	0.024	0.042	0.088
Retail	21,597	0.130	0.337	0	0	0
RV	21,597	0.028	0.017	0.017	0.024	0.035
SHR	21,597	32.026	102.195	0.601	2.963	14.814
Size	21,597	6677.137	19683.152	216.294	1013.437	3695.220
SP500	21,597	0.301	0.459	0	0	1
SVI	21,597	3.631	0.555	3.368	3.772	4.031
Turnover	21,597	0.040	0.037	0.015	0.030	0.053
Urban	21,597	0.356	0.479	0	0	1

Variable definitions are listed in Appendix A.

variables for the announcement window, [0,1], and a five-day pre-announcement window, [–5,–1]. To measure PEAD, we use a 60-trading-day window, [2,61], similar to prior literature (e.g., Livnat and Mendenhall 2006; Hirshleifer et al. 2009; Ayers et al. 2011), as Bernard and Thomas (1989) show that the majority of drift occurs in the first 60 trading days after the announcement.

Descriptive Statistics

Table 1, Panels B, C, and D report sample characteristics. Observations are evenly distributed from 2005 through 2011. Geographically, 13.22 percent of sample firms are headquartered in California, followed by Texas (11.40 percent) and New York (8.64 percent). In addition, sample firms are mainly in the retail (13 percent), business services (10.66 percent), and electronic equipment (5.21 percent) industries.

Table 2 presents summary statistics. All financial statement variables are winsorized at the 1st and 99th percentiles. We take logs for all search-related variables. Our sample is weighted toward large firms (median market capitalization of $1,013 million), with a median of six analysts following the firm and 55.3 percent institutional ownership.

IV. EMPIRICAL RESULTS

The next subsection reports results related to search behavior. The "Propensity Score Matching" subsection examines the market response around earnings announcements. We discuss additional analyses in the "Local Bias in Search and the Market Response around Earnings Announcements" subsection.

Local Bias in Google Search and Related Factors

We first examine the average distance of an individual searching for a firm from the firm's headquarters, using the simplifying assumption that searches originate from the population center of a state. We find that an investor searching for a firm is located, on average, 1,081 miles from the firm's headquarters. Ivkovic and Weisbenner (2005, Table 1) report that the average distance between an investor and the headquarters of firms in their portfolio is 917 miles. This suggests that "local bias" in search activity is similar in magnitude to local bias in stock ownership documented in prior literature for earlier (pre-internet) periods.[8]

We also compare the geographic distribution of search with randomly distributed search activity using a bootstrap analysis and internet user locations, estimated using data from the Census Bureau's 2007 Current Population Survey, "School Enrollment and Internet Use" (see: https://www.census.gov/prod/techdoc/cps/cpsoct07.pdf). If internet users search for companies without regard to distance, then 13 percent of our sample firms would have their home states as their top search state. Instead, 20 percent of our firms do. For 81 percent of firm-years, the firm's headquarters state is ranked higher (has more searches) than expected. This is significantly higher than a random 50 percent frequency, with $p < 0.001$.[9]

Overall, it appears that investors display local bias in their search behavior. We next examine the relation between this local bias in search and firm characteristics related to overall visibility. While the two are distinct concepts—how many individuals are interested in a firm is different from which individuals are interested—it is likely that the two are related. We expect more visible firms to have lower local bias. We estimate the following model at the firm-year level:

$$\begin{aligned}\%Local = {} & \beta_0 + \beta_1 Ln(SVI) + \beta_2 \#\ of\ News + \beta_3 Urban + \beta_4 Ln(Size) + \beta_5 Adv\ Exp + \beta_6 Ln(EMP) + \beta_7 Ln(SHR) \\ & + \beta_8 Ln(AF) + \beta_9 IO + \beta_{10} SP500 + \beta_{11} Retail + \beta_{12} BM + \varepsilon. \end{aligned} \tag{2}$$

Variables are computed on an annual basis. Appendix A provides detailed definitions. *Ln*(*SVI*) is the mean of weekly log Google SVI for the firm, measuring the overall level of search activity in the given year compared to other years, capturing variation over time in a firm's visibility to search-using investors (Da et al. 2011; Drake et al. 2012). *# of News* is the number of articles mentioning the firm in the *Wall Street Journal, New York Times, USA Today,* and *Washington Post,* associated with visibility (Bushee et al. 2010; Soltes 2010). We include *Urban,* an indicator for whether the firm is located in one of the ten most populous cities, as firms in urban locations are more visible to investors (Loughran and Schultz 2005). *Ln*(*Size*) is the log of market equity value: Coval and Moskowitz (1999) show that local bias is weaker for larger firms. We include *Adv Exp,* advertising expense scaled by sales, since advertising is related to investor awareness (Grullon, Kanatas, and Weston 2004; Lou 2014). We include the number of employees (*Ln*(*EMP*)) and shareholders (*Ln*(*SHR*)), since firms with more of either may be more visible to investors (e.g., Hong, Kubik, and Stein 2008; Bushee et al. 2010). Both higher analyst following (*Ln*(*AF*)) and higher institutional ownership (*IO*) are associated with higher firm visibility (e.g., Bushee and Miller 2012). Ivkovic and Weisbenner (2005) find that local bias is weaker for Standard & Poor's (S&P) 500 firms (*SP500* indicator). We suggest that retail firms (*Retail* indicator) may be more visible to the average individual, since they are consumer-facing. Finally, we include the book-to-market ratio, *BM,* as low *BM* firms may be "glamour" stocks in favor with investors (Lakonishok, Shleifer, and Vishny 1994). For all regressions onward, we run pooled ordinary least square (OLS) regressions, estimate standard errors with one-dimensional clustering by firm, including year fixed effects for Equation (2) and two-dimensional clustering by quarter and firm for the other analyses (Petersen 2009; Gow, Ormazabal, and Taylor 2010). We also include state fixed effects in all regressions.

We present the results in Table 3. Columns (1) and (2) use the full sample, while Columns (3) and (4) restrict the sample to firm-years for which we have press coverage data. We include industry fixed effects in Columns (2) and (4). As expected, we find that almost all of the visibility variables are related to lower local bias in Google search (lower *%Local*). Higher search levels (*Ln*(*SVI*)), newspaper coverage (*# of News*), urban firms, larger firms, firms with more employees, shareholders, analyst

[8] We further verify that *%Local* is related to local bias from prior literature by comparing it to ownership-based local bias measures, using brokerage account data from the 1991–1996 period (described in Barber and Odean [2000]), as in Ivkovic and Weisbenner (2005). Our untabulated results show a positive significant 35 percent correlation between local bias of ownership in the earlier period and *%Local* for firms that survive the entire window. Both variables also have similar determinants.

[9] This is consistent with the finding of Brown, Stice, and White (2015) that overall search drops disproportionately when safe driving laws inhibit search activity from headquarter-state investors.

TABLE 3

Determinants of Local Bias in Google Search Volume

	Full Sample		Subsample with Media Coverage Data	
	(1)	**(2)**	**(3)**	**(4)**
Ln(*SVI*)	−0.044***	−0.043***	−0.026***	−0.025***
	(0.009)	(0.009)	(0.010)	(0.010)
# of News			−0.037***	−0.029***
			(0.010)	(0.010)
Urban	−0.015*	−0.013**	−0.017***	−0.017**
	(0.008)	(0.005)	(0.005)	(0.008)
Ln(*Size*)	−0.013**	−0.011*	−0.013**	−0.011***
	(0.006)	(0.006)	(0.006)	(0.004)
Adv Exp	−0.010	−0.007	−0.004	−0.016*
	(0.008)	(0.008)	(0.007)	(0.010)
Ln(*EMP*)	−0.066**	−0.081**	−0.074***	−0.091***
	(0.027)	(0.035)	(0.026)	(0.020)
Ln(*SHR*)	−0.164***	−0.184***	−0.165***	−0.182***
	(0.049)	(0.050)	(0.056)	(0.057)
Ln(*AF*)	−0.183**	−0.154	−0.188***	−0.176***
	(0.089)	(0.087)	(0.068)	(0.064)
IO	−0.016*	−0.016***	−0.018***	−0.018**
	(0.009)	(0.006)	(0.005)	(0.008)
SP500	−0.047***	−0.050***	−0.045**	−0.051**
	(0.018)	(0.018)	(0.020)	(0.021)
BM	−0.042	−0.049*	−0.053**	−0.053**
	(0.029)	(0.029)	(0.021)	(0.021)
Retail	−0.009		−0.019	
	(0.016)		(0.019)	
State Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	No	Yes	No	Yes
n	5,821	5,821	3,975	3,975
Adjusted R^2	19.70%	21.90%	20.66%	23.34%

***, **, * Denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, using two-tailed tests.
This table presents results of estimating ordinary least squares regressions based on Equation (2). The dependent variable is the percent of all searches for the firm's ticker that originate within 250 miles of the firm's headquarters (*%Local*). The distance is measured between the firm's headquarters location and the population center of each state. *%Local* is measured contemporaneously. The full sample consists of firms listed on the major exchanges from 2005 through 2011. The subsample with media coverage is from 2005 through 2008. Numbers in parentheses are standard errors, calculated using clustering by firm.
Variable definitions are listed in Appendix A.

following, institutional ownership, S&P 500 firms, and firms with higher book-to-market ("glamour" stocks) are all associated with significantly lower local bias in search in most cases. Using two-tailed tests, the significance level is at the 5 percent level or better except for *Urban* in Column (1), *Ln*(*Size*) in Column (2), *IO* in Column (1), *BM* in Column (2) (all significant at the 10 percent level), and analyst following in Column (2) (insignificant). The only two visibility variables for which we do not find significant results are *Adv Exp* (insignificant in Columns (1)–(3), significant at the 10 percent level in Column (4)) and *Retail*.

While there is clearly a strong and statistically significant relation between local bias in search and firm visibility, it is important to note that firm visibility does not fully explain the local bias in search. This empirical result is consistent with our expectations that there are other sources of variation in local bias beyond simply overall firm visibility. For example, a firm that is more involved with the local community or a firm that is headquartered in a region with stronger social ties among local residents and, thus, more local information transfer, may have higher local bias in investor interest, despite being of similar size, analyst coverage, etc., as another firm. The adjusted R^2 in Table 3 ranges from 19.70 percent to 23.34 percent. The highest correlation between *%Local* and the other variables in Equation (2) (untabulated) is 24.8 percent.

These results suggest two important considerations for our analysis: First, it is important to control for overall firm visibility, and second, there is likely to be significant variation in *%Local* even after controlling for overall visibility. We take multiple approaches to address this. First, in our cross-sectional regressions, we include relevant firm-specific variables as control variables. Second, we use propensity score matching (PSM) to obtain matched pairs of firms that are similar along this set of dimensions, but differ in terms of *%Local*. Third, we conduct an instrumental variable analysis employing an instrument associated with higher *%Local,* but similar or higher overall visibility. Thus, low overall visibility is unlikely to drive effects documented for *%Local* using this instrument.

Propensity Score Matching

It is possible that visibility affects the market response around earnings announcements in ways that linear models will not sufficiently control for. To address this issue, we use Propensity Score Matching (PSM) to form firm-year matched pairs that are most similar along the set of firm characteristics included in Equation (2) (the "covariates"), but are most dissimilar in terms of their local bias in Google search (*%Local*).[10] Recall from the previous subsection that there is significant variation in *%Local* even after controlling (linearly) for the large set of visibility-related variables in Equation (2). After matching on these firm characteristics, any difference in market responses around earnings announcements can be more appropriately attributed to differences in local bias rather than to differences in overall visibility.

We construct the matched sample using a nonbipartite matching algorithm suggested by Derigs (1988), Hirano and Imbens (2004), and Lu, Greevy, Xu, and Beck (2011). The algorithm creates optimally matched pairs that minimize the average distance between pairs along the set of covariates on which we match. We match within year, without replacement.

Table 4 presents the descriptive statistics for the treatment (high *%Local*) and control (low *%Local*) samples. We compare the mean, median, and distribution of each covariate and *%Local* and test for differences using a t-test, Wilcoxon Z-test, and Kolmogorov-Smirnov test. We also examine the equivalent of univariate results for our main tests: summary statistics for abnormal bid-ask spreads and abnormal trading volumes and correlations between *CAR* and *SUE* as a measure of ERC and PEAD.

Table 4, Panel A displays the comparison of the covariates. The smaller the differences between the treatment and control groups in these variables, the better the match. We find no significant differences between the two samples in *Ln*(*SVI*), *Urban, Ln*(*Size*), *Adv Exp, Ln*(*EMP*), *Ln*(*AF*), *SP500, Retail,* and *# of News* for the subsample with those data available. *IO* differs using the Kolmogorov-Smirnov test; however, the mean values (medians) differ by only 0.6 percent (3.3 percent) between the two samples. The distribution and median of *BM* show statistically significant differences. However, the mean values for the two samples differ by only 3 percent, which is not statistically significant. In addition, the treatment sample has *lower* mean and median book-to-market than the control sample, counter to the intuition that "glamour" or growth stocks (low *BM*) will have higher visibility and, thus, lower local bias. Finally, we find that treatment firms have 29 percent (24 percent) higher mean (median) *Ln*(*SHR*) than control firms, with statistically significant differences in the mean, median, and distribution.[11]

On all dimensions except *Ln*(*SHR*), we find a strong match between the two groups. However, given the differences in this variable, we acknowledge that covariate balance is not fully achieved. The pattern of having unbalanced covariates is common given the difficulties of matching firms along multiple dimensions (see, e.g., Crawford, Roulstone, and So 2012; Brochet, Miller, and Srinivasan 2014). In untabulated analyses, we follow two recommended approaches to test whether our results are driven by this imbalance. First, we estimate ordinary least squares models of the outcome variables (market responses) as a function of the treatment variable (high versus low *%Local*) and the full set of control variables used in the propensity score model, using the matched samples (Ho, Imai, King, and Stuart 2007). Second, we exclude firm pairs with the largest differences in *Ln*(*SHR*) to obtain covariate balance. Specifically, we drop the 13 percent of pairs with the poorest match along the dimension of *Ln*(*SHR*), resulting in statistically insignificant differences in *Ln*(*SHR*), and replicate our tests. In both cases, results are similar to those reported in the paper. While we are unable to obtain full covariate balance, these robustness tests suggest that our results are not driven by the remaining imbalance.

Table 4, Panel B reports the comparison of the variables of interest, *%Local, AbSpreads*[0,1], *AbVol*[0,1], *AbSpreads*[−5,−1], and *AbVol*[−5,−1]. Consistent with having identified pairs that differ significantly along the dimension of local bias in search, *%Local* is significantly higher in the treatment group than the control group. Consistent with our predictions for the relation between the market responses around earnings and *%Local,* we find that *AbSpreads*[0,1], *AbVol* [0,1], *AbSpreads*[−5,−1], and *AbVol*[−5,−1] each differ in the expected directions, with p-values of < 0.001 in each case. With regard to ERCs and PEAD,

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[10] We do not include all of these control variables in each model because we do not expect all of them to be related to the different dependent variables. However, we include the full set of variables in our PSM to obtain a single set of matched pairs.

[11] *SHR* is the number of shareholders of record. For all shares held "in street name," the shareholder of record is the investor's brokerage house (e.g., TD Ameritrade). Thus, a single shareholder of record may represent thousands of investors. This makes the *Ln*(*SHR*) variable particularly noisy and difficult to interpret.

TABLE 4

Descriptive Statistics for the Propensity Score Matched Treatment (*High_%Local*) and Control (*Low_%Local*) Samples

Panel A: Covariate Descriptive Statistics and Tests of Differences

	Treatment Mean	Control Mean	Treatment Median	Control Median	t-test	Wilcoxon Z-test	Kolmogorov-Smirnov D-test
Ln(SVI)	3.589	3.593	3.738	3.743	0.29	0.09	0.01
# of News[a]	0.696	0.697	1	1	0.08	0.10	0.01
Urban	0.360	0.364	0	0	0.38	0.38	0.00
Ln(*Size*)	6.946	6.990	7.034	7.099	0.94	0.98	0.02
Adv Exp	0.010	0.010	0.000	0.000	0.29	0.87	0.02
Ln(*EMP*)	0.982	1.058	1.194	1.280	1.51	1.54	0.03
Ln(*SHR*)	0.675	0.868	0.689	0.853	3.68***	3.24***	0.05***
Ln(*AF*)	1.728	1.747	1.852	1.872	0.93	0.76	0.02
IO	0.481	0.487	0.556	0.589	0.66	0.90	0.05***
SP500	0.303	0.315	0	0	1.12	1.12	0.01
Retail	0.130	0.133	0	0	0.29	0.29	0.00
BM	0.556	0.573	0.455	0.486	1.39	2.98***	0.05***

Panel B: *%Local, AbSpreads,* and *AbVol* Descriptive Statistics and Tests of Differences

	Treatment Mean	Control Mean	Treatment Median	Control Median	Predicted Difference (Treatment − Control)	t-test	Wilcoxon Z-test	Kolmogorov-Smirnov D-test
%Local	0.209	0.173	0.115	0.073	+	5.97***	5.18***	0.10***
AbSpreads[0,1]	0.037	0.010	0.001	−0.009	+	6.03***	6.57***	0.19***
AbVol[0,1]	0.624	0.680	0.610	0.674	−	−6.31***	−6.20***	0.08***
AbSpreads[−5,−1]	0.016	0.009	−0.001	−0.006	+	5.02***	3.88***	0.06***
AbVol[−5,−1]	0.055	0.034	0.055	0.030	+	4.91***	545***	0.12***

Panel C: Pearson Correlations between *CAR* and *SUE* and Test of Differences

	Treatment	Control	Predicted Difference (Treatment − Control)	Z-Score Test
Corr(*CAR*[0,1], *SUE*)	0.053	0.276	−	−5.43***
Corr(*CAR*[−5,−1], *SUE*)	0.249	0.035	+	7.14***
Corr(*CAR*[2,61], *SUE*)	0.161	0.044	?	4.02***

***, **, * Denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests when there is a directional prediction, and two-tailed tests otherwise.

[a] *# of News* is matched from 2005 through 2008.

This table presents descriptive statistics for the treatment (*High_%Local*) and control (*Low_%Local*) samples constructed through propensity score matching (PSM). The firms are matched according to the most similar conditional probability of treatment, but the largest difference in the observed level of treatment. There are 2,716 matched pairs. Panels A and B present mean and median values. The last three columns present the statistics of a paired t-test for the difference in mean, a Wilcoxon test for rank-sum difference in the median, and a Kolmogorov-Smirnov test for difference in the distribution across the treatment and control samples. In Panels B and C, the "Predicted Difference (Treatment − Control)" columns show the sign of the predicted difference in the given measure between the treatment and control groups, based upon H1, H2, and H3. Panel C reports the statistics of Fisher's Z-score test for the difference in Spearman correlation between *CAR* for the given windows and *SUE*.

Variable definitions are listed in Appendix A.

measured by the correlations between *CAR* and *SUE,* Panel C shows that the treatment group has significantly lower correlation for the announcement window (lower ERC) and significantly higher correlations before and after the announcement window (higher anticipation and higher PEAD). Thus, the univariate comparisons in Table 4 are consistent with H1–H3.

Local Bias in Search and the Market Response around Earnings Announcements

Market Response at the Earnings Announcement Date

To test H1, we focus on the incremental effect of (lagged) local bias, *%Local,* on the market response to the earnings announcement. Note that in all remaining tests focusing on the impact of local bias on the market response around earnings announcements, we use lagged local bias in our regressions. Because our variables are defined on an annual basis, it is possible that local bias in a given year is affected by an earnings announcement early in the year. For example, if the firm has a large earnings surprise early in the year, then it may draw non-local investor attention. To reduce the possibility of such reverse causality affecting results, we use lagged local bias. However, results are robust to using contemporaneous local bias.

To examine the relation between local bias in search and information asymmetry, H1(a), we regress *AbSpreads*[0,1] on the quarterly decile rank of lagged *%Local, R_%Local,* normalized to range from −0.5 to +0.5, as well as a set of control variables. For the PSM sample, we use *High_%Local,* an indicator that takes the value 1 (0) for treatment (control) firms instead. If more non-local search decreases information asymmetry, similarly to wider dissemination of earnings news (Bushee et al. 2010), then we should find an increase in abnormal spreads for higher *%Local*.[12] We estimate the following model:

$$\begin{aligned} AbSpreads[0,1] = {} & a_0 + a_1 R\_AbsSUE + a_2 R\_\%Local(High\_\%Local) + a_3 chSVI + a_4 Ln(Size) + a_5 BM + a_6 IO \\ & + a_7 Ln(AF) + a_8 Ln(SHR) + a_9 Turnover + a_{10} RV + a_{11} AbsCAR[0,1] + a_{12} RECPRC \\ & + a_{13} Ln(\#ofRevision) + a_{14} MF + \varepsilon, \end{aligned} \tag{3}$$

where *AbSpreads*[0,1], *R_AbsSUE, R_%Local,* and *High_%Local* are defined above; *chSVI* is the natural logarithm of the firm's weekly national SVI minus the median value of the firm's SVI over the previous ten weeks (Da et al. 2011). Following prior literature (Bamber and Cheon 1995; Bamber, Barron, and Stober 1997; Bushee et al. 2010), we also include other market characteristics that affect spreads: prior-quarter turnover (*Turnover*), stock return volatility (*RV*), the absolute value of returns during the earnings announcement window (*AbsCAR*[0,1]), and the reciprocal of stock price (*RECPRC*). We also control for analyst forecast revision frequency (*Ln(# of Revision)*) and the issuance of a management forecast (*MF*) between the fiscal quarter-end date and the earnings announcement date, as these affect market responses to earnings (Francis and Soffer 1997; Drake et al. 2012).

Table 5, Panel A reports results. The first (second) two columns report results for the full and PSM samples using the random walk (analyst forecast) based absolute earnings surprise to control for earnings news. As expected, we find significantly positive coefficients on *R_%Local* and *High_%Local* in all four specifications, with p-values of < 0.01. We focus on the PSM treatment and control firms (low and high *%Local* matched samples) to gauge economic significance, as these samples are well matched along other dimensions and, thus, control nonlinearly for other factors. The standard deviation of *AbSpreads*[0,1] is 0.386 (Table 2). Thus, compared with control firms, the treatment firms (*High_%Local*) experience 10.9 percent (Column (2)) and 11.9 percent (Column (4)) of a standard deviation higher *AbSpreads*[0,1]. By comparison, Bushee et al. (2010, Tables 1 and 3) find that a one-standard-deviation change in press coverage is associated with a change in abnormal spreads of 6.5 percent of a standard deviation. Thus, the magnitude of the effect for geographic dispersion of search is comparable to the effect for press coverage. In contrast, higher abnormal search volume, *chSVI,* is associated with significantly *higher* bid-ask spreads, the opposite effect of proportionally more non-local investor search (i.e., lower *%Local*). This further suggests that it is not the amount of search or the level of visibility that drives the local bias result. The results for other control variables, unreported for brevity, are generally in expected directions. These results, given the inclusion of control variables and the matching done for Columns (2) and (4), suggest that more non-local search reduces information asymmetry, measured by bid-ask spreads, incremental to factors examined in prior literature.

To examine the relation between local bias in search and abnormal trading volume (*AbVol*[0,1]), we employ a specification similar to the one we use to analyze *AbSpreads*[0,1].[13] We estimate the following model:

$$\begin{aligned} AbVol[0,1] = {} & \sigma_0 + \sigma_1 R\_AbsSUE + \sigma_2 R\_\%Local(High\_\%Local) + \sigma_3 chSVI + \sigma_4 BM + \sigma_5 Ln(Size) + \sigma_6 Ln(\#\ of\ Revision) \\ & + \sigma_7 IO + \sigma_8 Ln(AF) + \sigma_9 MF + \sigma_{10} R\_EA + \sigma_{11} EV + \sigma_{12} EP + \sigma_{13} MKVol[0,1] + \varepsilon, \end{aligned} \tag{4}$$

where *AbVol*[0,1], *R_AbsSUE, R_%Local, High_%Local, chSVI, BM, Ln(Size), Ln(# of Revision), IO, LnAF,* and *MF* are defined as before. The additional variables are: quarterly decile rank of the number of other-firm earnings announcements on the same day (*R_EA*) (Hirshleifer et al. 2009), earnings volatility and persistence over the prior four years (*EV* and *EP*)

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12 Similar to Bushee et al. (2010), we focus on the main effect for the relation between our variable of interest and abnormal bid-ask spreads, and do not include an interaction term between the variable and *R_AbsSUE*. However, our results are robust to inclusion of an interaction term. The coefficients on *R_%Local* and *High_%Local* continue to be significantly positive at the 1 percent level. The coefficients on *R_AbsSUE* ∗ *R_%Local* and *R_AbsSUE* ∗ *High_%Local* are significantly positive at the 1 percent level.

13 Similar to Hirshleifer et al. (2009), we focus on the main effect for the relation between our variables of interest and abnormal trading volume, and do not include an interaction term between our variable and *R_AbsSUE*. However, our results are robust to inclusion of an interaction term. The coefficient on *R_%Local* continues to be significantly negative, with p-values of 0.018 (0.021) using random walk (analyst forecast) based earnings surprises. The coefficient on *R_AbsSUE* ∗ *R_%Local* is significantly negative, with p-value of 0.005 (0.013), an additional indication of weaker investor reactions to earnings announcements with higher *%Local*. We find very similar results when using *High_%Local* and its interaction with *R_AbsSUE*.

TABLE 5

Market Responses around Earnings Announcements
The Earnings Announcement Window

Panel A: *AbSpreads*[0,1]

	Predicted Sign	Random Walk-Based Absolute Earnings Surprise: Full Sample	Random Walk-Based Absolute Earnings Surprise: PSM Sample	Analyst Forecast-Based Absolute Earnings Surprise: Full Sample	Analyst Forecast-Based Absolute Earnings Surprise: PSM Sample
R_AbsSUE		0.004	0.006	0.005	0.007
		(0.007)	(0.007)	(0.007)	(0.007)
R_%Local	+	0.013***		0.011***	
		(0.005)		(0.004)	
High_%Local	+		0.042***		0.046***
			(0.007)		(0.007)
chSVI		0.094**	0.095**	0.095***	0.101***
		(0.040)	(0.048)	(0.028)	(0.030)
Controls		Yes	Yes	Yes	Yes
State Fixed Effect		Yes	Yes	Yes	Yes
n		21,597	19,833	17,842	15,996
Adjusted R^2		5.05%	8.02%	5.33%	9.14%

Panel B: *AbVol*[0,1]

	Predicted Sign	Random Walk-Based Absolute Earnings Surprise: Full Sample	Random Walk-Based Absolute Earnings Surprise: PSM Sample	Analyst Forecast-Based Absolute Earnings Surprise: Full Sample	Analyst Forecast-Based Absolute Earnings Surprise: PSM Sample
R_AbsSUE	+	0.106***	0.105***	0.203***	0.203***
		(0.013)	(0.017)	(0.013)	(0.019)
R_%Local	−	−0.019***		−0.016***	
		(0.006)		(0.006)	
High_%Local	−		−0.0286***		−0.0246***
			(0.011)		(0.005)
chSVI	+	0.002***	0.003***	0.002***	0.003***
		(0.000)	(0.001)	(0.000)	(0.001)
Controls		Yes	Yes	Yes	Yes
State Fixed Effect		Yes	Yes	Yes	Yes
n		21,597	19,833	17,842	15,996
Adjusted R^2		12.16%	11.90%	13.00%	12.88%

Panel C: *CAR*[0,1]

	Pred. Sign	Random Walk-Based Earnings Surprise: Full Sample	Random Walk-Based Earnings Surprise: PSM Sample	Analyst Forecast-Based Earnings Surprise: Full Sample	Analyst Forecast-Based Earnings Surprise: PSM Sample
R_SUE	+	0.076***	0.077***	0.061***	0.062***
		(0.019)	(0.018)	(0.014)	(0.015)
R_%Local		−0.003		−0.002	
		(0.002)		(0.002)	
R_SUE ∗ R_%Local	−	−0.012***		−0.013***	
		(0.004)		(0.005)	
High_%Local			−0.001		−0.001
			(0.001)		(0.001)
R_SUE ∗ High_%Local	−		−0.026***		−0.027***
			(0.008)		(0.009)

(continued on next page)

TABLE 5 (continued)

	Pred. Sign	Random Walk-Based Earnings Surprise		Analyst Forecast-Based Earnings Surprise	
		Full Sample	**PSM Sample**	**Full Sample**	**PSM Sample**
chSVI		−0.002	−0.001	−0.001	0.000
		(0.002)	(0.003)	(0.002)	(0.003)
R_SUE ∗ chSVI	+	0.018***	0.015**	0.033***	0.035**
		(0.007)	(0.008)	(0.008)	(0.009)
Controls		Yes	Yes	Yes	Yes
R_SUE ∗ Controls		Yes	Yes	Yes	Yes
State Fixed Effect		Yes	Yes	Yes	Yes
R_SUE ∗ State Fixed Effect		Yes	Yes	Yes	Yes
n		21,597	19,833	17,842	15,996
Adjusted R^2		2.84%	2.80%	12.50%	12.65%

***, **, * Denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests when there is a directional prediction, and two-tailed tests otherwise.
This table presents the results of estimating ordinary least squares regressions. Estimations are based on Equations (3), (4) and (5) for Panels A, B, and C, respectively. The dependent variables are abnormal bid-ask spreads in Panel A, abnormal trading volume in Panel B, and cumulative abnormal returns in Panel C, over trading days 0 and 1 around the earnings announcement, where day 0 is the earnings announcement date. *%Local* is measured in year *t*−1. The full sample consists of quarterly earnings announcements of firms listed on the major exchanges from 2005 through 2011. The PSM sample uses propensity score matched treatment and control samples, where propensity scores were calculated based on the conditional probability of having a certain level of the treatment conditional on economic characteristics in Equation (2). The firms are matched according to the most similar conditional probability of treatment, but the largest difference in the observed level of treatment. The left-most (right-most) columns display results for *SUE* based on random walk (analyst-based) expectations. *R_AbsSUE* is the decile rank of absolute earnings surprise (Panels A and B). *R_SUE* is the decile rank of earnings surprise (Panel C). For brevity, the coefficients of control variables and the interactions of control variables and *R_SUE* are not reported. Numbers in parentheses are standard errors, calculated using two-dimensional clustering by calendar quarter and firm.
Variable definitions are listed in Appendix A.

(Landsman and Maydew 2002; Drake et al. 2012), and market-wide trading volume over the earnings announcement window (*MKVol*[0,1]).

We predict a negative value for $\hat{\sigma}_2$, consistent with lower trading volume around earnings announcements for firms with proportionally more local investors. Results are displayed in Table 5, Panel B. The coefficients on *R_%Local* and *High_%Local* are negative and statistically significant (p-values $<$ 0.01). Treatment firms (*High_%Local* = 1) experience 4.85 percent (4.17 percent) of one-standard-deviation lower *AbVol*[0,1] compared with control firms, in Column (2) (Column (4)). This is eight to ten times the effect of a one-standard-deviation change in abnormal nationwide search levels, *chSVI*. Overall, the results indicate that the extent of local bias in search is significantly related to abnormal volume, consistent with H1(b).

In H1(c), we predict a lower ERC if local bias in search is higher, given that we expect non-local investors to react more strongly than locals to the earnings announcement. We estimate the following regression to examine the initial ERC:

$$\begin{aligned} CAR[0,1] = {} & \beta_0 + \beta_1 R\_SUE + \beta_2 R\_\%Local(High\_\%Local) + \beta_3 R\_SUE{*}R\_\%Local(R\_SUE{*}High\_\%Local) + \beta_4 Controls \\ & + \beta_5 R\_SUE{*}Controls + \varepsilon, \end{aligned} \tag{5}$$

where *CAR*[0,1] is defined in Section III, subsection "Market Response Measures"; *R_SUE* is the quarterly decile rank of standardized unexpected earnings; *Controls* is a set of variables including *chSVI, BM, Ln*(*Size*), *R_EA, Ln*(*# of Revisions*), *IO, LnAF, Turnover, MF, EV,* and *EP,* as defined above. These variables are associated with announcement window ERCs in prior studies (e.g., earnings volatility and persistence: Collins and Kothari [1989]; institutional ownership: Teoh and Wong [1993]; analyst following: Shores [1990]; analyst forecast frequency: Francis and Soffer [1997]; earnings announcements made by other firms: Hirshleifer et al. [2009]). The term $\hat{\beta}_1$ captures the average ERC, while $\hat{\beta}_3$ captures the incremental ERC related to higher local bias. We predict a negative value for $\hat{\beta}_3$.

Table 5, Panel C presents the results from estimating Equation (5). Consistent with the ERC literature, *CAR*[0,1] is positively associated with the earnings surprise, *R_SUE*. In addition, the result for control variables and their interactions with *R_SUE* (unreported for brevity) are generally consistent with prior literature. The estimated coefficient $\hat{\beta}_3$ on the interaction terms *R_SUE ∗ R_%Local* and *R_SUE ∗ High_%Local* are significantly negative (p-values $<$ 0.01). Comparing the coefficients on *R_SUE* and *R_SUE ∗ High_%Local,* high local bias firms (*High_%Local* = 1) experience ERCs over 30 percent lower than those of low local bias firms (34 percent in Column (2), 43 percent in Column (4)). Thus, higher local bias is associated with significantly lower ERCs.

Overall, the results displayed in Table 5 provide evidence that higher local bias is associated with higher information asymmetry, as captured by bid-ask spreads, and a weaker investor response, as measured by trading volume and ERC, at the time of earnings announcements. These results are consistent with predictions from both local information advantage and familiarity bias, and provide evidence consistent with local bias having a significant impact on the market response to information, even during the internet era.

Market Response in the Pre-Announcement Period

To test H2, we focus on the incremental effect of lagged local bias, *%Local,* on the market response during the week before the earnings announcement. We predict that information asymmetry is higher and there is more earnings-related trading in the pre-announcement period when *%Local* is high, due to local information advantage. Empirically, we replace *AbSpreads*[0,1], *AbVol*[0,1], and *CAR*[0,1] in Equations (3), (4), and (5) with *AbSpreads*[–5,–1], *AbVol*[–5,–1], and *CAR*[–5,–1], respectively, and adjust *AbsCAR* and *MKVol* accordingly. Other variables are unchanged.

Table 6 reports the results for the pre-announcement window. Focusing on *AbSpreads*[–5,–1] in Panel A, we find significantly positive coefficients on *R_%Local* and *High_%Local,* with p-values of < 0.01. Higher local bias is associated with 9.06 percent (9.43 percent) of a standard-deviation increase in *AbSpreads*[–5,–1], comparing low and high *%Local* matched samples, using the random walk-based (analyst-based) earnings surprise, in Column (2) (Column (4)).

Focusing on *AbVol*[–5,–1] in Table 6, Panel B, the coefficients on *R_%Local* and *High_%Local* are significantly positive, with p-values of < 0.01. Higher local bias is associated with 34.4 percent (40.4 percent) of a standard-deviation higher *AbVol*[–5,–1], comparing low and high *%Local* matched samples, in Column (2) (Column (4)).

Finally, H2c predicts that firms with higher *%Local* will have pre-announcement returns more predictive of the upcoming earnings surprise. Consistent with some anticipation of the upcoming news, the coefficient on *R_SUE* is significantly positive in all models. However, this anticipation is higher for firms with higher local bias. The estimated coefficients on the interaction terms, *R_SUE* ∗ *R_%Local* and *R_SUE* ∗ *High_%Local,* are all significantly positive at the 1 percent level. Comparing coefficients, the pre-announcement window ERC is 10.4 percent (10.5 percent) higher for high *%Local* firms, in Column (2) (Column (4)). While the magnitude of this ERC effect is smaller than for announcement window ERC, the result still suggests an economically meaningful difference in the anticipation of earnings news.

All of these results are consistent with the predictions of local information advantage. Specifically, the proportionally larger number of local investors in high *%Local* firms are more likely to trade on private information in the pre-announcement window. Thus, these firms, with higher *%Local,* experience higher pre-announcement information asymmetry, trading volumes, and returns that better anticipate the upcoming earnings announcement.

Note that we find a positive relation between the abnormal level of search, *chSVI,* and abnormal volume in Table 6, Panel B, and the pre-announcement window ERC in Panel C, consistent with Drake et al. (2012). This further emphasizes the difference between having a lower *level* of overall search and having more *local bias* of search.[14]

Post-Earnings Announcement Drift

To test H3, we replace *CAR*[0,1] in Equation (5) with *CAR*[2,61]. Based upon the familiarity bias explanation of local bias, we predict that PEAD is stronger when *%Local* is high, due to the more biased reactions of local investors. Note that to the extent that the local information advantage explanation of local bias dominates, we would likely not find this result. Under local information advantage, there is no clear prediction for the effect of local bias on PEAD, and PEAD may even be lower for higher local bias. Given this, we use two-tailed tests for the relation between PEAD and local bias. Table 7 reports the results.

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[14] To better understand the relation between our results and those in Drake et al. (2012), we first replicate the key results from Drake et al. (2012). We confirm that pre-announcement trading volume and returns are more strongly predictive of the coming earnings surprise when abnormal search, *chSVI* in our case, is higher in our sample. We then examine results for subsamples of firms with low and high *%Local*. We find that the *chSVI* effect is stronger for firms with higher *%Local,* suggesting that local search in the pre-announcement window has a stronger impact on abnormal trading volume and returns predicting earnings information than non-local search. This is consistent with local information advantage.

TABLE 6

Market Responses around Earnings Announcements
The Pre-Announcement Window

Panel A: *AbSpreads*[–5,–1]

	Predicted Sign	Random Walk-Based Absolute Earnings Surprise: Full Sample	Random Walk-Based Absolute Earnings Surprise: PSM Sample	Analyst Forecast-Based Absolute Earnings Surprise: Full Sample	Analyst Forecast-Based Absolute Earnings Surprise: PSM Sample
R_AbsSUE		–0.002	–0.002	–0.003	–0.003
		(0.006)	(0.006)	(0.004)	(0.004)
R_%Local	+	0.008***		0.009***	
		(0.002)		(0.004)	
High_%Local	+		0.015***		0.015***
			(0.003)		(0.003)
chSVI		0.003	0.015***	0.011***	0.006*
		(0.004)	(0.004)	(0.004)	(0.004)
Controls		Yes	Yes	Yes	Yes
State Fixed Effect		Yes	Yes	Yes	Yes
n		21,597	19,833	17,842	15,996
Adjusted R^2		8.21%	10.22%	5.62%	8.25%

Panel B: *AbVol*[–5,–1]

	Predicted Sign	Random Walk-Based Absolute Earnings Surprise: Full Sample	Random Walk-Based Absolute Earnings Surprise: PSM Sample	Analyst Forecast-Based Absolute Earnings Surprise: Full Sample	Analyst Forecast-Based Absolute Earnings Surprise: PSM Sample
R_AbsSUE	+	0.108**	0.103***	0.113**	0.114**
		(0.058)	(0.044)	(0.054)	(0.054)
R_%Local	+	0.057***		0.042***	
		(0.016)		(0.017)	
High_%Local	+		0.104***		0.122***
			(0.021)		(0.023)
chSVI	+	0.011***	0.011***	0.011***	0.012***
		(0.003)	(0.003)	(0.003)	(0.003)
Controls		Yes	Yes	Yes	Yes
State Fixed Effect		Yes	Yes	Yes	Yes
n		21,597	19,833	17,842	15,996
Adjusted R^2		4.52%	4.32%	4.72%	4.60%

Panel C: *CAR*[–5,–1]

	Pred. Sign	Random Walk-Based Earnings Surprise: Full Sample	Random Walk-Based Earnings Surprise: PSM Sample	Analyst Forecast-Based Earnings Surprise: Full Sample	Analyst Forecast-Based Earnings Surprise: PSM Sample
R_SUE	+	0.049***	0.043***	0.030***	0.040***
		(0.011)	(0.013)	(0.013)	(0.016)
R_%Local		–0.002		–0.001	
		(0.001)		(0.002)	
*R_SUE * R_%Local*	+	0.003***		0.005***	
		(0.001)		(0.001)	
High_%Local			0.000		0.000
			(0.001)		(0.001)

(continued on next page)

TABLE 6 (continued)

	Pred. Sign	Random Walk-Based Earnings Surprise		Analyst Forecast-Based Earnings Surprise	
		Full Sample	PSM Sample	Full Sample	PSM Sample
R_SUE ∗ High_%Local	+		0.005***		0.004***
			(0.001)		(0.001)
chSVI		0.003	0.003	0.004	0.004
		(0.004)	(0.004)	(0.004)	(0.004)
R_SUE ∗ chSVI	+	0.022***	0.025***	0.024***	0.025***
		(0.007)	(0.009)	(0.009)	(0.011)
Controls		Yes	Yes	Yes	Yes
R_SUE ∗ Controls		Yes	Yes	Yes	Yes
State Fixed Effect		Yes	Yes	Yes	Yes
R_SUE ∗ State Fixed Effect		Yes	Yes	Yes	Yes
n		21,597	19,833	17,842	15,996
Adjusted R^2		1.17%	1.25%	1.69%	1.73%

***, **, * Denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests when there is a directional prediction, and two-tailed tests otherwise.

This table presents the results of estimating ordinary least squares regressions. Estimations are based on Equations (3), (4), and (5). The dependent variables are abnormal bid-ask spreads, abnormal trading volume, and cumulative abnormal returns five trading days prior to the earnings announcement date, in Panels A, B, and C, respectively. *%Local* is measured in year *t*–1. The full sample consists of quarterly earnings announcements of firms listed on the major exchanges from 2005 through 2011. The PSM sample uses propensity score matched treatment and control samples, where propensity scores were calculated based on the conditional probability of having a certain level of the treatment conditional on economic characteristics in Equation (2). The firms are matched according to the most similar conditional probability of treatment, but the largest difference in the observed level of treatment. The left-most (right-most) columns display results for *SUE* based on random walk (analyst-based) expectations. *R_AbsSUE* is the decile rank of absolute earnings surprise (Panels A and B). *R_SUE* is the decile rank of earnings surprise (Panel C). For brevity, the coefficients of control variables and the interactions of control variables and *R_SUE* are not reported. Numbers in parentheses are standard errors, calculated using two-dimensional clustering by calendar quarter and firm.

Variable definitions are listed in Appendix A.

As expected, we find a positive coefficient on *R_SUE,* implying that there is PEAD. The results for control variables and their interactions with *R_SUE* (unreported for brevity) are generally consistent with prior literature. As predicted by familiarity bias, the coefficients on the interaction terms *R_SUE ∗ R_%Local* and *R_SUE ∗ High_%Local* are significantly positive using both random walk earnings surprise (Columns (1) and (2)) and analyst forecast earnings surprise (Columns (3) and (4)). The increase is statistically significant in all models (p-values < 0.06). The increase in drift for higher *%Local* is 11.9 percent (10.4 percent) in Column (2) (Column (4)), comparing low and high *%Local* matched samples.[15]

This result shows that subsequent PEAD is significantly stronger when local bias is higher or, put another way, PEAD is significantly weaker when a firm has proportionally more non-local investors. Note that there is no significant drop in drift associated with higher levels of abnormal search. The coefficients on the interaction term *R_SUE ∗ chSVI* are small, positive in three of four cases, and statistically insignificant. While search levels are associated with higher abnormal trading volume and higher ERC, they are not associated with lower drift. This is consistent with the idea that *who* is searching is important (e.g., locals, who may be trading due to familiarity bias) beyond simply *how many* individuals are searching.

Overall, the results reported in Tables 5, 6, and 7 are consistent with lower local bias, e.g., proportionally more non-local search, enhancing the initial market response to firms' public earnings announcements. In addition, our results are consistent

[15] We conduct two additional analyses regarding PEAD. First, to examine the evolution of post-earnings announcement returns, we conduct tests for one-, six-, and 12-month windows. The local bias-related increase in drift, captured by the coefficient for *R_SUE ∗ R_%Local,* is largest for the one-month window, and is less positive and statistically insignificant for the six- and 12-month windows. These results suggest that local bias increases PEAD for up to three months after the earnings announcement. After that, return differences related to local bias, specifically to familiarity bias, diminish and are subsumed by other factors. Second, we replace *R_SUE* with *R_CAR*[0,1] as an alternative measure of earnings window information. This provides a model-agnostic estimate of drift that also incorporates additional information announced at the time of the earnings announcement (Brandt, Kishore, Santa-Clara, and Venkatachalam 2007). The coefficient for *R_CAR*[0,1] ∗ *R_%Local* (*R_CAR*[0,1] ∗ *High_%Local*) continues to be significantly positive, with a similar or even higher economic magnitude. This suggests that the measured increase in drift is not due to a difference in the appropriateness of the earnings expectations models across firms or due to other earnings announcement window information. Instead, firms with more local bias have a stronger market underreaction to the full set of earnings announcement window information, as measured by stronger *CAR*[0,1]-based drift. This is consistent with Huberman's (2001) assertion that familiarity-biased investors trade due to general optimism rather than specific information.

TABLE 7

Market Responses around Earnings Announcements
Post-Earnings Announcement Cumulative Abnormal Returns

	Pred. Sign	Random Walk-Based Earnings Surprise: Full Sample	Random Walk-Based Earnings Surprise: PSM Sample	Analyst Forecast-Based Earnings Surprise: Full Sample	Analyst Forecast-Based Earnings Surprise: PSM Sample
R_SUE	+	0.073***	0.076**	0.064**	0.063**
		(0.024)	(0.024)	(0.026)	(0.023)
R_%Local		0.004		0.000	
		(0.015)		(0.020)	
*R_SUE * R_%Local*	?	0.006**		0.005*	
		(0.003)		(0.003)	
High_%Local			0.004		0.001
			(0.011)		(0.010)
*R_SUE * High_%Local*	?		0.009***		0.007***
			(0.002)		(0.002)
chSVI		0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
*R_SUE * chSVI*		−0.001	0.000	0.000	0.000
		(0.001)	(0.000)	(0.001)	(0.000)
Controls		Yes	Yes	Yes	Yes
*R_SUE * Controls*		Yes	Yes	Yes	Yes
State Fixed Effect		Yes	Yes	Yes	Yes
*R_SUE * State Fixed Effect*		Yes	Yes	Yes	Yes
n		21,597	19,833	17,842	15,996
Adjusted R^2		1.15%	1.41%	1.30%	1.38%

***, **, * Denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests when there is a directional prediction, and two-tailed tests otherwise.
This table presents the results of estimating ordinary least squares regressions. Estimations are based on Equation (6). The dependent variable is cumulative abnormal return over 60 trading days after the earnings announcement (*CAR*[2,61]), starting day 2 of the earnings announcement date. *%Local* is measured in year *t*−1. The full sample consists of quarterly earnings announcements of firms listed on the major exchanges from 2005 through 2011. The PSM sample uses propensity score matched treatment and control samples, where propensity scores were calculated based on the conditional probability of having a certain level of the treatment conditional on economic characteristics in Equation (2). The firms are matched according to the most similar conditional probability of treatment, but the largest difference in the observed level of treatment. The left-most (right-most) columns display results for *SUE* based on random walk (analyst-based) expectations. *R_SUE* is the decile rank of earnings surprise. Numbers in parentheses are standard errors, calculated using two-dimensional clustering by calendar quarter and firm.
Variable definitions are listed in Appendix A.

with higher local bias enhancing the incorporation of private information into prices in the pre-announcement period. Finally, the results are consistent with familiarity bias having a significant impact, based upon the result of higher PEAD for higher local bias. Thus, our results support H1, H2, and H3 for local bias having a significant impact on the market's reaction to earnings information, and suggest that both local information advantage and familiarity bias play an important role in the effect of local bias on market reactions around earnings announcements. As discussed in footnote 1 and Section II, this is consistent with local information advantage and familiarity bias each being a significant driver of local bias, most likely for different firms or different sets of investors.

Additional Analyses

In this section, we report several additional analyses, including a two-stage least squares approach, an examination of changes in local bias, and additional sensitivity analyses.

Two-Stage Least Squares Analyses

To further address potential concerns that local bias is endogenous and that this endogeneity drives our observed results, we use two-stage least squares (2SLS) as an alternative approach. The 2SLS approach requires at least one exogenous (instrumental) variable for estimating the endogenous variable. In our case, the ideal instrument correlates with *%Local,* but not with market responses around earnings announcements (e.g., *AbSpreads*[0,1]). We use whether a firm is listed as one of the best employers in its headquarters state on a within-state "best employer" list ($Best\ Employer_{home\_state}$) in a given year as our instrumental variable for *%Local* in that year.[16] We expect higher local visibility when a firm appears on a "best employer" list within its home state. In particular, we assume that such a listing will increase local visibility more than non-local visibility. This results in an increase in *%Local,* even as overall visibility stays the same or increases. Thus, we have the opposite relation between *%Local* and overall visibility than we normally expect, allowing us to better disentangle the effects of high local bias versus low overall visibility. Finally, there is no obvious reason that being included on a state-specific best employer list would directly affect the market response around earnings announcements. If there is an effect, then it would be through the mechanism of local visibility, i.e., *%Local*.

Table 8 reports the results for the 2SLS analyses. Panel A shows the result of the first-stage regression, estimating Equation (2) supplemented with the instrumental variable $Best\ Employer_{home\_state}$. As expected, $Best\ Employer_{home\_state}$ is positively associated with *%Local*. The F-statistic ($F = 14.53$, $p < 0.001$) exceeds the recommended critical value of $F = 8.96$ with one instrument (Stock, Wright, and Yogo 2002; Larcker and Rusticus 2010). Thus, $Best\ Employer_{home\_state}$ is a strong and statistically valid instrument. Panels B and C report the results for the second-stage model, where we replace *R_%Local* with the decile rank of the *predicted* value of lagged *%Local, R_Pred*(*%Local*), obtained from the first-stage estimation result. Results are consistent with our main results and statistically significant at the 1 percent level or better in all cases, with magnitudes that are similar to, or sometimes much higher than, the coefficient estimates reported in our main tables. Overall, the results from our 2SLS analysis suggest that endogeneity is not driving the results we report.

Changes Analysis

If the geographic dispersion of search for a firm is highly persistent, then reverse causality is an important concern despite our use of lagged dispersion. In this section, we examine changes in the annual level of local bias in search. We sort firms into terciles in each year *t* based on $\%Local_t - \%Local_{t-1}$. The highest, H, (lowest, L) tercile experiences a statistically significant average increase (decrease) in *%Local* of 0.15 (0.15), 58 percent (56 percent) of a standard deviation. For each tercile, we examine market response measures for the years before and after the change in *%Local* (Yr_{t-1} and Yr_{t+1}).

To examine the change in *AbSpreads*[0,1], *AbVol*[0,1], *AbSpreads*[−5,−1], and *AbVol*[−5,−1], we estimate Equations (3) and (4) without *R_%Local* for each tercile, before and after the change in local search. We focus on the estimated intercept in the regression, which captures average abnormal bid-ask spreads and abnormal trading volume for the given sample after controlling for other determinants. To examine the changes in ERC and PEAD, we estimate Equation (5), removing *R_%Local* and *R_SUE* ∗ *R_%Local*. We focus on the changes in the coefficients of *R_SUE*. Table 9 reports values for the H and L terciles in both years, the relevant differences, and the difference-in-differences. Panels A and B present results for the announcement window (H1), while Panels C and D present results for the pre- and post-announcement windows (H2, H3).

Focusing on the bottom row of each panel, across all 14 analyses, we find no differences between H and L firms before their changes in *%Local*. However, after the changes in *%Local,* all but one measure differ significantly. In all 14, the difference-in-differences is statistically significant at the 5 percent level or better. Overall, we find that changes in *%Local* are associated with significant changes in the market response around earnings announcements. The economic magnitudes of these changes are also large. Comparing the difference-in-differences to the average values in Yr_{t-1}, the changes range from 55 percent (drop in the announcement window ERC in Panels A and B) to over 280 percent (increase in pre-announcement abnormal spreads in Panels C and D) of pre-change values.

Thus, we find an economically and statistically significant decrease in the market responses at the time of the earnings announcements, an increase in pre-announcement informed trading, and an increase in PEAD for firms with the largest increases in local bias when compared to firms with the largest drops. We find no significant differences between the two groups before the changes, and many significant differences after. Thus, reverse causality and persistent firm characteristics are both unlikely to drive our results. These results also suggest that a firm that hopes to create a stronger market response to its earnings announcements might do so by increasing non-local investor interest, and thereby reducing local bias, rather than simply increasing total investor interest.

[16] The lists are collected from local business journals, Chamber of Commerce, or newspapers for 44 states plus the District of Columbia. We were unable to obtain lists from Alabama, Rhode Island, South Dakota, South Carolina, and Tennessee. In addition, we use lists from 2006 onward, as list data before 2006 are sparse.

TABLE 8

Two-Stage Least Squares (2SLS) Analysis
With Best Employer Lists in Headquarter State as the Instrumental Variable

Panel A: First-Stage Regression

	%Local
Best Employer$_{home\_state}$	0.253***
	(0.004)
Ln(SVI)	−0.044***
	(0.008)
Urban	−0.013*
	(0.007)
Ln(Size)	−0.013***
	(0.003)
Adv Exp	−0.010
	(0.012)
Ln(EMP)	−0.090***
	(0.033)
Ln(SHR)	−0.158***
	(0.045)
Ln(AF)	−0.185***
	(0.050)
IO	−0.015*
	(0.008)
SP500	−0.050***
	(0.019)
BM	−0.060**
	(0.026)
Retail	−0.009
	(0.013)
Year Fixed Effect	Yes
State Fixed Effect	Yes
Industry Fixed Effect	No
n	5,163
Adjusted R^2	20.48%
First-Stage Partial F-statistic	14.53
	($p < 0.001$)

Panel B: Second-Stage Regressions, Random Walk-Based Earnings Surprise

	***AbSpreads* [0,1]**	***AbVol* [0,1]**	***CAR* [0,1]**	***AbSpreads* [−5,−1]**	***AbVol* [−5,−1]**	***CAR* [−5,−1]**	***CAR* [2,61]**
R_AbsSUE	0.007	0.151***		−0.002	0.102***		
	(0.007)	(0.017)		(0.006)	(0.043)		
R_SUE			0.046***			0.045***	0.098***
			(0.012)			(0.018)	(0.023)
R_Pred(%Local)	0.056***	−0.058***	−0.008	0.004***	0.028***	0.009	0.012
	(0.013)	(0.016)	(0.006)	(0.001)	(0.008)	(0.006)	(0.016)
R_SUE ∗ R_Pred(%Local)			−0.019***			0.009***	0.009***
			(0.005)			(0.002)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R_SUE ∗ Controls	NA	NA	Yes	NA	NA	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(continued on next page)

TABLE 8 (continued)

	AbSpreads [0,1]	*AbVol* [0,1]	*CAR* [0,1]	*AbSpreads* [−5,−1]	*AbVol* [−5,−1]	*CAR* [−5,−1]	*CAR* [2,61]
R_SUE ∗ *State Fixed Effect*	No	No	Yes	No	No	Yes	Yes
n	18,965	18,965	18,965	18,965	18,965	18,965	18,965
Adjusted R^2	2.96%	12.11%	2.87%	2.05%	4.34%	1.27%	1.83%

Panel C: Second-Stage Regressions, Analyst Forecast-Based Earnings Surprise

	AbSpreads [0,1]	*AbVol* [0,1]	*CAR* [0,1]	*AbSpreads* [−5,−1]	*AbVol* [−5,−1]	*CAR* [−5,−1]	*CAR* [2,61]
R_AbsSUE	0.008	0.204***		−0.003	0.114***		
	(0.007)	(0.019)		(0.004)	(0.040)		
R_SUE			0.053***			0.055***	0.095***
			(0.015)			(0.018)	(0.024)
R_Pred(%Local)	0.070***	−0.057***	−0.013	0.005***	0.035***	0.008	0.012
	(0.018)	(0.014)	(0.006)	(0.001)	(0.007)	(0.006)	(0.019)
R_SUE ∗ *R_Pred(%Local)*			−0.012***			0.009***	0.009***
			(0.004)			(0.002)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R_SUE ∗ *Controls*	NA	NA	Yes	NA	NA	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R_SUE ∗ *State Fixed Effect*	No	No	Yes	No	No	Yes	Yes
n	17,104	17,104	17,104	17,104	17,104	17,104	17,104
Adjusted R^2	2.96%	12.94%	12.74%	2.83%	4.60%	1.74%	1.87%

***, **, * Denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests when there is a directional prediction, and two-tailed tests otherwise.
This table presents the results of the 2SLS analysis using the subsample of state-years for which we have a best employer list. Panel A presents the first-stage regression result for *%Local* based on Equation (2), supplemented with the instrumental variable *Best Employer*$_{home\_state}$. Second-stage results are presented in Panels B and C, estimated based on Equations (3), (4), and (5), where *R_%Local*$_{t-1}$ is replaced with the predicted values *R_Pred(%Local*$_{t-1}$) based on the first-stage regression result. The dependent variables in Panels B and C are as listed in the column headings and as defined in Appendix A. The left-most columns display results using the decile rank of (absolute) earnings surprise values based on random walk expectations, while the right-most columns present results for (absolute) earnings surprise values calculated using analyst-based expectations. For brevity, the intercept, the coefficients of control variables, and the interactions of control variables and *R_SUE* are not reported. Numbers in parentheses are standard errors, calculated using one-dimensional clustering by firm in Panel A and two-dimensional clustering by calendar quarter and firm in Panels B and C.
Variable definitions are listed in Appendix A.

Sensitivity Analyses

Our primary local bias measure has several advantages, such as cancelling out the Google Trends scaling factor and measuring "local" similarly to prior literature. However, we examine the robustness of our results to alternate definitions. We use *%Local* rather than rank; the firm's top search state as the "center" for the distance calculation; contemporaneous *R_%Local* rather than lagged; 50 miles and 500 miles to define an investor as local rather than 250; a distance-based measure based upon a calculation of the average distance of investor searches from headquarters. Results are generally robust, with only six cases of insignificant results out of the 84 relevant tests (five for top search state as "center," suggesting that headquarters is appropriate).

We conduct two analyses for which we expect weaker results if the underlying driver of our primary results is local bias. First, we examine a variable capturing the breadth of investor search rather than local bias specifically, *R_Sum_of_State_SVI*.[17] Our predictions are based upon local bias, so we expect the key factor to be whether investors are local or not. Breadth and local bias are likely to be related, and the correlation between the two variables is −29.33 percent. In all cases except

[17] *R_Sum_of_State_SVI* is defined as the sum of the state-specific SVI values for the given firm and taking the rank. A firm with higher *R_Sum_of_State_SVI* has more evenly distributed search across the country.

TABLE 9

Changes in Geographic Dispersion and Market Responses around Earnings Announcements

Panel A: Announcement Window, Random Walk-Based Earnings Surprise

	***AbSpreads*[0,1]**			***AbVol*[0,1]**			***CAR*[0,1]**		
	Intercept: Equation (3)			**Intercept: Equation (4)**			**ERC: Equation (5)**		
	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$
H	0.031	0.119	0.088***	0.738	0.247	−0.491***	0.073	0.031	−0.042***
	(0.029)	(0.024)	(0.027)	(0.117)	(0.153)	(0.135)	(0.014)	(0.014)	(0.015)
L	0.044	0.072	0.028	0.953	0.973	−0.020	0.074	0.073	−0.001
	(0.020)	(0.022)	(0.021)	(0.114)	(0.116)	(0.115)	(0.016)	(0.013)	(0.014)
H − L	−0.013	0.047**	**0.060****	−0.216	−0.726***	**−0.471*****	−0.001	−0.042***	**−0.042*****
	(0.025)	(0.023)	**(0.026)**	(0.117)	(0.126)	**(0.120)**	(0.015)	(0.014)	**(0.016)**

Panel B: Announcement Window, Analyst Forecast-Based Earnings Surprise

	***AbSpreads*[0,1]**			***AbVol*[0,1]**			***CAR*[0,1]**		
	Intercept: Equation (3)			**Intercept: Equation (4)**			**ERC: Equation (5)**		
	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$
H	0.038	0.127	0.089***	0.831	0.298	−0.534***	0.062	0.018	−0.044***
	(0.028)	(0.022)	(0.025)	(0.112)	(0.155)	(0.134)	(0.015)	(0.015)	(0.015)
L	0.054	0.073	0.019	1.014	0.806	−0.208*	0.064	0.058	−0.006
	(0.028)	(0.031)	(0.030)	(0.119)	(0.115)	(0.117)	(0.015)	(0.016)	(0.016)
H − L	−0.016	0.054**	**0.070*****	−0.183	−0.508***	**−0.742*****	−0.003	−0.040***	**−0.038****
	(0.026)	(0.027)	**(0.027)**	(0.113)	(0.137)	**(0.126)**	(0.015)	(0.016)	**(0.017)**

Panel C: Pre-/Post-Announcement, Random Walk-Based Earnings Surprise

	***AbSpreads*[−5,−1]**			***AbVol*[−5,−1]**			***CAR*[−5,−1]**			***CAR*[2,61]**		
	Intercept: Equation (3)			**Intercept: Equation (4)**			**ERC: Equation (5)**			**ERC: Equation (5)**		
	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$
H	0.015	0.049	0.033***	0.050	0.144	0.095**	0.049	0.084	0.035***	0.059	0.134	0.075***
	(0.013)	(0.012)	(0.013)	(0.036)	(0.039)	(0.038)	(0.012)	(0.013)	(0.014)	(0.023)	(0.021)	(0.021)
L	0.014	0.010	−0.005	0.067	0.084	0.017	0.042	0.047	0.005	0.064	0.073	0.009
	(0.018)	(0.011)	(0.014)	(0.035)	(0.035)	(0.035)	(0.014)	(0.014)	(0.015)	(0.026)	(0.029)	(0.027)
H − L	0.001	0.039***	**0.038*****	−0.017	0.060	**0.077****	0.007	0.037***	**0.030****	−0.005	0.061**	**0.066****
	(0.017)	(0.011)	**(0.013)**	(0.036)	(0.037)	**(0.037)**	(0.013)	(0.014)	**(0.014)**	(0.025)	(0.024)	**(0.029)**

Panel D: Pre-/Post-Announcement, Analyst Forecast-Based Earnings Surprise

	***AbSpreads*[−5,−1]**			***AbVol*[−5,−1]**			***CAR*[−5,−1]**			***CAR*[2,61]**		
	Intercept: Equation (3)			**Intercept: Equation (4)**			**ERC: Equation (5)**			**ERC: Equation (5)**		
	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$	Yr_{t-1}	Yr_{t+1}	$Yr_{t+1-t-1}$
H	0.013	0.057	0.044***	0.084	0.194	0.110***	0.032	0.063	0.032***	0.061	0.133	0.072**
	(0.014)	(0.018)	(0.017)	(0.035)	(0.039)	(0.037)	(0.013)	(0.013)	(0.013)	(0.028)	(0.028)	(0.028)
L	0.014	0.020	0.006	0.085	0.107	0.021	0.038	0.035	−0.003	0.061	0.048	−0.013
	(0.016)	(0.019)	(0.018)	(0.038)	(0.037)	(0.038)	(0.013)	(0.012)	(0.013)	(0.027)	(0.031)	(0.029)
H − L	−0.002	0.037*	**0.038****	−0.001	0.088**	**0.089****	−0.007	0.028**	**0.035*****	0.000	0.085***	**0.085*****
	(0.016)	(0.019)	**(0.017)**	(0.036)	(0.039)	**(0.038)**	(0.013)	(0.013)	**(0.013)**	(0.028)	(0.029)	(0.029)

(continued on next page)

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TABLE 9 (continued)

***, ** * Denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, using two-tailed tests for the difference and difference-in-differences coefficients.
This table presents the results of difference-in-differences analyses of (1) the changes in intercepts from estimating Equations (3) and (4) excluding the *R_%Local* term, for *AbSpreads*[0,1], *AbVol*[0,1], *AbSpreads*[−5,−1], and *AbVol*[−5,−1], respectively, between High change of *%Local* and Low change of *%Local* before and after the change year; and (2) the change in estimated coefficients on earnings surprise (*R_SUE*) from estimating Equation (5) excluding the *R_%Local* and *R_SUE* ∗ *R_%Local* terms, for *CAR*[0,1], *CAR*[−5,−1], and *CAR*[2,61], between High change of *%Local* and Low change of *%Local* before and after the change year. High (Low) change of *%Local* is defined as the top (bottom) tercile of change of *%Local* from year *t*−1 to year *t*. The difference-in-differences coefficients and standard errors are shown in bold. The sample consists of quarterly earnings announcements of firms listed on the major exchanges from 2005 through 2011. Numbers in parentheses are standard errors, calculated using two-dimensional clustering by calendar quarter and firm.
Variable definitions are listed in Appendix A.

AbSpreads[−5,−1] and *AbVol*[−5,−1], we find similar results, but of smaller magnitude, if we substitute *R_Sum_of_State_SVI* for *R_%Local* in our regressions. However, in all but one test, the relevant coefficient becomes insignificant or changes sign if we include both variables together. These results suggest that the key factor driving our results is not breadth, but rather local bias, as we predict.

Second, we partition the sample based on S&P 500 Index membership. Consistent with prior literature (Ivkovic and Weisbenner 2005; Ivkovic et al. 2008), we expect results to be weaker for S&P 500 firms, which have a high level of national visibility, if the underlying driver of our results is local bias. For non-S&P 500 firms, our expected results are significant at the 1 percent level or better in 13 out of 14 analyses, and at the 5 percent level in the last. In contrast, results are significant in the expected directions for only six out of 14 analyses at the 10 percent level or better for S&P 500 firms, with much smaller estimated effects. This supports the conclusion that local bias impacts the market response around earnings announcements, given that the possible local bias effects are much weaker for S&P 500 firms.

Regarding other variables, we use an alternate method to compute abnormal spreads using daily high and low prices, as in Corwin and Schultz (2012), and verify that results are robust to smaller changes in variable definitions (e.g., using the average of the highest and lowest trading price during the day to calculate $\$vol_t$ or using a 60-trading-day window to calculate abnormal variables). Results are robust. We also replicate the analyses for the 2005–2008 subsample with an additional control variable for the number of major newspapers covering the firm during the earnings announcement window (the data are described in detail in Soltes [2010]). The effects of *%Local* are all in the expected directions and statistically significant at the 5 percent level.

While 2SLS is one approach to address possible correlated omitted variable biases ("hidden bias"), PSM provides an alternate method. The potential problem is that omitted variables correlated with *%Local* differ across the treatment and control samples. Failing to include those variables would alter the assignment of firms to the two samples and, thus, bias results. To assess the sensitivity of the results to "hidden bias," we follow a bounding approach (Rosenbaum 2002, 2007; Armstrong, Blouin, and Larcker 2012) in which we assume that the "hidden bias" causes the odds ratio of treatment assignment to differ from 50 percent/50 percent. There is no specific suggested bounding limit (Rosenbaum 2002, 2007); however, we find that even if we assume that correlated omitted variables shift the assignment of firms to a 65 percent/35 percent probability, our results remain significant in the expected directions (p-values at 5 percent or better), suggesting that correlated omitted variables are unlikely to drive our results.

Finally, we exclude each of the following sets of firms in separate tests: firms located in Washington, as Microsoft's Bing search engine is likely to be more popular in Washington State; financial and technology firms, since financial (technology) firms tend to be geographically concentrated around New York City (in California); and firms headquartered in California, Texas, and New York, as one-third of our sample firms are located in these three large states. We also separately examine firms in the western and eastern portions of the U.S., due to differing state sizes, and firms in states with or without larger financial services industries, given potentially different investor sophistication in these areas. Our inferences remain unchanged. Coefficients are consistently significant in the expected directions, and are of fairly similar magnitude.

V. CONCLUSION

We document that local bias affects investors' internet search behavior. We find that investors search more heavily for companies headquartered near them than for distant companies. This local bias in investor search is of similar magnitude to local bias of ownership during the early 1990s. We predict and find that this local bias in search impacts the market response around earnings announcements. Firms with higher local bias in search experience higher abnormal bid-ask spreads, lower trading volumes, and lower earnings response coefficients (ERCs) around earnings announcements, consistent with non-local investors reacting more strongly to public information announcements such as an earnings announcement. Moreover, consistent with local information advantage driving a portion of observed local bias, we find that firms with higher local bias have higher abnormal bid-ask spreads and trading volumes before the earnings announcement, and higher pre-announcement ERCs, consistent with more privately informed trading prior to the earnings announcement. Finally, consistent with familiarity bias also driving a significant portion of total local bias, we find that post-earnings announcement drift is higher for firms with higher local bias in search.

These results hold cross-sectionally, comparing matched firms, and using an instrumental variables approach. Finally, examining changes, we find that firms with the largest increases in local bias, relative to firms with the largest decreases, experience a significant drop in the market response to their earnings announcements, an increase in pre-announcement privately informed trading, and an increase in drift.

While prior literature has established that location affects investors, our paper examines the effect of local bias on the market response to earnings information—before, during, and after the earnings announcement. This has not been previously examined, and our results show that local bias has a statistically and economically significant impact on market response. Moreover, research on local bias uses primarily pre-internet data, while our paper documents significant local bias, which has economically meaningful effects, during the internet era.

Practitioners with an interest in improving firm visibility and the market response to firm information, such as executives and investor relations professionals, will benefit from realizing the importance of non-local investors. The results of our analysis suggest that while increasing the number of interested investors is important, increasing non-local investor interest in the firm also matters. Researchers interested in the dissemination of information, and investor responses, will also want to consider the role of geography in coverage and investor reactions. Finally, our results reinforce the message of Kedia and Rajgopal (2011) and DeFond, Francis, and Hu (2011) that monitors, such as auditors or the SEC, may want to consider the role of geography in their own monitoring activities. Geography can be of significant importance even in the internet age, due to the role it plays in where individuals direct their attention, the private information they have access to (i.e., local information advantage), and the biases they are subject to (i.e., familiarity bias).

REFERENCES

Armstrong, C., J. Blouin, and D. Larcker. 2012. The incentives for tax planning. *Journal of Accounting and Economics* 53 (1/2): 391–411. doi:10.1016/j.jacceco.2011.04.001

Ayers, B. C., O. Z. Li, and P. E. Yeung. 2011. Investor trading and the post-earnings-announcement drift. *The Accounting Review* 86 (2): 385–416. doi:10.2308/accr.00000027

Bamber, L. S., and Y. S. Cheon. 1995. Differential price and volume reactions to accounting earnings announcements. *The Accounting Review* 70 (3): 417–441.

Bamber, L. S., O. Barron, and T. Stober. 1997. Trading volume and different aspects of disagreement coincident with earnings announcements. *The Accounting Review* 72 (4): 575–597.

Barber, B., and T. Odean. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance* 55 (2): 773–806. doi:10.1111/0022-1082.00226

Bernard, V., and J. Thomas. 1989. Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research* 27 (3): 1–36. doi:10.2307/2491062

Bernard, V., and J. Thomas. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13 (4): 305–340. doi:10.1016/0165-4101(90)90008-R

Bhattacharya, N. 2001. Investors' trade size and trading responses around earnings announcements: An empirical investigation. *The Accounting Review* 76 (2): 221–244. doi:10.2308/accr.2001.76.2.221

Blankespoor, E., B. P. Miller, and H. D. White. 2014. Initial evidence on the market impact of the XBRL mandate. *Review of Accounting Studies* 19 (4): 1468–1503. doi:10.1007/s11142-013-9273-4

Brandt, M. W., R. Kishore, P. Santa-Clara, and M. Venkatachalam. 2007. *Earnings Announcements are Full of Surprises*. Working paper, Duke University and University of California, Los Angeles.

Brochet, F., G. Miller, and S. Srinivasan. 2014. Do analysts follow managers who switch companies? An analysis of relationships in the capital markets. *The Accounting Review* 89 (2): 451–482. doi:10.2308/accr-50636

Brown, N. C., H. Stice, and R. M. White. 2015. Mobile communication and local information flow: Evidence from distracted driving laws. *Journal of Accounting Research* 53 (2): 275–329. doi:10.1111/1475-679X.12077

Bushee, B., and G. S. Miller. 2012. Investor relations, firm visibility, and investor following. *The Accounting Review* 87 (3): 867–897. doi:10.2308/accr-10211

Bushee, B., J. Core, W. Guay, and S. Hamm. 2010. The role of the business press as an information intermediary. *Journal of Accounting Research* 48 (1): 1–19. doi:10.1111/j.1475-679X.2009.00357.x

Christophe, S. E., M. G. Ferri, and J. J. Angel. 2004. Short-selling prior to earnings announcements. *Journal of Finance* 59 (4): 1845–1876. doi:10.1111/j.1540-6261.2004.00681.x

Collins, D., and S. Kothari. 1989. An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. *Journal of Accounting and Economics* 11 (2/3): 143–181. doi:10.1016/0165-4101(89)90004-9

Copeland, T. E., and D. Galai. 1983. Information effects on the bid-ask spread. *Journal of Finance* 38 (5): 1457–1469. doi:10.1111/j.1540-6261.1983.tb03834.x

Corwin, S. A., and P. Schultz. 2012. A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance* 67 (2): 719–760. doi:10.1111/j.1540-6261.2012.01729.x

Coval, J. D., and T. J. Moskowitz. 1999. Home bias at home: Local equity preference in domestic portfolios. *Journal of Finance* 54 (6): 2045–2073. doi:10.1111/0022-1082.00181

Coval, J. D., and T. J. Moskowitz. 2001. The geography of investment: Informed trading and asset prices. *Journal of Political Economy* 109 (4): 811–841. doi:10.1086/322088

Crawford, S. S., D. T. Roulstone, and E. C. So. 2012. Analyst initiations of coverage and stock return synchronicity. *The Accounting Review* 87 (5): 1527–1553. doi:10.2308/accr-50186

Da, Z., J. Engelberg, and P. Gao. 2011. In search of attention. *Journal of Finance* 66 (5): 1461–1499. doi:10.1111/j.1540-6261.2011.01679.x

DeFond, M. L., J. R. Francis, and X. Hu. 2011. *The Geography of SEC Enforcement and Auditor Reporting for Financially Distressed Clients*. Working paper, University of Southern California, University of Missouri, and University of Oregon.

Derigs, U. 1988. Solving non-bipartite matching problems via shortest path techniques. *Annals of Operations Research* 13 (1): 225–261. doi:10.1007/BF02288324

Drake, M. S., D. T. Roulstone, and J. R. Thornock. 2012. Investor information demand: Evidence from Google searches around earnings announcements. *Journal of Accounting Research* 50 (4): 1001–1040. doi:10.1111/j.1475-679X.2012.00443.x

Drake, M. S., N. M. Guest, and B. J. Twedt. 2014. The media and mispricing: The role of the business press in the pricing of accounting information. *The Accounting Review* 89 (5): 1673–1701. doi:10.2308/accr-50757

Easley, D., and M. O'Hara. 1992. Time and the process of security price adjustment. *Journal of Finance* 47 (2): 577–605. doi:10.1111/j.1540-6261.1992.tb04402.x

Engelberg, J. E., and C. A. Parsons. 2011. The causal impact of media in financial markets. *Journal of Finance* 66 (1): 67–97. doi:10.1111/j.1540-6261.2010.01626.x

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33 (1): 3–56. doi:10.1016/0304-405X(93)90023-5

Fama, E. F., and K. R. French. 1997. Industry costs of equity. *Journal of Financial Economics* 43 (2): 153–193. doi:10.1016/S0304-405X(96)00896-3

Francis, J., and L. Soffer. 1997. The relative informativeness of analysts' stock recommendations and earnings forecast revisions. *Journal of Accounting Research* 35 (2): 193–211. doi:10.2307/2491360

Glosten, L. R., and P. R. Milgrom. 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics* 14 (1): 71–100. doi:10.1016/0304-405X(85)90044-3

Gow, I., G. Ormazabal, and D. Taylor. 2010. Correcting for cross-sectional and time-series dependence in accounting research. *The Accounting Review* 85 (2): 483–512. doi:10.2308/accr.2010.85.2.483

Grullon, G., G. Kanatas, and J. P. Weston. 2004. Advertising, breadth of ownership, and liquidity. *Review of Financial Studies* 17 (2): 439–461. doi:10.1093/rfs/hhg039

Hirano, K., and G. W. Imbens. 2004. The propensity score with continuous treatments. In *Applied Bayesian Modeling and Causal Inference from Incomplete Data Perspectives,* edited by Gelman, A. and X. L. Meng, 73–84. West Sussex, England: John Wiley.

Hirshleifer, D., J. N. Myers, L. A. Myers, and S. H. Teoh. 2008. Do individual investors drive post-earnings-announcement drift? Direct evidence from personal trades. *The Accounting Review* 83 (6): 1521–1550. doi:10.2308/accr.2008.83.6.1521

Hirshleifer, D., S. S. Lim, and S. H. Teoh. 2009. Driven to distraction: Extraneous events and underreaction to earnings news. *Journal of Finance* 64 (5): 2289–2325. doi:10.1111/j.1540-6261.2009.01501.x

Ho, D., K. Imai, G. King, and E. Stuart. 2007. Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis* 15 (3): 199–236. doi:10.1093/pan/mpl013

Holthausen, R. W., and R. E. Verrecchia. 1990. The effect of informedness and consensus on price and volume behavior. *The Accounting Review* 65 (1): 191–208.

Hong, H., J. D. Kubik, and J. C. Stein. 2008. The only game in town: Stock-price consequences of local bias. *Journal of Financial Economics* 90 (1): 20–37. doi:10.1016/j.jfineco.2007.11.006

Huberman, G. 2001. Familiarity breeds investment. *Review of Financial Studies* 14 (3): 659–680. doi:10.1093/rfs/14.3.659

Ivkovic, Z., and S. Weisbenner. 2005. Local does as local is: Information content of the geography of individual investors' common stock investments. *Journal of Finance* 60 (1): 267–306. doi:10.1111/j.1540-6261.2005.00730.x

Ivkovic, Z., C. Sialm, and S. Weisbenner. 2008. Portfolio concentration and the performance of individual investors. *Journal of Financial and Quantitative Analysis* 43 (3): 613–656. doi:10.1017/S0022109000004233

Ke, B., and K. Petroni. 2004. How informed are actively trading institutional investors? Evidence from their trading before a break in a string of consecutive earnings increases. *Journal of Accounting Research* 42 (5): 895–927. doi:10.1111/j.1475-679X.2004.00160.x

Kedia, S., and S. Rajgopal. 2011. Do the SEC's enforcement preferences affect corporate misconduct? *Journal of Accounting and Economics* 51 (3): 259–278. doi:10.1016/j.jacceco.2011.01.004

Kim, O., and R. E. Verrecchia. 1991. Trading volume and price reactions to public announcements. *Journal of Accounting Research* 29 (2): 302–321. doi:10.2307/2491051

Kim, O., and R. E. Verrecchia. 1997. Pre-announcement and event-period private information. *Journal of Accounting and Economics* 24 (3): 395–419. doi:10.1016/S0165-4101(98)00013-5

Krinsky, I., and J. Lee. 1996. Earnings announcements and the components of the bid-ask spread. *Journal of Finance* 51 (4): 1523–1535. doi:10.1111/j.1540-6261.1996.tb04078.x

Lakonishok, J., A. Shleifer, and R. W. Vishny. 1994. Contrarian investment, extrapolation, and risk. *Journal of Finance* 49 (5): 1541–1578. doi:10.1111/j.1540-6261.1994.tb04772.x

Landsman, W. R., and E. L. Maydew. 2002. Has the information content of quarterly earnings announcements declined in the past three decades? *Journal of Accounting Research* 40 (3): 797–808. doi:10.1111/1475-679X.00071

Larcker, D. F., and T. O. Rusticus. 2010. On the use of instrumental variables in accounting research. *Journal of Accounting and Economics* 49 (3): 186–205. doi:10.1016/j.jacceco.2009.11.004

Lee, C. M. 1992. Earnings news and small traders: An intraday analysis. *Journal of Accounting and Economics* 15 (2/3): 265–302. doi:10.1016/0165-4101(92)90021-S

Livnat, J., and R. R. Mendenhall. 2006. Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research* 44 (1): 177–205. doi:10.1111/j.1475-679X.2006.00196.x

Lou, D. 2014. Attracting investor attention through advertising. *Review of Financial Studies* 27 (6): 1797–1829. doi:10.1093/rfs/hhu019

Loughran, T., and P. Schultz. 2005. Liquidity: Urban versus rural firms. *Journal of Financial Economics* 78 (2): 341–374. doi:10.1016/j.jfineco.2004.10.008

Lu, B., R. Greevy, X. Xu, and C. Beck. 2011. Optimal nonbipartite matching and its statistical applications. *American Statistician* 65 (1): 21–30. doi:10.1198/tast.2011.08294

Malloy, C. 2005. The geography of equity analysis. *Journal of Finance* 60 (2): 719–755. doi:10.1111/j.1540-6261.2005.00744.x

Miller, G., and D. M. Shanthikumar. 2012. *The Press and Local Information Advantage*. Working paper, University of Michigan and University of California, Irvine.

Petersen, M. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22 (1): 435–480. doi:10.1093/rfs/hhn053

Rosenbaum, P. R. 2002. *Observational Studies*. Second edition. Berlin, Germany: Springer Series in Statistics. doi:10.1007/978-1-4757-3692-2

Rosenbaum, P. R. 2007. Sensitivity analysis for m-estimates, tests, and confidence intervals in matched observational studies. *Biometrics* 63 (2): 456–464. doi:10.1111/j.1541-0420.2006.00717.x

Seasholes, M. S., and N. Zhu. 2010. Individual investors and local bias. *Journal of Finance* 65 (5): 1987–2010. doi:10.1111/j.1540-6261.2010.01600.x

Shanthikumar, D. 2012. Consecutive earnings surprises: Small and large trader reactions. *The Accounting Review* 87 (5): 1709–1736. doi:10.2308/accr-50188

Shores, D. 1990. The association between interim information and security returns surrounding earnings announcements. *Journal of Accounting Research* 28 (1): 164–181. doi:10.2307/2491221

Soltes, E. 2010. *News Dissemination and the Impact of the Business Press*. Working paper, Harvard University.

Stock, J. H., J. H. Wright, and M. Yogo. 2002. A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business and Economic Statistics* 20 (4): 518–529. doi:10.1198/073500102288618658

Teoh, S., and T. Wong. 1993. Perceived auditor quality and the earnings response coefficient. *The Accounting Review* 68 (2): 346–366.

APPENDIX A

Variable Definitions

Variable	Definition
%Local	The percentage of total state search volume that originates from states with population centers within 250 miles of the firm's headquarters. Excludes Alaska and Hawaii. (Google Trends; 2010 Census; Compustat)
# of News	The number of articles in the *Wall Street Journal, New York Times, USA Today,* and *Washington Post* that mention the firm during the earnings announcement window when examining announcement window responses, and during the pre-announcement window when examining pre-announcement window responses. 2005 through 2008. (Soltes 2010)
Ln(*# of Revision*)	Natural logarithm of (1 + the number of analyst earnings forecast revisions between the fiscal quarter-end date and the earnings announcement date). (Compustat, I/B/E/S)
AbSpreads[0,1] *AbSpreads*[−5,−1]	The difference between average bid-ask spreads over the earnings announcement window [0,1] (five trading days prior to the announcement date [−5,−1]) and the average bid-ask spreads over trading days [−41, −11]. Day 0 is the earnings announcement date. Bid-ask spread is the difference between an offer price and a bid price divided by the midpoint of the offer and bid price (and multiplied by 100). (CRSP)
AbVol[0,1] *AbVol* [−5,−1]	The difference between average log dollar volume over the earnings announcement window [0,1] (five trading days prior to the announcement date [−5,−1]) and the average log dollar volume over trading days [−41, −11]. Day 0 is the earnings announcement date. Daily dollar trading volume is the product of the daily closing price and the daily number of shares traded. (CRSP)
Adv Exp	Advertising expense (annual) scaled by sales. (Compustat)
BM	Book value of common equity divided by market value of equity (Size). Annual basis for Tables 3–4. Quarterly basis for Table 5 onward. (Compustat)
CAR[0,1] *CAR*[−5,−1] *CAR*[2,61]	Size- and book-to-market-adjusted cumulative abnormal returns over the earnings announcement window [0,1], five trading days prior to the announcement date [−5,−1] or the post-announcement drift period [2,61]. Day 0 is the earnings announcement date. (CRSP)
AbsCAR[0,1]	The absolute value of *CAR*[0,1].
AbsCAR[−5,−1]	The absolute value of *CAR*[−5,−1].
EP	Quarterly Earnings persistence (B_1) over the past four years. B_1 is estimated using the following regression: $Earnings_q = B_0 + B_1 * Earnings_{q-1} + e$. (Compustat)
EV	Standard deviation of quarterly earnings over the past four years. (Compustat)
IO	Percent of shares owned by institutions. Annual data for Tables 3–4. Quarterly data for Table 5 onward. (Thomson Reuters 13F)
Ln(*AF*)	Natural log of 1 plus the median number of analysts following the firm. Annual data for Tables 3–4. Quarterly data for Table 5 onward. (I/B/E/S)
Ln(*EMP*)	Natural log of 1 plus the number of employees. (Compustat)
Ln(*SHR*)	Natural log of 1 plus the number of shareholders of record. (Compustat)
MF	1 if managers issue a forecast between the fiscal quarter-end date and the earnings announcement date, and 0 otherwise. (First Call)
MKVol[0,1] *MKVol*[−5,−1]	Market-wide average daily trading volume during earnings announcement window [0,1], or five trading days prior to the announcement date [−5,−1]. (CRSP)
R_EA	Normalized quarterly decile rank of the number of earnings announcement of other firms on the same day as the given firm's earnings announcement. (Compustat; I/B/E/S)
Retail	1 if a firm is in the food products, candy and soda, retail, consumer goods, apparel, or entertainment industries, and 0 otherwise. (Compustat; Fama and French 1997)
RECPRC	Reciprocal of stock price on the fiscal quarter-end date. (Compustat)
RV	The standard deviation of daily raw return in the prior quarter. (CRSP)
Size	Stock price times number of shares outstanding. Annual data for Tables 3–4. Quarterly data for Table 5 onward. (Compustat)
Ln(*Size*)	Natural log of size.
SP500	1 if the firm is in the S&P 500 Index, and 0 otherwise. (Compustat)
SUE	The difference between actual EPS and benchmark EPS, scaled by stock price at the fiscal quarter-end date. For *RW_SUE,* the actual EPS is actual EPS before extraordinary items from Compustat and benchmark EPS is last year's same quarter EPS. For *AF_SUE,* the actual EPS is the actual EPS from I/B/E/S and benchmark EPS is the median analyst forecast EPS. (Compustat; CRSP; I/B/E/S)
Abs_SUE	The absolute values of *SUE*.
Ln(*SVI*)	The natural log of (1 + weekly SVI). (Google Trends)

(continued on next page)

APPENDIX A (continued)

Variable	Definition
chSVI	The natural log of $\{1 + (\text{weekly SVI} - \text{median SVI over the previous ten weeks})\}$.
Turnover	Quarterly average of monthly trading volume scaled by the total number of shares outstanding. (CRSP)
Urban	1 if a firm's headquarters is located in one of the ten largest metropolitan areas, and 0 otherwise. (2010 Census; Compustat)