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Abstract

Local companies attract significantly more attention from investors than nonlocal companies, especially at times of news releases and high volatility. Attention is causally related to perceived proximity: after a firm is acquired by a nonlocal one, local investors re-allocate attention away from it more than nonlocal investors; conversely, COVID-19 travel restrictions led investors to reallocate attention towards local companies and away from nonlocal ones, especially those harder to reach. Finally, local attention predicts volatility, bid-ask spreads, and nonlocal attention, but not vice-versa. Our findings suggest that the geography of attention is shaped by local investors' information-processing advantage, not familiarity bias.

JEL classification: D83, G11, G12, G14, G50, L86, R32.

Keywords: attention, local investors, distance, familiarity, news, liquidity, volatility.

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1 Introduction

As attention is a scarce resource (Kahneman, 1973), investors can be expected to direct it preferentially to news they are better at understanding (Van Nieuwerburgh and Veldkamp, 2009), and skew their trading activity and portfolios towards the corresponding assets (Barber and Odean, 2007; Van Nieuwerburgh and Veldkamp, 2010). We apply this idea to the geography of investor attention: local information processing advantage is shown to account not only for investor attention's skew towards local firms but also for its response to news volume, volatility, and investors' perceived distance from companies. In contrast, familiarity, as measured by company advertising on sales, is associated with a geographically widespread attention to firms, which reduces the attention gap between local and nonlocal ones.

Our findings are consistent with a model where investors optimally allocate their attention and are better at processing information about local stocks. In equilibrium, local investors pay more attention to news about local stocks than nonlocal investors to exploit their information-processing advantage. This attention gap grows when news precision and/or fundamental volatility rise. Moreover, the stronger the local-nonlocal attention gap, the more informative the order flow and the wider the bid-ask spread. When the model is extended to encompass a familiarity bias toward local assets, it predicts that this bias tends to reduce investors' attention toward local assets, consistent with our evidence.

Our empirical analysis builds on a measure of attention based on the Google web searches of U.S. stocks, in line with Da, Engelberg, and Gao (2011), Engelberg and Parsons (2011), and Andrei and Hasler (2014).[1] This approach provides a fine-grained measure of retail investor attention, as we can track web searches of a given stock depending on the state of the search, thus discriminating between local and nonlocal web searches. An advantage of a web-based measure of attention is that, differently from other media, the Google search engine enables virtually all investors to access news about local and nonlocal firms equally so that any systematic difference in search intensity will likely reflect intentional choices rather than differential search costs.

Equipped with this measure of investors' attention, we find that, on average, investors devote twice as much attention to news about companies headquartered in their state than elsewhere. News volume and volatility amplify this gap: local investors react about 10 times more than nonlocal ones to increases in the number of news items about local companies (whether positive or negative) and 13 times more to an increase in their

[1] A similar approach is also used by Ben-Rephael, Da, and Israelsen (2017), who, however, rely on Bloomberg as a tool to gather financial information, as they focus on the attention of institutional investors.

return volatility. Moreover, local attention reacts more strongly and faster than nonlocal attention to earnings announcements, even at intraday frequency.

This attention gap and its response to news and volatility are more consistent with local investors being better at processing news about local companies than it is with a familiarity bias. Indeed, we find that, if anything, familiarity tends to reduce the attention gap between local and nonlocal investors rather than contributing to explain it: the attention gap shrinks for stocks comparatively familiar to investors, i.e., those issued by companies spending more on advertising per dollar of sales. This is consistent with an extension of the model that allows investors' valuation to be driven to some extent by a familiarity bias rather than purely by rational calculus: insofar as familiarity leads investors to place more weight on their prior and less on knowledge extracted from news, the information processing advantage of local investors shrinks, thus reducing their superior incentive to pay attention to news.

Notably, the evidence is consistent with investors' attention being causally related to their perception of a firm's proximity, as events that trigger an increase in the perceived distance between investors and firms are associated with a drop in their level of attention. Focusing on such shocks to perceived proximity enables us to abstract from possible effects of home bias in local investors' portfolios on their attention, that is, any familiarity bias crystallized in their portfolios.

We focus on two such shocks. The first is the acquisition of a firm by a nonlocal company. The resulting drop in the firm's perceived proximity turns out to be associated with a switch of local attention away from the acquired firm and towards the acquiring firm, consistent with the perception of the former becoming less local and the latter more local. The reallocation of local attention is more substantial for small target firms, whose former localness is more easily diluted by an out-of-state acquisition. The reallocation of attention is weaker for high-advertising targets, in line with the idea that familiarity tends to reduce the relevance of geographic proximity for investors' attention.

The second shock we analyze is the increase in the perceived distance of nonlocal firms due to 2020 pandemic-related travel restrictions. We document that the COVID-19 outbreak was associated with an increase in the gap between local and nonlocal attention; moreover, the relative attention paid to nonlocal stocks dropped more for firms in locations that had fewer flights to and from the area after the pandemic. Also in this case, the reallocation of attention is much weaker for high-advertising firms, again in line with the prediction that familiarity reduces the relevance of geographic distance for investors' attention.

Finally, an increase in our local attention measure is associated with a subsequent increase in return volatility, in the bid-ask spread and nonlocal attention. However, it is not predicted by these variables. This pattern is consistent with the attention of local investors increasing their information advantage, thus inducing market makers to protect themselves with wider bid-ask spreads while at the same time accelerating price discovery and increasing volatility. Empirically, these findings dovetail with those reported by Shive (2012), who examines the effect of drops in local investors' trading activity due to large power outages, and finds that during local blackouts bid–ask spreads narrow and firm-specific price volatility drops. This is consistent with the view that local investors are informed traders whose orders tend to reduce market liquidity and increase volatility.

Our evidence suggests that the well-known local bias tendency to overweight the portfolio in stocks issued by nearby firms (Coval and Moskowitz, 1999; Grinblatt and Keloharju, 2001) stems from an information-processing advantage of local investors, as argued by Van Nieuwerburgh and Veldkamp (2009), rather than from behavioral biases, such as familiarity (Huberman, 2015), loyalty (Cohen, 2008) or patriotism (Morse and Shive, 2011). This is not a foregone conclusion, considering that according to Grinblatt and Keloharju (2001), the evidence on the local portfolio bias of Finnish households "seems to support the hypothesis that the degree of these effects is inversely related to investor sophistication." However, others provide evidence that proximity confers an information advantage. Malloy (2005) shows that local analysts' forecasts better predict stock returns and earn abnormal returns on their local assets, Ivković and Weisbenner (2005) find the average household generates an additional annualized return of 3.2% from its local holdings relative to its nonlocal holdings, suggesting that local investors can exploit local knowledge, and Massa and Simonov (2006) document that Swedish households' that tend to concentrate holdings in stocks geographically or professionally close to them earn higher returns than they would otherwise. Hence, these studies suggest that households' strong preference for local investments is driven by information rather than behavioral bias.

Characterizing local retail investors as possessing superior information processing skills may seem surprising, considering that Barber and Odean (2000, 2001, 2007, 2013) present retail investors as noise traders, subject to all kinds of behavioral biases. However, more recent research documents retail investors play a substantial role in price discovery. Kaniel, Saar, and Titman (2008) find that individual investor sentiment predicts future returns, and this information content is distinct from that of past returns or past volume. Kaniel, Liu, Saar, and Titman (2012) provide evidence of informed trading by individual investors around earnings announcements, showing that their aggregate trading behavior predicts large abnormal returns on and after announcements. Relatedly, Kelley and Tetlock (2013) show that orders by retail investors positively predict firms' monthly stock returns with no evidence of return reversal and contribute to market efficiency. Friedman and Zeng (2021) find that retail trader activity on the Robinhood platform is associated with prices being more responsive to earnings surprises. Finally, Boehmer, Jones, Zhang, and Zhang (2020) document that retail trades on OTC markets are well informed, and Boehmer and Song (2021) find that retail short sellers' trades predict negative stock returns, suggesting that they profitably exploit public information, especially when it is negative.[2]

Even more relevant to the present paper, recent work shows that attention by retail investors, particularly local ones, predicts subsequent risk-adjusted returns. Based on brokerage account data, Gargano and Rossi (2018) measure retail investors' attention based on the time they spend looking at data available via their brokerage account, finding that they devote more attention to local stocks, that their attention predicts the risk-adjusted returns of stocks, and is particularly profitable when trading stocks with high uncertainty when a lot of public information is available. Relatedly, Cziraki, Mondria, and Wu (2021), who also use Google-search data to measure attention, find that stocks featuring an abnormally large gap between local and nonlocal investor attention earn higher risk-adjusted returns. This also applies to institutional investors: Dyer (2021) constructs a measure of attention by these investors based on their requests for financial information from the SEC and finds that they acquire not only approximately 20% more financial information for local stocks than nonlocal ones but also that local investors are faster in acquiring public information and make better trading decisions when acquiring it. While the findings of these studies are consistent with ours, we focus on a different research question, namely, whether the gap between local and nonlocal investors' attention stems from a local information advantage or a familiarity bias and whether this attention gap is causally related to investors' perceived distance from companies.

The rest of the paper proceeds as follows. Section 2 presents the model and the predictions that guide our empirical analysis. Section 3 describes the data. Section 4 presents the empirical analysis of the geography of investor attention and its correlation with news intensity, stock return volatility, and firms' advertising expenditure. Section 5 presents the evidence that investor attention is causally related to perceived proximity to firm headquarters: specifically, Subsection 5.1 analyzes the response of local and nonlocal attention to changes in perceived firm proximity due to M&A activity, while Subsection 5.2 analyses responses to the increase in perceived distance of nonlocal firms due to COVID-19-related travel restrictions. Next, Section 6 analyzes the times series relationships among local and nonlocal attention, stock return volatility, and bid-ask spreads. Section 7 concludes.

[2] Along the same lines, Guiso and Jappelli (2020) find that household investments in information are associated with significantly higher returns to financial wealth, based on survey data for the customers of a leading Italian bank.

2 Model

We present a simple model of investor attention allocation, trading decisions, and asset price determination, whose predictions will guide the empirical analysis of subsequent sections. We start from a baseline setting in which local investors are better at processing information about local assets than about nonlocal ones and rationally take this into account in allocating their attention, forming expectations, and trading the two types of assets. We then extend the model to consider the possibility that local investors suffer to some extent from a familiarity bias that affects their attention allocation and trading decisions. The model predicts that while a superior ability to process information about local assets tends to skew local investors' attention towards news about these assets, familiarity bias has the opposite effect, as it enhances local investors' reliance on prior beliefs and reduces their attention to new information.

In the baseline model, where all investors are rational in forming their expectations, their behavior is analyzed by extending the Glosten and Milgrom (1985) model to a setting where traders can update their beliefs about asset values by paying attention to news at a cost and optimally allocate attention across assets.

The analysis is presented concerning a stock issued by a representative local firm. Still, it applies symmetrically to a stock issued by a nonlocal firm, which nonlocal investors are assumed to be better at analyzing. The price of the stock is set by risk-neutral and competitive dealers, who receive buy and sell orders for each stock from two types of investors: information-based investors, who trade with probability π, and noise traders, who buy or sell the stock with equal probability, and trade with frequency $1 - \pi$. All market participants place orders of a fixed size, for simplicity, standardized to 1. Suppose both local and nonlocal investors choose to devote attention to the news. In that case, the pool of informed traders is composed of an equal number of these two subgroups, respectively indexed by $i = L, N$, and each of them manages to place an order with the same probability $\pi/2$. If only members of a single group choose to pay attention, they manage to place their orders with probability π. Whether either type of investor chooses to devote attention to news and thus become informed is determined in equilibrium.

The fundamental value of the stock is $v \in \{v_b, v_g\} = \{\overline{v} - \sigma, \overline{v} + \sigma\}$, where $\overline{v}$ is its unconditional value and $\sigma = (v_g - v_b)/2$ measures its volatility. Before trading, investors observe a signal $s \in \{v_b, v_g\}$ that is correlated with the value of the stock. The informativeness of the signal depends on the quality q of the news release (e.g., the detail and timeliness) and on the level of attention $a_i \in [0, 1/q]$ that investor i chooses to devote to the signal before trading. The greater the news quality and attention, the higher the probability of correctly estimating the probability distribution of the asset's value:

$\Pr(s = v|v, a_i, q) = (1 + q \cdot a_i)/2$: by paying more attention, investors read the signal more accurately. An investor i who chooses $a_i = 0$ would learn nothing from the signal: $\Pr(s = v|v, a_i, q) = 1/2$, while the investor at the maximal attention level $a_i = 1/q$ would find the signal perfectly informative: $\Pr(s = v|v, a_i, q) = 1$.

However, greater precision comes at an increasing cost, implying decreasing returns to attention: the cost of information processing is $C_i(a_i, \theta_i)$, with $\partial C_i/\partial a_i > 0$ and $\partial^2 C_i/\partial a_i^2 > 0$, where the parameter θ_i measures investor i's ability to glean price implications from the news. Local investors are assumed to be better at processing information about local stocks ($\theta_L > \theta_N$) for any given attention level. For concreteness, we posit a quadratic cost function: $C_i(a_i, \theta) = a_i^2/\theta_i$. The greater θ_i, the easier it is for investor i to gauge the asset value's response to news.

2.1 Local information advantage

We first determine the allocation of attention and the equilibrium of the model under the assumption that, apart from noise traders, all investors–whether local or not–behave rationally: nonlocal investors are aware of being less skilled than local ones at processing information about local stocks, and take this rationally into account in their market behavior. Thus, as in Tirole (2009), Van Nieuwerburgh and Veldkamp (2009) and Van Nieuwerburgh and Veldkamp (2010), this version of the model does not posit any form of bounded rationality: both local and nonlocal investors decide rationally how much information they wish to process, knowing that lower attention may lead to more mistakes in trading.

The expected stock value from an investor's standpoint depends on her choice of attention a and the signal s:

$$\widehat{v}(a, s) \equiv \mathbb{E}[v|s] = \frac{1}{2} \times \begin{cases} (1 + qa)v_g + (1 - qa)v_b & \text{if} \quad s = v_g, \\ (1 - qa)v_g + (1 + qa)v_b & \text{if} \quad s = v_b. \end{cases} \tag{1}$$

where $(1 + qa)/2$ is the conditional probability of the asset being high-value when the investor chooses attention a and receives a high-value signal.[3] This probability is an increasing function of the investor's attention a: in the limiting case $a = 0$, the estimate

[3]To see why, recall that the prior probability of asset value v_j is $\Pr(v = v_j) = 1/2$ for $j = b, g$, and that the conditional probability that the signal is correct given an attention level a is $\Pr(s = v_j|a, v = v_j) = (1 + qa)/2$. So the conditional probability that the investor assigns to $v = v_g$ upon observing $s = v_g$ is

$$\Pr(v = v_g|a, s = v_g) = \frac{\Pr(s = v_g|a, v = v_g)\Pr(v = v_g)}{\Pr(s = v_g)} = \frac{\frac{1+qa}{2}\frac{1}{2}}{\frac{1+qa}{2}\frac{1}{2} + \left(1 - \frac{1+qa}{2}\right)\frac{1}{2}} = \frac{1 + qa}{2}.$$

Symmetrically, since the conditional probability that the signal is wrong is $\Pr(s = v_j|a, v = v_i) = (1 -$

$\widehat{v}$ would be the unconditional average $\overline{v}$, whereas in the polar opposite case $a = 1/q$, the estimate would be perfectly precise. Thus, in equilibrium, each investor holds a posterior belief $\widehat{v}(a_i, s)$ whose precision depends on the chosen attention level.

Dealers are assumed to devote no attention to the processing of news, as they are taken to specialize in trading rather than the analysis of stock fundamentals, also because they can infer already processed information at no cost directly from the order flow. With no loss of generality, we focus on the case where investors receive good news $s = v_g$, so that they may wish to buy at the ask price p_A (the analysis being symmetric for the case of bad news $s = v_b$ and trading at the bid price p_B). Investor i chooses her attention level a_i so as to maximize her expected utility:

$$\max_{a_i \in [0,1]} \frac{1}{2}\left[\pi\left(\widehat{v}\left(a_i, s = v_g\right) - p\right) - \frac{a_i^2}{\theta_i}\right] = \frac{1}{2}\left[\pi(\overline{v} - p_A + q a_i \sigma) - \frac{a_i^2}{\theta_i}\right], \text{ for } i \in \{L, N\}, \quad (2)$$

where the first term is the investor's expected profit (earned with probability π), and the second is her attention costs.[4] The objective function (2) is increasing and strictly concave in a_i, and its parameters are assumed to be such that even local investors choose an interior solution $a_L^* < 1/q$. Hence, the optimal choice of attention is

$$a_i^* = \frac{\theta_i \pi q \sigma}{2}, \quad (3)$$

so that an interior solution $a_L^* < 1/q$ requires $\theta_L < 2/(\pi q^2 \sigma)$, i.e. imposes an upper bound on the information-processing ability of local investors. In equilibrium, local investors devote more attention to local stocks than nonlocal ones, i.e., there is an attention gap:

$$a_L^* - a_N^* = \frac{\pi q \sigma}{2}(\theta_L - \theta_N) > 0. \quad (4)$$

This immediately yields the following comparative statics:

Proposition 1 (Optimal attention and local-nonlocal attention gap) *If the local investor's attention problem has an interior solution, the optimal attention level a_i^* of investor i is increasing in her information processing efficiency θ_i. The attention levels of*

$qa)/2$ for $i \neq j$, the conditional probability that the investor assigns to $v = v_b$ upon observing $s = v_g$ is

$$\Pr\left(v = v_b | a, s = v_g\right) = \frac{\Pr\left(s = v_g | a, v = v_b\right)\Pr(v = v_b)}{\Pr\left(s = v_g\right)} = \frac{\frac{1-qa}{2}\frac{1}{2}}{\frac{1+qa}{2}\frac{1}{2} + \left(1 - \frac{1+qa}{2}\right)\frac{1}{2}} = \frac{1-qa}{2}.$$

[4] Both terms are divided by 2, as expected profits are obtained on the ask side only when news is positive, which occurs with 50% probability, and only half of the total attention costs are covered by gains obtained by buy orders placed at the ask when news is positive, the other half being covered by gains obtained by sell orders placed at the bid when news is negative.

local and nonlocal investors and their differences are increasing in information quality q, order execution probability $\pi/2$, and stock volatility σ.

These results are intuitive: more capable investors devote greater attention to news as they face lower processing costs, especially if news conveys precise information, fundamentals are volatile (as volatility makes information more valuable), and there is a higher chance of trading on information.

As market makers earn zero expected profits,[5] the ask-side half-spread is

$$p_A - \overline{v} = \frac{\pi}{2} q\sigma (a_L^* + a_N^*) = \frac{1}{2}\overline{\theta}(\pi q \sigma)^2, \tag{5}$$

since total investors' attention is $a_L^* + a_N^* = \overline{\theta}\pi q\sigma$, where $\overline{\theta} \equiv (\theta_L + \theta_N)/2$ is the average information processing ability. Hence:

Proposition 2 (Equilibrium bid-ask spread) *The equilibrium bid-ask spread is increasing in the investors' average information processing efficiency $\overline{\theta}$, the quality of information q, the probability of informed trading π, and fundamental volatility σ.*

Note that since by (4) changes in information quality q and volatility σ affect local more than nonlocal investors' attention, the response of the bid-ask spread to changes in q or σ predicted by equation (5) travels more via the change in the attention of local investors, a_L^*, than via that of nonlocal ones, a_N^*. Hence, empirically one should expect the bid-ask spread to be more strongly correlated with local rather than nonlocal attention.

Finally, we must verify whether both types of investors wish to pay any attention to news in equilibrium, as initially assumed. This is not a foregone conclusion, as the adverse selection generated by attention may raise the bid-ask spread so much as to make informed trading unprofitable. In equilibrium, investor i expects not to incur losses when devoting attention[6] if and only if

$$\theta_i \geq 2\pi\overline{\theta} = \pi(\theta_L + \theta_N). \tag{6}$$

[5]Market makers' zero profit condition on the ask side is

$$\mathrm{E}(\Pi_A) = \frac{\pi}{2}\left(p_A - \overline{v} - q\sigma a_L^*\right) + \frac{\pi}{2}\left(p_A - \overline{v} - q\sigma a_N^*\right) + (1-\pi)\left(p_A - \overline{v}\right) = 0.$$

[6]The relevant non-negativity condition of investor i's equilibrium expected profits is

$$\mathrm{E}(\Pi_i) = \frac{1}{2}\left[\pi(\overline{v} - p_A + q a_i^* \sigma) - \frac{a_i^{*2}}{\theta_i}\right] = \frac{\pi^2 q^2 \sigma^2}{4}\left(\frac{\theta_i}{2} - \pi\overline{\theta}\right) \geq 0.$$

This condition indicates that the frequency of informed trading π reduces investors' incentives to devote attention by raising the bid-ask spread. Condition (6) is more stringent for nonlocal than for local investors, as $\theta_L > \theta_N$. Hence, as shown in the Appendix:

Proposition 3 (Frequency of informed trading and investors' attention) *If the frequency of informed trading π is less than $\theta_N/(\theta_N + \theta_L)$, all investors pay attention to news; otherwise, only local investors pay attention to news, provided $\pi \leq 1/2$.*

Interestingly, the participation constraint of nonlocal investors ($\pi < \theta_N/(\theta_N + \theta_L)$) implied by (6) can be re-interpreted as placing a limit on the informational advantage of local investors over nonlocal ones, as it can be restated as $\theta_L/\theta_N < (1-\pi)/\pi$: if the locals' advantage θ_L/θ_N exceeds this threshold, nonlocal investors' attention drops to zero, and so does their market participation as informed traders.

If the local investor advantage θ_L/θ_N increases with the nonlocal investors' distance from the company's location, distance will raise the attention gap between them: as distance increases, the attention gap $a_L^* - a_N^*$ increases in proportion to θ_L/θ_N and, as this exceeds the threshold $(1-\pi)/\pi$, nonlocal investors' attention vanishes, while local investors' attention doubles (from $\theta_L \pi q \sigma/2$ to $\theta_L \pi q \sigma$, because now they trade with probability π instead of $\pi/2$). Hence, nonlocal investors exit the market beyond a critical distance, their attention being 'crowded out' by local investors. The model easily generalizes to multiple classes (or even a continuum) of nonlocal investors, each located at a different distance from the issuer's location, hence at an increasing disadvantage relative to local investors: their attention will be declining in their distance from the issuing firm, down to zero for the marginal nonlocal investor.

The model can also be modified to encompass a time dimension, assuming, for instance, that informed investors can place their orders in one of two periods and that greater attention enables them to process information about stocks faster and, therefore to be more likely to trade on news in the first rather than the second period (the probability of early trading being an increasing function of attention). In this alternative formulation, the greater ability of local investors to process local news would confer them an advantage of speed rather than precision. By exerting greater attention, they could expect to trade before nonlocal investors and reap greater informational rents. The main prediction of this version of the model would be qualitatively similar to those of the model presented above, except for the additional prediction that local attention and trading would be predictors of nonlocal attention and trading over time.

2.2 Biased local investors

In the above baseline model, informed investors are assumed to be rational in choosing their attention level and forming expectations. In what follows, we extend the model to allow informed investors to be less than fully rational in forming their expectations about stocks, in the sense that these expectations can, to some extent, be driven by prior beliefs affected by a familiarity bias, defined as the tendency to evaluate favorably companies to which the investor has been persistently exposed in the past, due to their intensive advertising and/or geographic proximity.

Specifically, we assume that with probability ϕ investors value assets according to the over-optimistic prior belief $b = v_g$, irrespective of the signal that they receive, and with probability $1 - \phi$ they behave as rational investors, buying or selling the asset depending on the rational estimate of the asset's value $\widehat{v}\,(a, s)$.[7] Hence, ϕ can be taken to be a measure of 'familiarity': this parameter can be viewed either as the fraction of investors who trust their prior beliefs rather than rational ones or as the probability weight that each of them places on the former rather than the latter.

We first analyze the case where familiarity is uncorrelated with a firm's geographic location, for instance, because it stems from the intensity of the firm's past advertising, which can assumed to affect local and nonlocal investors equally ($\phi_L = \phi_N \equiv \phi$). Next, we shall turn to the case where familiarity stems from the firm's location, local stocks being familiar to local investors but not to nonlocal ones ($\phi_L \equiv \phi > \phi_N = 0$). We will see that in both cases, the familiarity bias reduces the attention gap between local and nonlocal investors, as it lessens the extent to which local investors exploit their information processing advantage and thus their greater incentive to pay attention to news.

Even in the presence of a familiarity bias, investors choose their attention level by maximizing their expected profits net of attention costs. To fix ideas, consider first the case where, despite the optimism due to familiarity, investors still wish to trade on bad news as well as good ones, namely, sell at the bid upon receiving bad news ($s = v_b$) and buy at the ask upon receiving good news ($s = v_g$), so that their attention choice problem is still symmetric as in the baseline model. In this case, which as will see arises for ϕ small enough, their optimal attention level a_i (for $i = L, N$) can be found by maximizing their payoff for the case where they receive good news and buy at the ask price p_A:

$$\max_{a_i \in [0,1]} \frac{1}{2} \left[\pi \left[\phi v_g + (1-\phi) \widehat{v}\,(a_i, s = v_g) - p_A \right] - \frac{a_i^2}{\theta_i} \right], \tag{7}$$

[7]Notice that the assumption that familiarity bias is associated with asset overvaluation is not required for the main result of this section: insofar as investors rely on prior beliefs, whether optimistic or pessimistic, they reduce their attention to news.

where the first term is the investors' expected profit and the second is their attention cost. The difference from the objective function (2) in the baseline model is that now investor i's expectation of the stock value is a weighted average of the prior belief v_g and of the rational estimate of the asset's value $\widehat{v}\,(a, s) = \overline{v} + q a_i \sigma$ from expression (1). Hence, investor i's optimal attention is decreasing in the strength of the familiarity bias ϕ:

$$a_i^* = \frac{\theta_i \pi q (1 - \phi) \sigma}{2}, \text{ for } i \in \{L, N\}\,, \tag{8}$$

As a result, the attention gap between local and nonlocal investors is smaller than in the baseline model by a factor of $1 - \phi$:

$$a_L^* - a_N^* = \frac{\pi q \sigma}{2}(1 - \phi)(\theta_L - \theta_N) > 0. \tag{9}$$

Hence, the stronger the familiarity bias, the lower the attention gap between local and nonlocal investors, even though, in the case at hand, they are assumed to be equally familiar with the stock. In the limit, the attention gap vanishes if $\phi = 1$, i.e., if stock valuation only reflects investors' prior beliefs. Intuitively, the greater is familiarity ϕ, the less investors rely on information they can extract from news, and thus, the less relevant becomes the local investors' information-processing advantage. The empirical prediction is that the local-nonlocal attention gap should be lower for more familiar companies, e.g., those that sell popular consumer brands and/or advertise very intensively.

A qualitatively similar but quantitatively stronger result is obtained if the familiarity bias stems from proximity, namely if local investors tend to overvalue local firms but not nonlocal ones. In this case, expression (8) only applies to local investors (i.e., for $i = L$), while the optimal attention of nonlocal ones is given by expression (3) (setting $i = N$). Hence, in this case, the attention gap becomes

$$a_L^* - a_N^* = \frac{\pi q \sigma}{2}[(1 - \phi)\theta_L - \theta_N)], \tag{10}$$

which is again decreasing in ϕ: familiarity reduces the local-nonlocal attention gap also when it stems from proximity. In this case the attention gap can even switch sign if the familiarity bias exceeds the information advantage of local investors, namely if $\phi > (\theta_L - \theta_N)/\theta_L$. Indeed, if local investors have no information-processing advantage for local stocks $(\theta_N) = \theta_L)$, their familiarity bias induces them to pay less attention to these stocks than nonlocal investors do.

However, the choice of a_L^* from expression (8) is optimal for local investors only if they wish to buy at the ask price p_A upon receiving good news and sell at the bid price p_B upon receiving bad news so that they gain from paying attention to news in both cases.

This is not the case if ϕ is large enough: the optimism induced by the familiarity bias can be so strong that upon receiving negative news they may not want to sell the stock and may even wish to buy it, effectively disregarding negative information.

To see this, consider that if local investors were to choose the level of attention a_L^* and receive bad news, they would form the following estimate of the stock's value:

$$\mathbb{E}\left[v|a_L^*, s = v^b\right] = \phi v^g + (1-\phi)(\overline{v} - q a_L^* \sigma) = \overline{v} + \phi\sigma - \frac{\pi q^2 \sigma^2 (1-\phi)^2 \theta_L}{2}. \tag{11}$$

To establish whether they wish to sell upon such news, this expression must be compared with the zero-profit bid price (obtained assuming that informed investors sell upon negative news):

$$p^B = \overline{v} - \frac{\pi^2 q^2 \sigma^2}{2} \cdot \frac{\theta_N + (1-\phi)\theta_L}{2}. \tag{12}$$

For the expression a_L^* from expression (8) to be optimal in equilibrium, the value placed on the stock by local investors according to expression (11) must be lower than the bid price in (12), namely:

$$\phi\sigma + \frac{\pi q^2 \sigma^2}{4}\left[\pi\theta_N + \pi(1-\phi)\theta_L - 2(1-\phi)^2\theta_L\right] < 0. \tag{13}$$

This condition (which is met for $\phi = 0$ under condition (6)) fails to hold for sufficiently high values of ϕ: a sufficient (but not necessary) condition for it to be violated is that $\phi > 1 - \pi/2$.[8] Hence, if the familiarity bias is sufficiently strong, investors will disregard bad news (though not good ones) in trading local stocks–the so-called 'ostrich effect.' If so, in the presence of negative news, the attention gap between local and nonlocal investors would switch sign, with only nonlocal investors paying attention to such news about local assets.

3 Data

We draw web search activity data from Google Trends (https://trends.google.com). Google does not provide detailed information about web searches by individual users but provides transformed measures that allow comparisons between states for a given firm and week or over time for a specific firm and state, but not both simultaneously. These data characteristics constrain our measurement of investor attention and require different data downloads to address the issues under analysis.

[8] In equilibrium, local investors will not sell the local stock if their valuation (11) also exceeds the zero-profit bid price obtained assuming that informed sell orders can only come from nonlocal investors, namely $p_B = \overline{v} - \frac{\pi^2 q^2 \sigma^2}{2-\pi}$, which is the case under condition $\phi > 1 - \pi/2$.

The measure that we use to study how attention to companies varies across the residents of different states (see Section 4) is constructed based on all weekly web searches performed in 2017 for each stock present in the S&P500 at the beginning of 2017 and whose issuer is headquartered in the United States. Our sample consists of 480 tickers and includes 1,244,800 firm-week observations. The index is based on the number of times users type a specific word, which, in our case, is a company ticker. However, Google does not provide the absolute number of web searches but a standardized index of searches: it aggregates web searches into weekly counts (scaled by a random sample of total Google searches) in each state; then it converts them into a score that equals 100 in the state where the ticker is most frequently searched (relative to a random sample of total Google searches in that state). By construction, in other states, the value ranges from 0 to 100, being scaled by the state where the ticker is most searched. For instance, if AAPL (the Apple ticker) is the most intensively searched in California (relative to total Google searches in California) in a given week, California gets a score of 100 for Apple in that week. A score of 20 for Apple in Texas means that searches in Texas are 1/5 of those in California.

So, our main attention metric – that we label `GSearch` – is the number of Google web searches for a given ticker, given week, and given state relative to the number of web searches for that ticker in the state where the ticker was searched the most in that week. By construction, each week, a ticker has a state where `GSearch` = 100. Formally, if G_{ist} denotes the Google searches for ticker i in state s and week t and G_{st} denotes total searches in that state and week, `GSearch` of stock i in state s and week t is

$$GSearch_{ist} = 100 \cdot \frac{G_{ist}/G_{st}}{G_{iSt}/G_{St}}, \tag{14}$$

where S is the state where the ratio G_{ist}/G_{st} is the largest in week t.

This variable is used as a proxy for relative retail investor attention, in line with Da, Engelberg, and Gao (2011), Engelberg and Parsons (2011), and Andrei and Hasler (2014).[9] Strictly speaking, it measures the search activity by any web user whose atten-

[9]Google search is widely used in the finance literature to measure attention. For instance, Bae and Wang (2012), who show that China-name stocks outperformed non-China-name stocks during China's 2007 stock market boom, find stronger outperformance for stocks that attract more attention, as measured by Google search. Benamar, Foucault, and Vega (2020) measure information demand using Google queries and find it to affect future interest rates. Relatedly, Focke, Ruenzi, and Ungeheuer (2019) investigate the effect of firm advertising on investor attention, using the Google search of ticker symbols as one of their measures of attention. Choi, Gao, and Jiang (2020) employ Google queries about climate change and find that people revise their beliefs and actions related to local temperature. Da, Engelberg, and Gao (2014) use Google queries to measure investor sentiment, predicting short-term return reversals, temporary increases in volatility, and mutual fund flows out of equity funds and into bond funds. They also report that in 2009 Google accounted for 72 percent of all search queries performed in the United States. Google search is also used by Andrei and Hasler (2014) as a proxy of attention, which affects

tion has turned to a stock. Still, web searches of stock tickers are so specific that potential investors most likely make them, the stock ticker being often unknown to laypeople. Furthermore, investors who search stock tickers on Google are most likely non-professional (retail) investors, as financial professionals typically use other channels to gather information about stocks (e.g., Bloomberg, as in Ben-Rephael, Da, and Israelsen (2017)). In what follows, we will check the robustness of this assumption.

By construction, `GSearch` only allows time-series comparisons of investor attention in relative terms, not absolute ones, being rebased to 100 each week. As the analysis of Section 4 focuses on the geography of retail investors' attention for a given company, this characteristic is not problematic and reduces potential confounding effects of time-series patterns in the absolute scale of the variable. We distinguish between local and nonlocal attention via the dummy variable `SameState`, which equals 1 for searches made by residents of the state where the company is headquartered and 0 otherwise, in keeping with previous research that identifies a company's location as that of its headquarters (Coval and Moskowitz, 1999; Grinblatt and Keloharju, 2001; Malloy, 2005; Ivković and Weisbenner, 2005).

In Section 5.1, instead, we wish to measure the dynamics of the attention of investors potentially affected by M&A-induced shocks in perceived firm proximity. To this aim, we download the time series of `GSearch` in the bidder's state and the target's state. This is possible because, as mentioned above, Google allows downloading the time series of web searches for one state at a time for a given firm, even though it does not allow downloads of such series for all states simultaneously. Finally, in Section 6, where we need to construct a panel of local and nonlocal attention for each firm and state, we download the aggregate time series for each ticker and combine this information with the measures employed in Section 4 to compute the time series of web searches made by local investors (i.e., residents of the state where the company is headquartered) and nonlocal investors (i.e. residents in all other states).

To characterize the geography of investor attention more finely, we also construct two continuous variables measuring the distance between the location of each company and the people searching for its ticker. The first, labeled `Distance`, measures the geographic distance (in thousands of kilometers) between a firm's headquarters and the capital of the state where the relevant web searches are done. The second, labeled `Cit10K`, is the (log of 1 plus the) respective state's name count in the company's annual report filed with the SEC on form 10-K and measures how relevant that state is to the company's activity,

stock return variance and risk premia, and by Hartzmark and Sussman (2019), who use it to measure the attention devoted by investors to the Morningstar sustainability rating system. Finally, Welch (2022) and Berger, Turner, and Zwick (2020) use Google Trends to measure public interest in COVID and demand in the housing market, respectively.

for instance, due to the location of its plants, warehouses, sales offices, and employees. This measure, proposed by García and Norli (2012), considers that a company's assets and activities may not be located in the same state as its headquarters and may be geographically dispersed across various states rather than concentrated in a single one.

We construct four variables to test how investor attention correlates with available public information. First, we measure the volume of information available nationwide about a given company by the variable `News`, defined as the (log of 1 plus the) number of news items published by Thomson Reuters regarding a given ticker and in a given week. We filter out research, videos, and stories related to the firm and count only headlines reported in English. As more news should also carry more information, this variable can be seen as an empirical counterpart of the information quality q in the model. A second variable measures the information locally available to investors in each US State about a given company, `LocalNews`, defined as the (log of 1 plus the) number of news items published by the local newspaper in a given state regarding a given ticker in a given week.[10] This variable will enable us to gauge whether the geography of attention is shaped by the greater access local investors have to local public information or rather by their superior ability to process information about local companies, stemming, for instance, from a better understanding of local businesses or access to private information about them. Thirdly, we measure the volatility of price-relevant news in a given week, `Vol`, by the absolute value of the weekly stock return (drawn from Thomson Reuters Eikon). This variable can be regarded as the empirical counterpart of the range of variation of firm value σ in the model. To capture the possible asymmetric effect of volatility on investors' attention at times of good and bad news, we also compute the absolute value of returns separately for weeks of negative and positive returns (when the indicator

[10] We link each newspaper to the state where it is published, except for three national newspapers: US Today (Virginia), Wall Street Journal, and The New York Times (both published in New York City). The local newspapers used are Alaska Dispatch News (Alaska), Arizona Republic (Arizona), Pine Bluff Commercial (Arkansas), The Sacramento Bee (California), Denver Post (Colorado), Hartford Courant (Connecticut), Cape Cod Times (Delaware), Tampa Bay Times (Florida), The Atlanta Journal - Constitution (Georgia), Honolulu Star (Hawaii), Idaho Statesman (Idaho), Chicago Tribune (Illinois), Indianapolis Star (Indiana), Des Moines Register (Iowa), Topeka Capital Journal (Kansas), Courier - Journal (Kentucky), Times - Picayune (Louisiana), Portland Press Herald (Maine), The Baltimore Sun (Maryland), Boston Globe (Massachusetts), Detroit News (Michigan), Minneapolis Star and Tribune (Minnesota), The Sun Herald (Mississippi), St. Louis Post - Dispatch (Missouri), The Billings Gazette (Montana), Lincoln Journal Star (Nebraska), Las Vegas Review - Journal (Nevada), Concord Monitor (New Hampshire), Press of Atlantic City (New Jersey), Albuquerque Journal (New Mexico), New York Post (New York), The Charlotte Observer (North Carolina), Bismarck Tribune (North Dakota), The Columbus Dispatch (Ohio), The Oklahoman (Oklahoma), The Oregonian (Oregon), Pittsburgh Post - Gazette (Pennsylvania), The Providence Journal (Rhode Island), The Post and Courier (South Carolina), The Dickinson Press (South Dakota), Chattanooga Times Free Press (Tennessee), The Houston Chronicle (Texas), The Salt Lake Tribune (Utah), The Burlington Free Press (Vermont), Virginian - Pilot (Virginia), Seattle Post - Intelligencer (Washington), Charleston Daily Mail (West Virginia), Milwaukee Journal Sentinel (Wisconsin), and Wyoming Tribune - Eagle (Wyoming).

variable `NegRet`=1 or 0, respectively). This enables us to test the so-called 'ostrich effect,' according to which investors pay more attention to good news (Galai and Sade, 2006).

As the model of Section 2.2 predicts that the attention that local investors pay to news regarding local stocks may be affected by their familiarity with these stocks, we measure the investors' degree of familiarity with each stock issuer by the ratio of advertising expenditures to total sales (`Advertising`), consistent with Grullon, Kanatas, and Weston (2004), and test how investors' attention responds to this indicator of firm visibility.[11] Since only 274 firms of our sample explicitly report advertising expenditures in their balance sheets, we use the standard imputation method to complete missing values based on firms' characteristics, namely, size (measured by the firm's market value), growth opportunities (measured by market-to-book value), and a dummy that equals 1 for firms selling the 500 most valuable and strongest American brands and 0 otherwise.[12]

Table 1 provides summary statistics of variables in our sample. On average, the frequency of stock searches in a state is about 20% the frequency of the searches in the state featuring the highest number of searches: the average value of `GSearch` is 20.14, while it would be about 100 if web searches were equally distributed across the states. This indicates that web searches tend to cluster in a few states. On average, the state name count in 10-K forms is 6,[13] and the distance between the company headquarters and web search location is about 1860 kilometers. The three geographic variables are strongly correlated: on average, the headquarters state is cited 79 times in the corresponding company's 10-K form, while other states are only cited 5 times. The difference between the two is statistically significant. Moreover, states located further away from the headquarters are far less frequently cited in the corresponding company's 10-K form, the correlation between `Cit10K` and distance being negative (-0.13) and statistically significant.

[Insert Table 1]

On average, about 90 news items are released per company week, and about 16 news pieces per company year appear in local newspapers. Firms vary considerably in their familiarity with investors: the ratio of their advertising expenditures to sales ranges from zero to 37%, with an average of 3%. The mean of the absolute weekly return (`Vol`) is about 2%, and the tenor of the news is negative in 43% of the cases.

[11] Grullon, Kanatas, and Weston (2004) show that firms with more advertising expenditures attract a larger number of both individual and institutional investors and have better liquidity and lower cost of capital. Other work has also shown that advertising can affect investors' behavior: Lou (2014) finds that advertising attracts investor attention so that managers use it opportunistically to affect short-term stock returns for their insider transactions. Product-market advertising is also strategically employed to signal higher firm valuation before equity issuance.

[12] Data is from the 2017 report available at https://brandirectory.com/rankings/us/2017)

[13] The averages of log variables are calculated before taking logs.

The number of company headquarters is highest in California (73 companies, about 15% of the total) and New York (62 companies, about 13% of the total). Ten states host no S&P500 company headquarters: Alaska, Hawaii, Kansas, Mississippi, New Hampshire, New Mexico, North Dakota, South Dakota, Vermont, West Virginia, and Wyoming. The highest average attention is recorded in New York states (27.39) and California (26.38), and the lowest in South Dakota and Wyoming, below 15. Hence, the states hosting more company headquarters also feature greater web search activity, likely driven by state-level characteristics such as population and economic activity.

4 Local and nonlocal attention

In this section, we start by documenting that investors pay more attention to local rather than nonlocal companies and then test whether the response of this attention gap to news availability and return volatility is in line with the model's predictions.

4.1 Local-nonlocal attention gap

In principle, the geography of investors' attention can be analyzed either from the standpoint of companies, testing whether they attract more attention from local or nonlocal investors, or the standpoint of investors, asking whether they devote more attention to local or nonlocal companies. Table 2 documents that proximity plays a sizeable and statistically significant role in investors' attention to firms when either of these perspectives is taken.

[Insert Table 2]

The table shows the distribution of company headquarters across states and the average level of web searches (as measured by the above-defined `GSearch` variable) by search states and by company headquarters states in 2017. For each of the states listed in column 1, local investors are defined as the residents of that state, and nonlocal investors as those residents in other states; symmetrically, local firms are defined as the companies whose headquarters are located in that state, and nonlocal firms as those with headquarters located elsewhere. Columns 2 and 3 report the number and fraction of company headquarters in the corresponding state indicated in column 1. Columns 4 and 5 report the average values of local investors' weekly web searches and those directed at local firms (whenever the state hosts at least one of the company's headquarters), respectively. By construction, the two average to the same figure (20.14) for the whole of the United States.

The subsequent table columns quantify the local-nonlocal attention gap in each state. The total searches directed at local firms (column 5) are decomposed into those made by same-state residents (column 6) and those made, on average, by residents of any other state (column 7).[14] Column 8 shows that the difference between the two is positive and significantly different from zero at the 1% level for all the states except for the District of Columbia (hosting a single company), Louisiana (3 companies), and Maryland (10 companies). Hence, seen from the perspective of the 480 firms in the sample, in most states, they receive significantly more attention from local rather than nonlocal investors.

Symmetrically, the last two columns of the table document the allocation of attention from the standpoint of investors: this time, the total searches made by local investors (column 4) are decomposed into those that these investors, on average, direct at local companies (again, column 6) and those that, on average, they direct at nonlocal companies (column 9). Column 10 shows that, also, in this case, the difference between the former and the latter is positive and statistically significant at the 1% level, except for Louisiana and Maryland, where it is positive but not significantly different from zero. Hence, in most states, the average investor devotes considerably more attention to local companies than nonlocal ones.

Irrespective of whether the geography of attention is measured from the standpoint of firms or investors, the country-wide average local-nonlocal attention gap is 23.23, namely, the difference between the average of local searches for local firms (42.90) and the average of nonlocal searches for such firms or, equivalently, the average of searches made by local investors on nonlocal firms (19.68), the latter two being identical by construction. Hence, Table 2 documents that firm geographic proximity plays an important role in the allocation of attention by U.S. retail investors: local attention is about twice as much as nonlocal attention. Figure 1 conveys this result graphically, plotting the web searches directed at firms in each state by local investors against those by nonlocal investors: all states (except for the above-mentioned three) lie above the bisector. The same picture emerges at the firm level: in Figure 2, most points, which represent combinations of local and nonlocal `GSearch` for each sample firm, lay above the bisector.

[Insert Figures 1 and 2]

[14] Note that the total number of searches in column 5 is a weighted average of the numbers of local and nonlocal searches for local firms shown in columns 6 and 7. By construction, this average is close to the number of nonlocal searches, weighted by 49/50 (the fraction of other states over the total), while local searches are weighted by 1/50.

4.2 Investor attention, proximity and news

Recall that the model in Section 2.1 predicts that, insofar as local investors are better at processing information regarding local firms, these should attract more attention from local rather than nonlocal investors. This attention gap should increase in response to greater availability of news and volatility. Moreover, the model extension presented in Section 2.2 predicts that, insofar as local investors also feature a familiarity bias in favor of local firms, the attention gap between local and nonlocal investors should be lower and may even switch sign if the familiarity bias is very strong. In this section, we test these predictions by estimating the following baseline model and several variants of it:

$$\texttt{GSearch}_{ist} = \boldsymbol{\beta}'\boldsymbol{x}_{ist} + \mu_i + \zeta_s + \tau_t + \epsilon_{ist}, \tag{15}$$

where $\texttt{GSearch}_{ist}$ is the web search activity for ticker i, in a week t and state s; $\boldsymbol{x}_{ist}$ is a vector including geographic/distance variables (`SameState`, `Distance`, or `Cit10k`), other news- and familiarity-related explanatory variables (i.e., `News`, `LocalNews`, `Vol`, `Advertising`), and their interactions; $\boldsymbol{\beta}$ is the vector of coefficients to be estimated, the parameters μ_i, ζ_s, and τ_t indicate firm, state and week fixed effects, and ϵ_{ist} is the error term. Via these fixed effects, the model controls for unobserved heterogeneity in attention between stocks and states and for aggregate time patterns. While model (15) suggests a multilevel structure of the data, this is not the case for our data, as each ticker i is searched in multiple states s.[15] By the same token, our data do not have a pure panel structure either, as at each date t web searches for a firm i vary across states s. Table 3 shows the OLS estimates of the coefficients of equation (14), with robust standard errors clustered at the firm level.

[Insert Table 3]

The estimated coefficient of the `SameState` dummy in the first row of the table indicates that `GSearch` is between 17 and 21 points larger in the state where the firm is headquartered than in other states, confirming the visual evidence in Figures 1 and 2. The estimate of the `Cit10K` variable in column 2 shows that investors' attention is greater in states that are more frequently cited in the respective companies' 10-K forms and thus are more relevant to their operations: a 1-percent increase in a state's name count is associated with a 2.44 point increase in `GSearch` in that state. The relationship between investors' attention and their distance from issuing firms goes beyond the distinction between in-state and out-of-state firms: in column 3, where the dummy `SameState` is

[15] Multilevel data have a hierarchical structure, featuring multiple units of analysis, each nested within the other.

replaced with the continuous variable `Distance`, we find that a 1,000 km increase in distance between a firm's headquarters and the state of the web search is associated with a drop in web searches of 0.65 points, that is, 75% of the sample average. These findings highlight the key role of geographic proximity in determining investor attention, in line with the model of Section 2.1.

To explore whether the local-nonlocal attention gap also responds to news and differences in the familiarity of firms as predicted by the model, in columns 4 and 5, we expand the specification to allow for the news-related variables (`News` and `LocalNews`) and volatility (`Vol`), as well as our measure of familiarity (`Advertising`). While news-related variables enter the specification both in level and interacted with the `SameState` dummy variable, the familiarity variable only enters via its interaction with the `SameState`, the variation in its level being entirely absorbed by firm-level fixed effects (unlike for variables that vary over time, such as `Vol`, or across states, such as `SameState`). However, the interaction of `Advertising` and `SameState` enables us to test the prediction of our model that familiarity should impact the attention of local and non-local investors differently.

The estimates in column 4 show that investors' attention is positively and significantly related to the number of financial news items (the coefficient of `News` being 0.20) but more so in the state where the firm is headquartered (the coefficient of the interaction `SameState` $\times$ `News` being 1.26 and significantly different from zero), again in line with the predictions of the model. To appreciate the economic significance of these results, since `GSearch` is a score ranging from 0 to 100, consider that a 1-standard-deviation increase in the number of news items relative to its sample average (from 90 to 237 news items) is associated with a 0.19 increase in nonlocal (i.e., out-of-state) web searches and a 1.92 increase in local (in-state) web searches. Hence, local investors react about 10 times more than nonlocal investors to news releases.[16]

The positive and significant coefficient of the `LocalNews` variable indicates that investors' attention responds to information published in local newspapers. However, such information does not elicit a stronger response from investors close to the company headquarters, considering that the interaction of this variable with `SameState` is not statistically different from zero. This suggests that local investors' advantage does not lie in their superior access to local news but in their greater ability to process publicly available information, in line with the model's assumptions in Section 2.1.

Changes in volatility also elicit widely different responses of nonlocal and local attention: in column 4, the coefficient of the interaction between `SameState` and `Vol` is 62.15,

[16] The effect of the number of news on nonlocal attention is given by $0.20\ln(147+90+1) - 0.20\ln(90+1) \approx 0.19$, while that on local attention is given by $(0.20\ln(247+90+1) + 1.26\ln(247+90+1) - 0.20\ln(90+1) - 1.26\ln(90+1) \approx 1.92$. Notice that we add 1 to the logarithm argument because `News` is defined as the log of one plus the number of news.

implying that an increase in weekly volatility by one standard deviation (2%) is associated with increases in nonlocal and local attention of 0.11 and 1.35 points, respectively.[17] In other words, an increase in volatility is associated with an increase in attention by local investors that is about 13 times larger than by nonlocal investors.

Interestingly, the coefficient of the interaction between the `Advertising` and the `SameState` variable is negative and statistically significant at the 10% level, indicating that more familiar firms attract less attention from local investors than from nonlocal ones, as predicted by the extended version of the model presented in Section 2.2. This dovetails with the hypothesis that the observed attention gap between local and nonlocal investors stems from an informational advantage of local investors rather than from a familiarity bias: the latter tends, if anything, to reduce this gap, in line with the idea that familiarity breeds inattention to news, and thus limits the advantage that investors have in processing news about local stocks.

A possible concern about the estimates shown in column 4 is that causality between our measure of investor attention and return volatility may be bi-directional, as highlighted by our model: on the one hand, more volatile returns should elicit greater attention; on the other, greater attention can be expected to increase the informational content of the order flow, and thus increase stock price volatility, as found by Andrei and Hasler (2014). To address the potential endogeneity of volatility due to reverse causality, we instrument the `Vol` variable and its interaction with the `SameState` dummy with industry-level return volatility and its interaction with that dummy: the number of web searches for a specific company should affect industry-level volatility less than firm-level volatility, being likely to focus mostly on idiosyncratic firm information. Column 5 presents 2SLS estimates of the specification shown in column 4 of the table. The estimates indicate that the baseline level of the local-nonlocal attention gap (captured by the coefficient of the `SameState` dummy) is very close to that obtained by OLS in column 4. Still, the response of local attention to volatility (the estimated coefficient of the interaction between `Vol` and the `SameState` dummy) is larger: hence, the endogeneity of stock return volatility appears to lead – if anything – to underestimating its impact on local investors' attention.

The last two columns of the table show that this differential impact of volatility on local and nonlocal attention applies both to good and bad news: when the specification of column 4 is estimated separately on the subsample with positive returns (column 6) and that with negative returns (column 7), the coefficient of the `Vol` variable and that of its interaction with `SameState` are positive and statistically different from zero in both cases. Indeed, the relevant coefficients are larger in the presence of negative returns

[17]The two figures result respectively from 5.33×0.02 and $(5.33 + 62.15) \times 0.02$.

than with positive returns, although the difference is not significantly different from zero. Furthermore, the coefficient of the advertising interaction is negative and not significantly different in the two cases, indicating that familiarity reduces the attention gap to the same extent for the good and bad news. Hence, the evidence is inconsistent with the 'ostrich effect,' i.e., investors paying less attention to their portfolios when receiving bad news than good ones (Galai and Sade, 2006; Karlsson, Loewenstein, and Seppi, 2009), and is instead consistent with the finding by Boehmer and Song (2021) that retail investors profitably exploit negative news by short-selling overvalued stocks.[18] Seen through the lens of the model in Section 2.2, this finding suggests that investors' familiarity bias (as measured by the parameter ϕ) is not so strong as to discourage them from paying attention to bad news.

To sum up, the results from Table 3 are in line with the model's main predictions: not only does local attention systematically exceed nonlocal attention, but the gap between the former and the latter is amplified by the volume of news and stock return volatility, and is reduced by local investors' familiarity with local stocks. This is consistent with the idea that the greater attention that local investors devote to local assets is driven by their information processing advantage rather than by a behavioral bias.

These results are quite robust, as shown by the checks and validation tests reported in Table A1 of the Web Appendix. One possible concern is that our sample may be biased towards a few states where firms cluster their headquarters. Indeed, 28% of the sample firms are headquartered in California or New York. Yet, upon re-estimating the specification of columns (1) and (4) of Table 3 without the observations for those two states, the estimates reveal an even stronger local-nonlocal attention gap (23.46 and 19.75) than when these observations are retained (20.74 and 17.94). Another possible concern is that the ticker of ten stocks in our data is a single letter,[19] so the number of searches for these companies may reflect typos by web users rather than intentional web searches. But when observations for these stocks are dropped, the results are unaffected. The results are also robust to excluding observations for firms whose names are quite similar to their respective tickers (e.g., CBS), as unreported results show. Further unreported analysis shows that the words most often searched in conjunction with our tickers are 'stock' and 'equity.'

[18] This result is in contrast with the evidence by Sicherman, Loewenstein, Seppi, and Utkus (2015), a difference that may stem from their measure of attention being based on investor online account logins. However, our measure will likely precede account logins, reflecting investors' first attempt to acquire information. Thus, it may be considered a more fine-grained measure of attention than account logins. Moreover, our measure of attention is likely to capture fewer self-selected individuals rather than a sample of individuals who already have an online account and log into it to place an order.

[19] This applies to Agilent Technologies, AT&T, Citigroup, Dominion Energy, Ford Motor, Kellogg, Loews, Macy's, Realty Income, and VISA.

We also perform a test to validate that the SameState variable captures the gap between local and nonlocal attention in Table 3, based on the idea that local attention should drop on state holidays compared to work days, as local investors would be distracted by leisure activities. Hence, we generate the dummy variable Holi, which equals 1 when a state-specific holiday occurs in a given week and 0 otherwise. We add this variable and its interaction with SameState to the specification. As expected, while on other days, local attention continues to exceed nonlocal attention, during such holidays, the gap drops significantly (by about 1/4).

Yet another concern may be that since by construction, the GSearch variable has positive finite support, the errors of our regressions may be non-normal, and the model predictions may fall outside the 0-100 interval. However, the results are qualitatively unaffected when this variable is replaced with its nonlinear transformation $\ln \frac{\texttt{GSearch}+10^{-7}}{100-\texttt{GSearch}+10^{-7}}$, which ranges between about -20 and $+20$.[20]

Finally, we conduct a falsification test to provide further evidence that the results are unlikely to be driven by unobservable characteristics of the states where the firm's headquarters are located. Specifically, we randomize the states of firms' headquarters while preserving the state-level frequencies of headquarters distribution in our sample by bootstrapping without replacement and forming 500 samples of firms with randomly assigned headquarters. Then, these data are used to re-estimate the specification in column 1 of Table 3 for each of the 500 samples. Suppose any underlying state-specific characteristics, where local investors search more intensively for firms, drove our results. We should expect similar results to those reported in Table 3 using randomized headquarters data. Reassuringly, with randomly assigned headquarters, the coefficient of the SameState variable is on average -0.0057 and is not statistically larger than zero at the 5% significance level for 496 of the 500 regressions. Hence, if company headquarters were randomly assigned, local web searches would unlikely exceed nonlocal ones.

4.3 Investor attention, proximity and earnings announcements

Earnings announcements provide a particularly suitable laboratory to investigate the differential sensitivity to news of local and nonlocal attention: the standardized and precisely timed news releases for all companies not only allow us to test whether local attention reacts to news releases but also whether it reacts more strongly and rapidly than the nonlocal attention. Figure 3 provides such evidence for the 1,738 quarterly earnings announcements published by firms in our sample during 2017 by plotting the change in local and nonlocal attention (ΔGSearch) and the gap between them around

[20]The tiny 10^{-7} value is added to the numerator and denominator to prevent the transformed variable from shooting to minus or plus infinity.

the announcement date and time.

[Insert Figure 3]

The top diagrams plot Δ`GSearch` by local and nonlocal investors in a 7-day window centered around the earnings announcement date (chart a) and the difference between them (chart b). The attention gap becomes statistically significant a day before the announcement date, as local attention increases while nonlocal attention does not and remains positive and significant on the announcement date. Both local and nonlocal attention decrease after the announcement, and once again, the decrease is stronger for local attention starting from the second day after the announcement. The time pattern is consistent with local investors perceiving a higher return for their attention effort in preparation for the news release and a lower return once the news becomes stale. A similar effect also emerges at the hourly frequency on the earnings announcement day: as shown in the bottom diagrams of Figure 3, in the two hours before the announcement, local attention exceeds nonlocal attention (chart c), resulting in a significantly positive attention gap (chart d). At the time of the announcement and in the three subsequent hours, attention by both types of investors decreases, albeit once again, local attention decreases significantly faster than nonlocal attention.

5 Shocks to Proximity and Attention Reallocation

The evidence presented in the previous section shows that U.S. companies attract more attention from local investors than nonlocal ones. The gap between the two is positively correlated with the volume of the news and return volatility and negatively with a proxy of familiarity, consistent with the predictions of our model. However, a concern is that this evidence does not isolate the effect of geographic proximity *per se* on investor attention from the effect of stock ownership, which may reflect a familiarity bias. Specifically, suppose that investors tend to overweight local stocks in their portfolios due to familiarity bias, as predicted by the model of Section 2.2, where local investors are more likely to buy local stocks than sell them. Then, it would be natural for them to pay more attention to local stocks, as the value of their wealth would be more affected by news about local stocks than nonlocal ones. In this case, the local-nonlocal attention gap might not stem from a comparative advantage of local investors being able to collect and/or process information about local stocks, as in the model of Section 2.1, but from familiarity bias, via the resulting home bias in stock ownership. While some specifications in Table 3 include firms' advertising-sales ratio as a proxy for familiarity, this variable may not fully capture investors' degree of acquaintance with stocks.

Hence, a sharper test of the hypothesis that the local skew in attention arises from a proximity-induced information advantage rather than from the familiarity of local assets requires us to focus on situations in which investors face a sudden change in their perceived proximity to a company, irrespective of their initial equity portfolio: for instance, in their eyes a formerly distant firm suddenly becomes closer to them, and, as such, easier to analyze and worthy of greater attention, even if they may have initially had little or no ownership stake in such a firm. The idea is that changes in the allocation of investors' attention to local and nonlocal stocks triggered by such "shocks to proximity" should, by construction, be unrelated to the familiarity bias crystallized over time in their portfolios.

This section considers how investors' attention changes in response to shocks to their perceived proximity to firms. We focus on two very different types of shocks: first, those induced by acquisitions of local firms by nonlocal ones (Section 5.1); second, those triggered by the COVID-19 pandemic, which has hindered travel to distant locations, raising the cost of collecting first-hand information about nonlocal firms relative to local firms, and thus increasing local investors' informational advantage for local stocks relative to nonlocal ones (Section 5.2).

5.1 M&A shocks to perceived proximity

In this section, we document the dynamics of local attention when an acquisition modifies the perception of a firm's proximity. To do so, we collect data about all 142 completed takeover announcements in 2017 concerning any U.S. company present in the S&P500, either as a bidder or as a target. From these, we remove the 38 cases where the acquisition targeted a firm headquartered in the same state as the acquirer since these cases are not associated with a change in the perceived distance of the relevant firms. Of the remaining 104 M&A transactions involving a bidder and a target located in different states (based on their respective headquarters locations), an S&P500 bidder initiates 82, and 22 are directed at an S&P500 target.

To measure the dynamics of investors' attention potentially affected by M&A-induced shocks in perceived firm proximity, we analyze the time series of `GSearch` both in the bidder's state and in the target's state. For the 82 transactions initiated by a bidder in our sample, we measure the web searches of the bidding firm's ticker both in its state and the target state. For the 22 transactions directed towards a target in our sample, we measure the web searches for the target's ticker both in its state and the bidder's state. Overall, these cross-state M&A transactions are not concentrated in only a few states: bidders are present in 27 states and targets in 29 states, naturally with a prevalence of the states hosting more company headquarters.

To measure the response of investors' attention to changes in perceived distance triggered by M&A announcements, we follow an approach akin to that of event studies, where a normal predicted value of the response variable is compared to its actual value to detect any event-induced anomaly. Specifically, we estimate linear fixed-effects models with individual company slopes to capture the potentially differential response of investors' attention towards the acquiring and the target firms, depending on their location (Wooldridge, 2010):

$$\texttt{GSearch}_{ist} = \mu_{is} + \sum_{k\in K} \delta^k_{is}\texttt{Post}^k_{ist} + \epsilon_{ist}, \tag{16}$$

where $\texttt{GSearch}_{ist}$ is the web search score for company i (either the bidder or the target company) in state s (either the bidder or the target state) and week t, $t = 0$ being the week of the acquisition announcement. The model is estimated over a time window encompassing 52 weeks before and 52 weeks after the announcement. The variables $\texttt{Post}^k_{ist}$ are indicator variables defined over the set $K = \{0, 1-8, 9-16, 17-24, 25-32, 33-40, 41-52\}$, which equal 1 in the weeks in the relevant interval (e.g., the interval $1-8$ indicates the weeks from 1 to 8), and 0 otherwise. The company fixed effect μ_{is} captures the pre-event average web searches of company i's ticker, while the δ^k_{is} coefficients measure the differential changes in web searches for its ticker in the post-acquisition period. Note that since this specification includes firm-specific intercepts and slopes, each company's effect of an acquisition announcement is measured separately. Then, the firm-specific effects δ^k_{is} are averaged separately for target and bidder companies and residents of their respective states. So this approach can be seen as a generalization of a fixed-effect model where slope coefficients are also allowed to vary between firms.[21]

Figure 4 illustrates the estimates of the δ^k_{is} coefficients in equation (16) and their respective 5% confidence bounds. The two upper charts show how, after the acquisition, the residents in the target state shift their attention toward the bidder and target companies, respectively. The two lower charts show how the residents in the bidder's state changed their attention towards the bidder and target companies. All four plots indicate that the announcement of the acquisition (at $t = 0$) is associated with a significant increase in attention in both states and to both types of companies, as one would expect, considering the positive correlation between news releases and investor attention documented in Section 4. Moreover, a pairwise comparison of the two top charts and the two bottom ones reveals that, during the post-acquisition year, investors reallocate their attention toward the bidder and away from the target company, probably because investors realize that after the acquisition the decision power over the target's policies shifts into the hands of the bidder's management. Note that the attention shift is not the mechanical result

[21] We also estimated models augmenting equation (16) with a variable measuring aggregate web searches in the whole US. However, since our specification includes firm-specific intercepts and slopes, the contribution of this additional variable is negligible.

of the target company being delisted, as post-delisting observations for target companies are dropped from the sample.

[Insert Figure 4]

Interestingly, the shift in attention away from the target company is far greater among residents in the target's state (second top chart) than among those in the bidder's state (second bottom chart). This is consistent with the idea that, after the acquisition, investors in the target state perceive a drop in the proximity of this company. In contrast, those in the acquiring company's state perceive increased proximity. Both groups of investors realize that the policies of the acquired company are now affected by decisions taken in the acquirer's state, even though its headquarters have not moved.

The reallocation of investors' attention from the target to the bidder in the post-acquisition period depends on the size of the acquired company, as illustrated in Figure 5, where the estimates referring to the change in attention in the target state (top charts) and the bidder state (bottom charts) are shown separately for the bidder company (left-hand charts) and the target company (right-hand charts). All four charts display the estimates separately for above-average-size companies (blue dots) and below-average-size acquisitions (red dots). The figure shows that for small target companies, investors lose interest in the acquired local company and barely pay more attention to the nonlocal acquiring company than before; instead, for large targets, investors significantly increase their attention towards the nonlocal acquiring company, while they pay the same attention to the target company as in the pre-acquisition year. This suggests that in the first case, the target company, being small, loses its 'local nature' as the acquisition dilutes it into a much larger nonlocal conglomerate, while in the second case, the target's large size warrants refocusing attention on the out-of-state acquirer. In other words, investors in the target company's state regard small same-state targets as less local and large out-of-state acquirers as more local.

[Insert Figure 5]

Figure 6 illustrates how the estimates change depending on investors' familiarity with the target company, as measured by its advertising activity. In this figure, blue dots refer to the estimates for companies with above-average advertising, and red dots to those for companies with below-average advertising. As in the previous figure, the top two charts refer to the attention of residents in the target's state, and the two bottom ones refer to the attention of residents in the bidder's state. In both cases, the left and right graphs, respectively, refer to changes in attention to the bidder and to the target. The upper-right chart is the only one where estimates appear to differ significantly depending on the level of advertising by the target firm: the attention that target state investors devote to the acquired company drops significantly more for low-advertising companies than for high-advertising ones, for which in fact their attention remains roughly at the pre-acquisition level. This squares with the prediction of the model of Section 2.2 that familiarity reduces the relevance of geographic proximity for investors' attention: the figure indicates that a perceived increase in distance due to an out-of-state acquisition reduces local investors' attention to the acquired firm only if they are not familiar with it. In all other charts of the figure, instead, the changes in investors' attention do not differ significantly between high- and low-advertising firms.

[Insert Figure 6]

While these results are shown graphically for ease of visualization, the Web Appendix presents a more conventional regression analysis: Table A2 analyzes the response of investor attention in the bidder and target states in the weeks around the M&A announcement ($t \in [-1, +1]$); Table A3 shows the long-term response of attention, based on a time window of 52 weeks before and 52 weeks after the announcement, with the coefficient of the `PostEvent` dummy variable capturing persistent changes in investors' attention; and Tables A3 and A4 repeat the estimation for the target state splitting the sample by the size and advertising activity of the acquired company, respectively. The results of the three tables confirm those of the plots in Figures 4 and 5.

5.2 COVID-19 shocks to proximity

The COVID-19 outbreak provides another opportunity to identify the causal relationship between investors' perceived proximity to firms and their attention to stocks. One effect of the pandemic has been restoring geographic proximity's relevance to economic choices by hindering travel activity. As a result, the COVID-19 outbreak can be expected to have reduced investors' ability to collect first-hand information about nonlocal stocks, thus making it harder for them to assess news found on the web about such companies compared to news about local companies. By the same token, the pandemic should have improved their comparative advantage in collecting and processing information about local stocks. Hence, the prediction is that COVID-19 should have triggered an increase in the local skew of investors' attention since it is a positive shock to the perceived distance of nonlocal companies.

To test this hypothesis, we download weekly data for the `GSearch` variable from 2 December 2019 to 17 May 2020, as done for the data used to estimate the models in Table 3, and use them to estimate model specifications that allow for different levels and sensitivities to distance of investors' attention before and after the inception of the pandemic. Using data drawn from the New York Times, we identify the week starting on 2 March 2020 as the week the pandemic became relevant in the eyes of the investors since the first fatality due to COVID-19 was reported on Saturday, 29 February, and deaths rose dramatically to 96 in the subsequent week (from 2 to 8 March 2020). Hence, we create a `DCovid` dummy that equals 1 starting on that week, and 0 before.[22]

Table 4 presents the results. The estimates reported in column 1 refer to the same model specification presented in column 1 of Table 3, and confirm that the local-nonlocal attention gap is also present in this more recent sample. The results in column 2 show that, since the onset of the pandemic, attention from retail investors not only increased significantly, in line with the strong increase in retail trading,[23] but did so particularly for local companies: the estimated coefficient of the interaction `SameState` × `DCovid` implies that local searches during the pandemic are more than twice as large as nonlocal searches ($2.31 = 4.21/1.82$), and the attention gap increases by almost one fourth its pre-COVID-19 period ($0.23 = 4.21/18.01$). Similar results are obtained by replacing the `SameState` dummy with the continuous `Distance` variable: the estimates shown in column (3) indicate that the rise in perceived distance triggered by the pandemic (`Distance` × `DCovid`) has reduced investors' attention for nonlocal stocks: the negative effect of distance on attention during the pandemic increases more than 10% from its previous value ($0.11 = 0.16/1.41$).

[Insert Table 4]

To further test the hypothesis that the drop in investors' attention for nonlocal stocks after the onset of the pandemic stems from an increase in the perceived distance due to travel restrictions, we collect data on the number of direct flights available between U.S. cities in any given month, to construct a variable capturing the availability of air travel from any state to the state where the headquarters of our sample companies are located (source: US Department of Transportation), both before and after the COVID-19 swept across the world (as defined above). Specifically, we merge the weekly number of searches made in any state for an out-of-state company with the total number of flights between the search state and the state of the company's headquarters.

These data enable us to construct a new variable, `AdjDistance`, namely, the ratio between the `Distance` variable and the number of monthly flights from the search state

[22] In that same week, the Google search for the word "COVID" increased more than 3 times compared to the previous week, the maximum growth rate reached by this proxy for the attention growth.

[23] According to estimates by JPMorgan, since the pandemic began, retail investors have accounted for a larger fraction of total trading volumes, ranging between 20 and 30 percent, as opposed to 10 to 15 percent before the pandemic (see The *Financial Times* "Is the army of lockdown traders here to stay?", 18 October 2021).

(i.e., the state where the web search occurs) to the headquarters state (i.e., the state where the company's headquarters are located). We increase by 1 the number of flights in the denominator of this fraction to avoid dividing by zero if no flights are available – hence, no passengers travel – between the search state and the headquarters state in a given week. So by construction, `AdjDistance` is decreasing in the number of flights between the two states, its maximum value being the physical distance between the two states (i.e., `Distance`) when the number of flights connecting them drops to zero.

During the COVID-19 period, the number of flights across states dropped dramatically, as illustrated by Figure 7: their median (mean) dropped from 133 (500) in February to 126 (470) in March and 28 (150) in April 2020. Flight cancellations were not uniform: they affected short-range flights more than long-range ones; moreover, relatively more flights were canceled on routes to and from some states, such as California and New York, because the pandemic more severely struck these states. Therefore, `AdjDistance` increased on average, but not uniformly for the whole country: it rose differently depending on how many flights were canceled across states during the pandemic.

[Insert Figure 7]

As a result, while `Distance` varies only across states, `AdjDistance` also varies over time and does so differently across states, capturing different increases in the difficulty of covering the distance between states by air travel and thus of collecting on-site information about distant companies. As such, this variable is a time-varying measure of the perceived distance between an investor and a company. Hence, we expect investors' attention not only to decrease in `AdjDistance`, but also to respond more to this variable during the pandemic when air travel became generally harder or impossible. Hence, the incremental response of attention to `AdjDistance` during the pandemic should be larger than the estimated response based on physical distance since it takes into account not only cross-sectional variation in the distance but also the differential time-series variation in the number of flights across states, consistently with the findings of Da, Gurun, Li, and Warachka (2021) on the impact of air travel on investors' portfolios.

The estimates obtained when perceived distance is measured by `AdjDistance` are consistent with all three predictions: (i) its coefficient is negative in both columns 4 and 5 of Table 4; (ii) the coefficient of its interaction with the COVID-19 dummy is also negative, revealing the incremental negative impact of COVID-19 on investor attention; (iii) this incremental impact is larger relative to the corresponding pre-COVID-19 effect in column 5 ($0.21/0.40 = 0.53$) than it is if estimated based on physical distance in column 3 ($0.16/1.41 = 0.11$). Intuitively, for any given physical distance between states, those harder to reach (i.e., with fewer flights) are perceived as being farther away, and the differential impact of COVID-19 is better captured by its interaction with such perceived distance than with physical distance. The specification reported in column 6, where physical distance and the number of flights are entered as separate variables (rather than as a ratio as in the `AdjDistance` variable), reveals that each of the two variables has a distinct explanatory value, the number of flights being particularly important after the onset of the pandemic.

The specification in column 7 of Table 4 explores whether investors' attention reacted differently to local news during the pandemic compared to normal times. First, the estimates for investor attention response to local news in normal times confirm the results found in Table 3: the coefficient of the `LocalNews` variable indicates that when local newspapers report news about a company located in the same state, the company attracts more attention from local and nonlocal investors alike, as the coefficient of the interaction with `SameState` is not significantly different from zero. But during the pandemic, news in the local press attracted more investor attention than usual, especially from locals, whose incremental response to local news was almost four times as large as that of nonlocal investors: the coefficient of the triple interaction (`SameState` x `DCovid` x `LocalNews`) is 4.30, while that of the interaction `DCovid` x `LocalNews`) is 1.16. This highlights the increased importance of local information at a time when investors were almost unable to travel and collect first-hand information in distant locations and, therefore, dovetails with the idea that the pandemic was seen by investors as a sudden increase in perceived distance, leading them to refocus on assets physically close to them.

Finally, we investigate whether the COVID-19 shock reshaped the geography of investors' attention differently for unfamiliar and familiar firms. To this purpose, in Table 5 we re-estimate the regressions shown in Table 4 separately for companies that are more familiar to investors and for those less familiar to them, familiarity being again measured by the `Advertising` variable. Odd-numbered columns report the results for companies with above-average advertising (`HAdv` = 1), while even-numbered columns report the results for companies with below-average advertising (`HAdv` = 0).

[Insert Table 5]

First, by comparing the estimates shown in columns 1 and 2 and those in columns 3 and 4, it is apparent that the coefficient of the `SameState` variable is larger for less familiar companies, confirming the results in previous tables and our model's prediction that familiarity reduces the relevance of geography for investors' attention. Moreover, in the COVID-19 period, the local-nonlocal attention gap widened more for low-advertising than for high-advertising firms, based on the coefficient of the interaction between the COVID-19 dummy and the `SameState` dummy in columns 3 and 4. This result is confirmed by the coefficients of the interactions of the COVID-19 dummy with adjusted distance (`AdjDistance`) in columns 5 and 6 and with the number of flights (`NFlights`) in columns 7 and 8: in both specifications, investors' attention not only decreases with flight-adjusted distance, and does so more during the pandemic, but responds more to it for less familiar companies than for more familiar ones: familiarity appears to have mitigated the negative effect of COVID-19 on investors' attention towards distant and hard-to-reach companies.

6 Attention, Volatility and Liquidity

So far, the empirical analysis has focused on the geography of investor attention and its determinants and on the extent to which they conform to the model's predictions in Section 2. But that model also predicts that the geography of investor attention affects market outcomes. Namely, local investors' attention should increase the price impact of orders – hence return volatility – and the bid-ask spread more than the attention of nonlocal investors. Moreover, as local investors' attention also grants them a time advantage in information processing over other investors, increases in local attention should precede those in nonlocal attention. In this section, we test these additional predictions.

To estimate the dynamic relationships between the variables of interest, our 2017 weekly data must be converted into a panel. The measures used in Section 4.2 allow for comparing local and nonlocal web searches within a week, not across weeks, since the data used so far `GSearch` is re-based each week. As mentioned, Google does not provide time series of web searches disaggregated by company and state for all states simultaneously. To circumvent this problem, for each week, we multiply the fraction of web searches regarding a given company occurring in each state by the aggregate number of searches occurring for that company in the whole U.S. in the same week. This produces two weekly time series for each company: the number of web searches made in the state where the company is headquartered, `LocalSearch`, and those made in other states, `NonLocalSearch`. Additionally, for each week and company, we construct time series of additional variables, i.e., return volatility, measured by the absolute value of weekly returns (`Vol`) and the average weekly spread (`Spread`).

Then, we estimate panel vector autoregressive (pVAR) models of the following type:

$$\boldsymbol{y}_{it} = \sum_{s=1}^{S} \boldsymbol{A}_s \boldsymbol{y}_{it-s} + \boldsymbol{\mu}_i + \boldsymbol{\epsilon}_{it} \tag{17}$$

where $\boldsymbol{y}_{it}$ is the vector of endogenous variables, $\boldsymbol{A}_s$ are matrices of parameters to be estimated, $\boldsymbol{\mu}_i$ is a vector of variable-specific firm fixed effects accounting for systematic cross-sectional heterogeneity and $\boldsymbol{\epsilon}_{it}$ is a vector of variable-specific idiosyncratic error terms. We estimate the system of equations (17) using the Generalized Method of Moments (GMM), as the fixed effects estimator would generate biased estimates due to the presence of lagged dependent variables. As Nickell (1981) notes, the problem arises because the demeaning process of the fixed effect estimators generates a correlation between regressors and error terms, causing endogeneity. Instead, the GMM estimator provides consistent estimates. Since the estimation requires stationarity, we first perform Fisher-type unit-root tests based on Phillips-Perron tests (Choi, 2001). Those tests reveal that the variables used in the analysis are stationary.

Table 6 presents the estimates of three different specifications of the system of equations (17): in the first, shown in column 1, the vector $\boldsymbol{y}_{it}$ only includes `LocalSearch` and `NonLocalSearch`; in the second (column 2) and the third (columns 3), the vector of endogenous variables also includes stock price volatility (`Vol`) and the weekly average bid-ask spread of the relevant company (`Spread`), respectively. The autoregressive order is one. We also estimate models with more lags, but we report results with a single lag as we find that this lag structure is sufficient to account for the dynamic features of the variables. Since data for the `Spread` variable feature outliers, we trim the top and bottom 1% of its distribution.

[Insert Table 6]

In the model estimates shown in column 1, both local and nonlocal attention feature autoregressive memory. But the most interesting result is that their time precedence relationship is asymmetric. While lagged `LocalSearch` has a strong predictive power for `NonLocalSearch`, the latter has little predictive power for the former. In other words, local attention anticipates nonlocal attention much more than the opposite. While we estimate simple temporal correlations, this result is consistent with the idea that local investors' attention gives them a time advantage over nonlocal investors.

The estimates shown in column 2 are obtained by adding return volatility (`Vol`) to local and nonlocal attention in the vector of endogenous variables. Besides confirming the time precedence between the two attention variables shown in column 1, the estimates of column 2 show that increases in attention predict increases in volatility, with local attention being a stronger predictor than nonlocal attention – the difference between the respective coefficients (0.96 and 0.63) being statistically significant. This aligns with our model's prediction that orders placed by local investors have stronger informational content than those placed by nonlocal investors. It is also consistent with other evidence that investors' attention amplifies asset volatility (Andrei and Hasler, 2014). Moreover, neither attention variable is predicted by absolute returns, as expected. It is worth relating these results to those presented in Table 3, which indicate that a rise in return volatility elicits a stronger contemporaneous increase in local rather than in nonlocal attention, also when the potential feedback of attention on volatility is controlled for with IV estimation. The estimates in column 2 of Table 6 investigate precisely this feedback effect from attention to volatility, exploiting the dynamic structure of the data, and show that also, in this case, the relationship is stronger for local attention.

Column 3 presents estimates of the dynamic relationship between attention and the bid-ask spread: both local and nonlocal web searches are positively and significantly correlated with subsequent values of the bid-ask spread. The difference between the two coefficients (0.26 and 0.34) is not statistically significant: increases in attention predict a drop in market liquidity, consistently with the model. However, there is no evidence of this dynamic relationship being stronger for local rather than nonlocal investors. Instead, the bid-ask spread has no predictive power for either investor group's attention.

7 Conclusion

Retail investors pay more than twice as much attention to news about firms whose headquarters are located in their state than firms elsewhere. This attention gap widens coincidentally with news releases (such as earnings announcements) and increases in return volatility. However, local investors' attention toward local companies does not stem from a familiarity bias: companies that spend more on advertising attract less local attention, other things equal.

These findings are consistent with a model where the local investors skew their attention allocation towards local assets because they are better at processing information about them rather than because of behavioral biases. They are also consistent with other recent work documenting that investors' attention predicts stock risk-adjusted returns and that this relationship is stronger for local investor attention (Gargano and Rossi (2018), Cziraki, Mondria, and Wu (2021) and Dyer (2021)).

Importantly, our evidence indicates that investors' attention is causally related to their perceived proximity to firms. First, after an out-of-state company acquires a firm, local investors switch their attention away from the acquired firm and towards the acquiring one more than the investors close to the acquiring firm. This is consistent with local investors perceiving the local company as more distant than before and investors in the acquiring firm's state considering the two firms as geographically closer. Second, the increase in perceived distance of nonlocal firms due to COVID-19-related travel restrictions has been associated with a greater local attention bias. The decline in the relative attention to nonlocal stocks has been stronger for firms in locations connected by fewer flights after the pandemic outbreak.

The evidence from these "perceived proximity shocks" indicates that the local attention bias documented in this paper is not simply a mechanical consequence of the local ownership bias shown by earlier studies such as Coval and Moskowitz (1999) and Grinblatt and Keloharju (2001), which in principle could stem from behavioral biases, such as familiarity. The evidence consistently shows that, if anything, investors' familiarity with a company (as measured by its advertising expenditure) tends to reduce the relevance of their proximity to the company as a determinant of their attention.

Finally, increases in local attention are shown to predict subsequent increases in return volatility and bid-ask spreads, as well as in nonlocal attention. In contrast, they are not predicted by them. This empirical finding is also consistent with an information-processing advantage of local investors: the greater informational content of their orders should trigger larger price movements and lead market makers to widen their bid-ask spread.

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Appendix

Proof of Proposition 3. Recalling that $\theta_L > \theta_N$, condition (6) is met for both investors if $\pi < \theta_N/(\theta_N + \theta_L) < 1/2$. In the region $\pi \in (\theta_N/(\theta_N + \theta_L), \theta_L/(\theta_N + \theta_L))$, there is no equilibrium where nonlocal investors are willing to exert attention. Still, to check that there is an equilibrium where local investors do, the equilibrium must be recalculated on the assumption that local investors are the only informed ones and trade with probability π rather than $\pi/2$. Absent nonlocal investors, local ones choose their attention level a_L to maximize their objective function:

$$\max_{a_i \in [0,1]} \pi(\overline{v} - p_A + q a_i \sigma) - \frac{a_L^2}{2\theta_L},$$

Hence, their optimal attention is

$$a_L^* = \theta_L \pi q \sigma, \tag{18}$$

the equilibrium bid-ask spread (deviation of the ask from the mid-price) is

$$p_A - \overline{v} = \pi q \sigma a_L^* = \theta_L (\pi q \sigma)^2,$$

and the local investors' expected profits are

$$\Pi_L = \pi(\overline{v} - p_A + q a_L^* \sigma) - \frac{a_L^{*2}}{2\theta_L} = \theta_L (\pi q \sigma)^2 \left(\frac{1}{2} - \pi \right), \tag{19}$$

which is positive for $\pi < 1/2$, i.e. the same condition for both types of investors to exert attention and trade when they are identical.

Figure 1
Scatterplot of average `GSearch` by state

This figure shows the scatterplots of local (y-axis) vs. nonlocal (x-axis) `GSearch` by state. The solid line is the bisector.

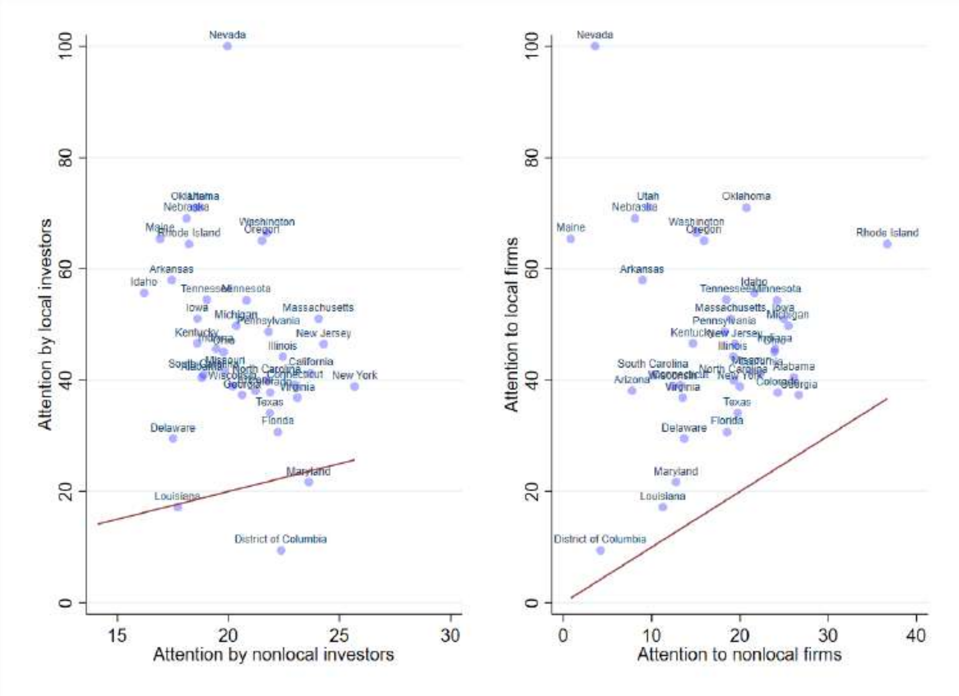


Figure 2
Scatterplot of average `GSearch` by firm

This figure shows the scatterplot of local (y-axis) vs. nonlocal (x-axis) `GSearch` by firms in our sample. The solid line is the bisector.

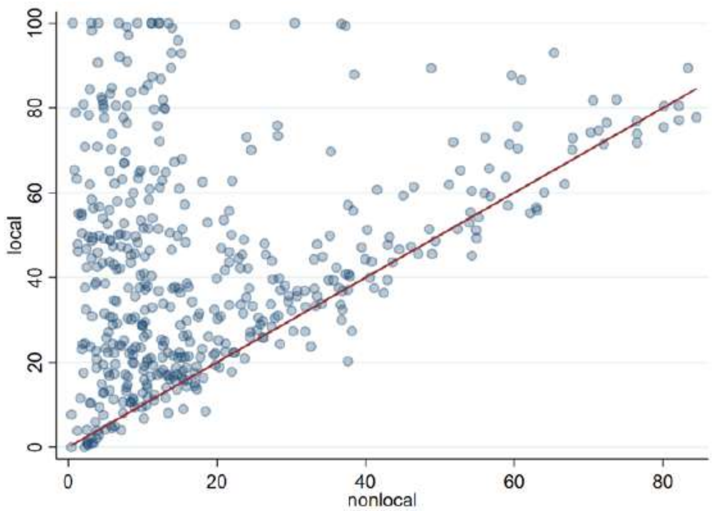


Figure 3
`GSearch` around earnings announcements

These figures show changes in attention (Δ`GSearch`) by local and nonlocal investors and in their attention gap around earnings announcements. The top diagram plots Δ`GSearch` by local and nonlocal investors in a 7-day window centered around the earnings announcement date (chart a), and the difference between them (chart b). The bottom diagram plots Δ`GSearch` by local and nonlocal investors in a 7-hour window centered around the earnings announcement time (chart c), and the difference between them (chart d). The whiskers indicate 5% confidence bounds.

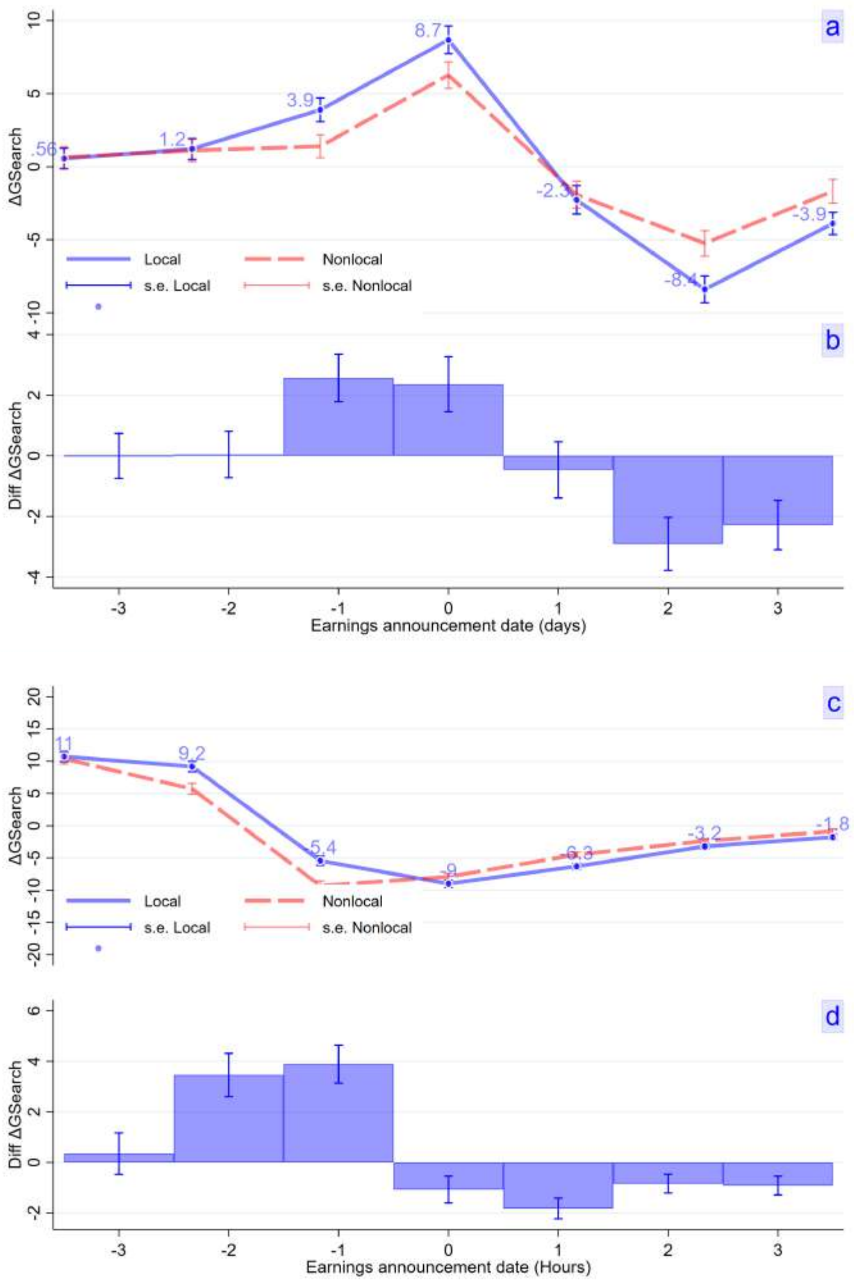


Figure 4
Post-acquisition changes in investor attention

These figures show the change in attention in the weeks following corporate acquisitions. The left diagrams plot `GSearch` referring to the stock of the bidder company in the target's state (upper chart) and in the bidder's state (lower chart). The right diagrams plot `GSearch` referring to the stock of the target's company in the target's state (upper chart) and in the bidder's state (lower chart). The whiskers indicate 5% confidence bounds.

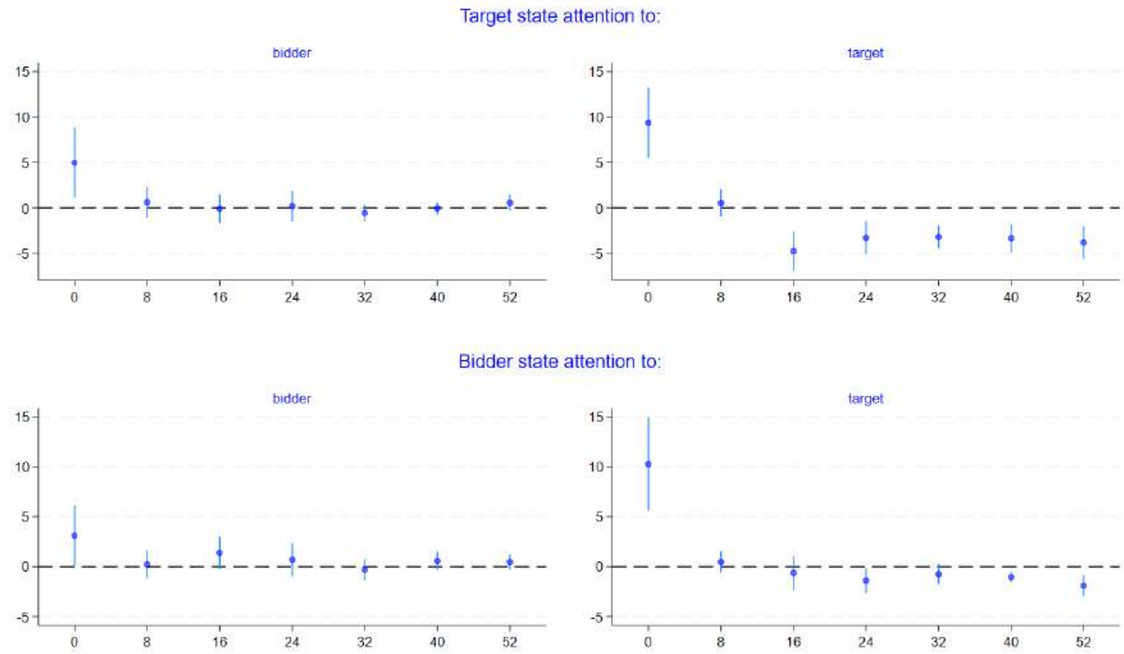


Figure 5

Post-acquisition changes in investor attention, by size of the target company

These figures show the change in attention by residents of the target company's state (top charts) and by residents of the bidder company's state (bottom charts) in the weeks following corporate acquisitions. The charts on the left plot changes in attention to the acquiring company (bidder) and those on the right changes in attention to the acquired company (target). The plot distinguishes acquisitions with above-average size (blue dots) from those with below-average size (red dots). The whiskers indicate 5% confidence bounds.

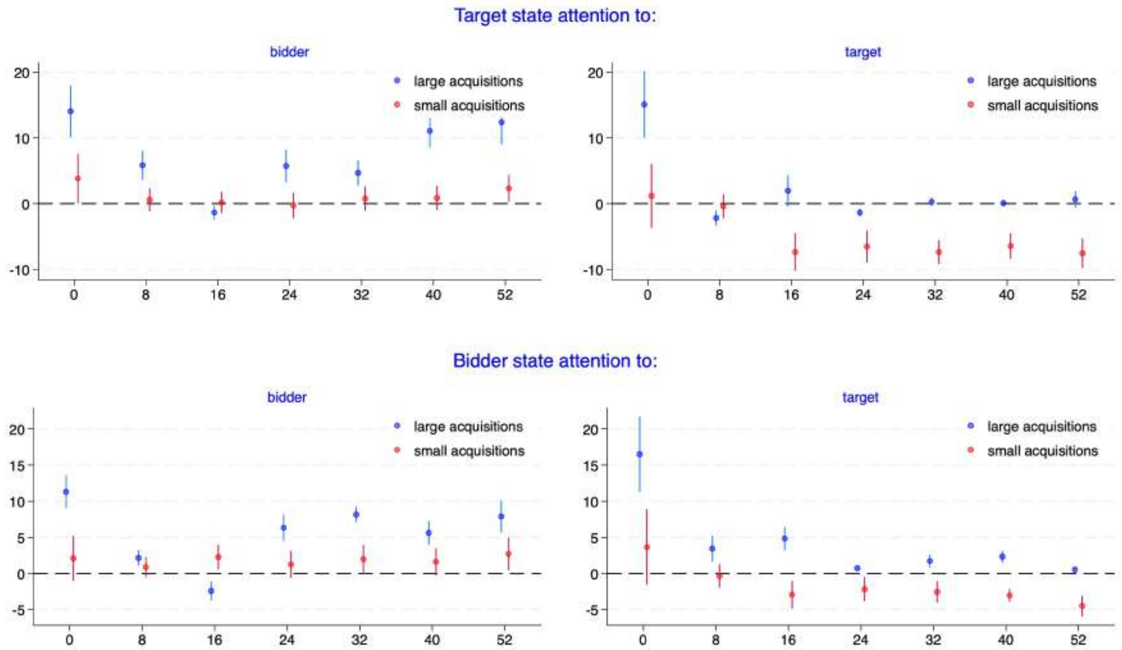


Figure 6
Post-acquisition changes in investors' attention, by advertising of the target company

These figures show the change in attention by residents of the target company's state (top charts) and by residents of the bidder company's state (bottom charts) in the weeks following corporate acquisitions. The charts on the left plot changes in attention to the acquiring company (bidder) and those on the right changes in attention to the acquired company (target). The plot distinguishes above-average advertising targets (blue dots) from below-average advertising targets (red dots). The whiskers indicate 5% confidence bounds.

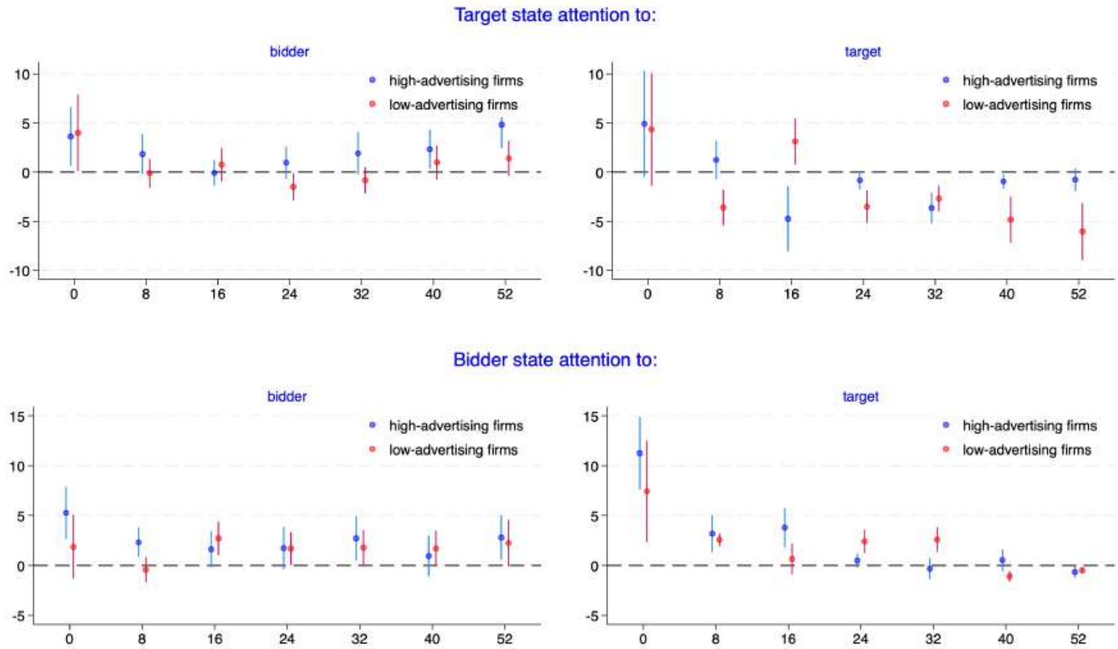
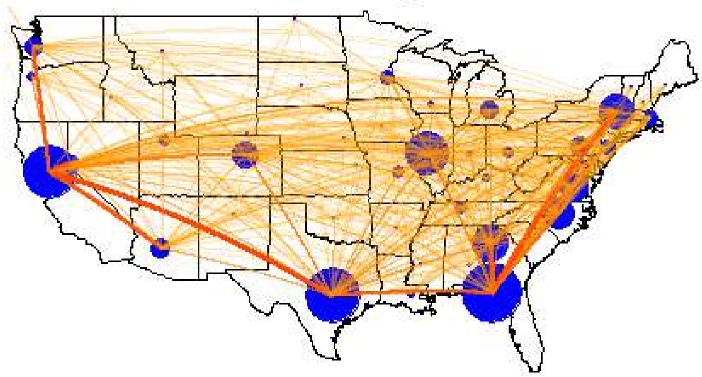


Figure 7
Flight connections between states: before vs. after COVID

The figure shows the number of flights connecting states in February and May 2020, respectively. The size of the blue circles measures the number of flights to the corresponding state. The darkness and thickness of the orange lines measure the number of active routes connecting a couple of states.

February



May

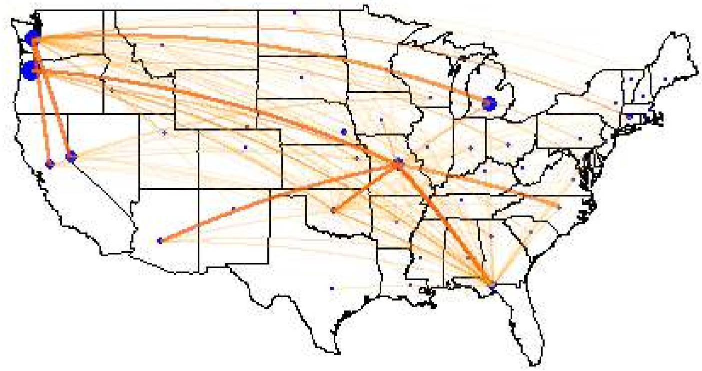


Table 1
Summary statistics

This table shows summary statistics for the variables used in the empirical analysis. All variables are described in Section 3. Reported statistics are means, standard deviations (SD), minima (Min), and maxima (Max). The total number of observations is 1,244,800.

	Mean	SD	Min	Max
`GSearch`	20.14	26.85	0.00	100.00
`SameState`	0.02	0.14	0.00	1.00
`Cit10K`	0.51	1.04	0	9.31
`Distance`	1.86	1.37	0.00	8.22
`News`	3.40	1.89	0.00	8.45
`LocalNews`	0.00	0.06	0.00	3.53
`Advertising`	0.03	0.03	0.00	0.37
`Vol`	0.02	0.02	0.00	0.72
`NegRet`	0.43	0.50	0.00	1.00

Table 2
Summary statistics by search state

This table shows the distribution of company headquarters across states and the mean of web searches (`GSearch`) by search states and company headquarters states in 2017. For each of the states listed in column 1, local investors are defined as the residents of that state, and nonlocal investors as those residents in other states; local firms as the companies whose headquarters are located in that state, and nonlocal firms as those whose headquarters are located in other states. Columns 2 and 3 report the number and fraction of company headquarters in the corresponding state indicated in column 1. Columns 4 and 5 show the mean total web searches made by local investors and those directed to local firms, respectively. Columns 6 and 7 show the mean web searches directed to local firms by local and nonlocal investors, respectively. Column 8 shows the difference between mean web searches directed to local firms by local and nonlocal investors. Column 9 shows the mean web searches directed to nonlocal firms by local investors. Column 10 reports the difference between mean web searches directed to local and tnonlocal firms by local investors. Significance code: * p<0.10, ** p<0.05, *** p<0.01.

(1) State name	(2) No. of firms	(3) % of firms	(4) Total searches by local investors	(5) Total searches for local firms	(6) Local searches for local firms	(7) Nonlocal searches for local firms	(8) Local-nonlocal gap: (6) − (7)	(9) Local searches for nonlocal firms	(10) Local-nonlocal gap: (6) − (9)
Alabama	2	0.42	18.89	26.41	40.47	26.12	14.35***	18.80	21.67***
Alaska			15.81					15.81	
Arizona	4	0.83	21.35	8.38	38.10	7.78	30.32***	21.21	16.88***
Arkansas	3	0.63	17.71	9.93	58.00	8.95	49.05***	17.45	40.55***
California	73	15.21	26.38	22.73	41.22	22.35	18.87***	23.71	17.51***
Colorado	10	2.08	22.20	24.54	37.76	24.27	13.5***	21.87	15.89***
Connecticut	14	2.92	23.46	13.77	39.10	13.25	25.85***	22.99	16.11***
Delaware	2	0.42	17.56	13.99	29.53	13.68	15.85***	17.51	12.02***
District of Columbia	1	0.21	22.34	4.31	9.42	4.20	5.22**	22.37	-12.94***
Florida	14	2.92	22.47	18.78	30.66	18.53	12.13***	22.22	8.44***
Georgia	16	3.33	21.17	26.86	37.35	26.64	10.71***	20.61	16.74***
Hawaii			19.17					19.17	
Idaho	1	0.21	16.29	22.33	55.67	21.65	34.03***	16.21	39.46***
Illinois	32	6.67	23.91	19.73	44.23	19.23	25.00***	22.45	21.78***
Indiana	7	1.46	19.83	24.41	45.60	23.97	21.63***	19.45	26.15***
Iowa	2	0.42	18.74	25.45	51.04	24.93	26.11***	18.60	32.44***
Kansas			21.12					21.12	
Kentucky	3	0.63	18.77	15.29	46.63	14.65	31.98***	18.59	28.03***
Louisiana	3	0.63	17.71	11.38	17.19	11.26	5.94***	17.71	-0.52
Maine	1	0.21	17.03	2.12	65.38	0.83	64.55***	16.93	48.45***
Maryland	10	2.08	23.58	12.93	21.69	12.75	8.93***	23.62	-1.93
Massachusetts	21	4.38	25.24	19.62	51.04	18.97	32.07***	24.06	26.98***
Michigan	10	2.08	20.93	25.96	49.76	25.47	24.29***	20.36	29.4***
Minnesota	13	2.71	21.72	24.78	54.34	24.18	30.17***	20.81	33.53***
Mississippi			16.66					16.66	
Missouri	10	2.08	20.31	21.71	41.60	21.30	20.29***	19.85	21.74***
Nebraska	2	0.42	18.33	9.33	69.07	8.11	60.96***	18.12	50.95***

(continues on next page)

Table 2
Summary statistics by search state (continued)

This table shows the distribution of company headquarters across states and the mean of web searches (`GSearch`) by search states and company headquarters states in 2017. For each of the states listed in column 1, local investors are defined as the residents of that state, and nonlocal investors as those residents in other states; local firms as the companies whose headquarters are located in that state, and nonlocal firms as those whose headquarters are located in other states. Columns 2 and 3 report the number and fraction of company headquarters in the corresponding state indicated in column 1. Columns 4 and 5 show the mean total web searches made by local investors and those directed to local firms, respectively. Columns 6 and 7 show the mean web searches directed to local firms by local and nonlocal investors, respectively. Column 8 shows the difference between mean web searches directed to local firms by local and nonlocal investors. Column 9 shows the mean web searches directed to nonlocal firms by local investors. Column 10 reports the difference between mean web searches directed to local andto nonlocal firms by local investors. Significance code: * p<0.10, ** p<0.05, *** p<0.01.

(1) State name	(2) No. of firms	(3) % of firms	(4) Total searches by local investors	(5) Total searches for local firms	(6) Local searches for local firms	(7) Nonlocal searches for local firms	(8) Local-nonlocal gap: (6) − (7)	(9) Local searches for nonlocal firms	(10) Local-nonlocal gap: (6) − (9)
Nevada	2	0.42	20.30	5.50	100.00	3.57	96.43***	19.96	80.04***
New Hampshire			19.36					19.36	
New Jersey	18	3.75	25.12	19.97	46.48	19.43	27.04***	24.29	22.19***
New Mexico			17.54					17.54	
New York	62	12.92	27.39	20.36	38.86	19.99	18.87***	25.68	13.18***
North Carolina	13	2.71	22.19	19.69	39.96	19.28	20.69***	21.72	18.25***
North Dakota			14.85					14.85	
Ohio	21	4.38	20.89	24.32	45.07	23.90	21.17***	19.79	25.29***
Oklahoma	4	0.83	18.94	21.73	70.99	20.72	50.26***	18.50	52.48***
Oregon	2	0.42	21.69	16.90	65.08	15.92	49.16***	21.51	43.57***
Pennsylvania	16	3.33	22.71	18.86	48.72	18.25	30.48***	21.81	26.92***
Rhode Island	4	0.83	18.61	37.23	64.44	36.67	27.76***	18.23	46.21***
South Carolina	1	0.21	18.94	10.78	40.98	10.16	30.82***	18.89	22.09***
South Dakota			14.86					14.86	
Tennessee	9	1.88	19.69	19.16	54.48	18.44	36.05***	19.02	35.46***
Texas	36	7.50	22.78	20.02	34.10	19.73	14.37***	21.86	12.24***
Utah	2	0.42	18.93	10.84	71.09	9.61	61.48***	18.71	52.38***
Vermont			15.89					15.89	
Virginia	16	3.33	23.56	13.96	36.86	13.50	23.36***	23.10	13.76***
Washington	12	2.50	22.86	16.11	66.47	15.08	51.39***	21.74	44.73***
West Virginia			16.63					16.63	
Wisconsin	8	1.67	20.50	12.89	38.93	12.36	26.57***	20.19	18.74***
Wyoming			14.11					14.11	
Total	480	100	20.14	20.14	42.90	19.68	23.23***	19.68	23.23***

Table 3
Investor attention, geographic proximity and news

This table shows estimates from the regression of `GSearch` on geographic variables (`SameState`, `Distance` or `Cit10K`), news-related variables (`News` and `LocalNews`), return volatility (`Vol`) and company familiarity (proxied by `Advertising`). All the regressions in the table are estimated by OLS except for those in column 5, where the specification of column 4 is re-estimated with 2SLS, instrumenting `Vol` and the interaction `SameState`×`Vol` by a volatility measure based on industry index returns and by its interaction with the `SameState` dummy. In columns 6 and 7, the regression is re-estimated separately for the subsamples with positive and negative stock returns, respectively (based on the dummy `NegRet`). All variables are described in Section 3. All specifications include week, state, and firm fixed effects. The inference is based on unit-cluster standard errors. t-statistics are reported in brackets. Significance code: * p<0.10, ** p<0.05, *** p<0.01.

	(1)	(2)	(3)	(4)	(5) IV	(6) NegRet = 0	(7) NegRet = 1
SameState	20.74***			17.94***	17.84***	18.72***	16.96***
	[16.94]			[6.92]	[17.99]	[6.97]	[6.57]
Cit10K		2.44***					
		[14.35]					
Distance			-1.39***				
			[-11.21]				
News				0.20***	0.22***	0.19**	0.23**
				[2.62]	[5.06]	[2.16]	[2.22]
SameState × News				1.26**	1.06***	1.18**	1.36**
				[2.27]	[8.87]	[2.09]	[2.44]
LocalNews				3.05***	2.85***	2.58*	3.62***
				[2.60]	[8.10]	[1.88]	[3.52]
SameState × LocalNews				-3.38	-2.31	-5.22	-0.89
				[-0.80]	[-1.23]	[-1.34]	[-0.16]
Vol				5.33***	7.37	3.54*	7.93***
				[3.32]	[1.64]	[1.85]	[3.07]
SameState × Vol				62.15***	101.14**	58.67***	65.10***
				[3.19]	[2.21]	[2.89]	[2.73]
SameState × Advertising				-83.60*	-81.10***	-89.54**	-76.61*
				[-1.94]	[-10.93]	[-2.00]	[-1.83]
firm FEs	yes	yes	yes	yes	yes	yes	yes
state FEs	yes	yes	yes	yes	yes	yes	yes
week FEs	yes	yes	yes	yes	yes	yes	yes
N	1244800	1215050	1244800	1244800	1124350	703500	541300
$\bar{R}^2$	0.488	0.482	0.479	0.489	0.022	0.487	0.492

Table 4
COVID-induced shocks to local and nonlocal investor attention

This table shows estimates from the regression of `GSearch` on distance measures (`SameState`, `Distance` or `AdjDistance`), the dummy `DCovid`, and the corresponding interaction terms. Coefficients are estimated by OLS. All variables are described in Section 3 and 5.2. All specifications include firm and state fixed effects. The inference is based on unit-cluster standard errors. t-statistics are reported in brackets. Significance code: * p<0.10, ** p<0.05, *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
`SameState`	19.94***	18.01***					17.24***
	[16.72]	[15.34]					[14.42]
`DCovid`		1.82***	2.20***		2.14***	2.07***	1.82***
		[9.70]	[9.96]		[10.69]	[9.12]	[9.73]
`SameState` × `DCovid`		4.21***					3.41***
		[8.62]					[6.26]
`Distance`			-1.41***			-1.33***	
			[-11.28]			[-9.13]	
`Distance` × `DCovid`			-0.16**			-0.12*	
			[-2.40]			[-1.77]	
`AdjDistance`				-0.44***	-0.40***		
				[-5.38]	[-4.47]		
`AdjDistance` × `DCovid`					-0.21***		
					[-3.81]		
`NFlights`						0.09	
						[1.01]	
`NFlights` × `DCovid`						0.32***	
						[3.84]	
`LocalNews`							1.81***
							[3.68]
`SameState` × `LocalNews`							2.98
							[1.51]
`DCovid` × `LocalNews`							1.16*
							[1.86]
`SameState` × `DCovid` × `LocalNews`							4.30**
							[2.40]
firm FEs	yes	yes	yes	yes	yes	yes	yes
state FEs	yes	yes	yes	yes	yes	yes	yes
N	560541	560541	560541	560541	560541	560541	560541
$\bar{R}^2$	0.488	0.490	0.482	0.479	0.480	0.482	0.490

Table 5
COVID-induced shocks to investor attention to familiar vs. unfamiliar firms

This table presents results of regressions of `GSearch` on distance measures (`SameState`, `Distance` or `AdjDistance`), the COVID-19 dummy `DCovid` and the respective interactions, estimated separately for companies featuring above-average familiarity (`HAdv` = 1) and below-average familiarity (`HAdv` = 0), respectively. Coefficients are estimated by OLS. All variables are described in Section 3 and 5.2. All specifications include firm and state fixed effects. The inference is based on unit-cluster standard errors. t-statistics are reported in brackets. Significance code: * p<0.10, ** p<0.05, *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HAdv = 1	HAdv = 0	HAdv = 1	HAdv = 0	HAdv = 1	HAdv = 0	HAdv = 1	HAdv = 0
SameState	16.38***	24.23***	14.87***	21.89***				
	[10.04]	[13.67]	[9.36]	[12.40]				
DCovid			1.44***	2.28***	1.70***	2.65***	1.56***	2.56***
			[5.98]	[7.68]	[6.46]	[8.59]	[5.00]	[7.65]
SameState × DCovid			3.28***	5.12***				
			[5.57]	[6.45]				
Distance							-0.96***	-1.81***
							[-5.31]	[-7.59]
Distance × DCovid							-0.06	-0.16
							[-0.56]	[-1.58]
AdjDistance					-0.34***	-0.49***		
					[-3.02]	[-3.44]		
AdjDistance × DCovid					-0.18**	-0.24***		
					[-2.41]	[-2.80]		
NFlights							0.16	0.02
							[1.46]	[0.14]
NFlights × DCovid							0.32***	0.34***
							[2.76]	[2.76]
firm FEs	yes	yes	yes	yes	yes	yes	yes	yes
state FEs	yes	yes	yes	yes	yes	yes	yes	yes
N	271728	272952	271728	272952	271728	272952	271728	272952
$\bar{R}^2$	0.497	0.466	0.498	0.469	0.492	0.454	0.493	0.457

Table 6
Local and nonlocal attention, return volatility and bid-ask spread

This table shows GMM estimates of panel VAR models whose endogenous variables are the number of weekly web searches by residents in the relevant company's state (`LocalSearch`) and by residents in other states (`NonLocalSearch`), the absolute value of the relevant stock return (`Vol`) and its average relative bid-ask spread (`Spread`) over the relevant week, using 2017 data. The inference is based on robust standard errors. z-statistics are reported in brackets. Significance code: * p<0.10, ** p<0.05, *** p<0.01.

	(1)	(2)	(3)
`LocalSearch` equation			
$\texttt{LocalSearch}_{t-1}$	0.11***	0.11***	0.12***
	[3.84]	[3.85]	[3.90]
$\texttt{NonLocalSearch}_{t-1}$	0.02***	0.02***	0.02***
	[2.68]	[2.66]	[2.78]
$\texttt{Vol}_{t-1}$		0.00	
		[0.06]	
$\texttt{Spread}_{t-1}$			0.00
			[0.28]
`NonLocalSearch` equation			
$\texttt{LocalSearch}_{t-1}$	0.23***	0.23***	0.23***
	[5.00]	[5.02]	[4.62]
$\texttt{NonLocalSearch}_{t-1}$	0.40***	0.40***	0.41***
	[9.48]	[9.47]	[8.61]
$\texttt{Vol}_{t-1}$		-0.00	
		[-0.78]	
$\texttt{Spread}_{t-1}$			0.00
			[0.36]
`Vol` equation			
$\texttt{LocalSearch}_{t-1}$		0.96***	
		[5.10]	
$\texttt{NonLocalSearch}_{t-1}$		0.63***	
		[5.32]	
$\texttt{Vol}_{t-1}$		-0.00	
		[-0.30]	
`Spread` equation			
$\texttt{LocalSearch}_{t-1}$			0.26***
			[4.98]
$\texttt{NonLocalSearch}_{t-1}$			0.34***
			[5.19]
$\texttt{Spread}_{t-1}$			0.36***
			[6.71]
N	23531	23531	18646

Web Appendix

Table A1
Robustness checks

This table presents robustness checks of the estimates presented in Table 3. Columns 1 and 5 show OLS estimates for the subsample that excludes firms headquartered in California and the State of New York. Columns 2 and 6 present OLS estimates for the subsample of firms with a ticker longer than one letter. Columns 3 and 7 display OLS estimates for specifications that include the dummy variable `Holi`. Columns 4 and 8 present OLS estimates for regressions where the attention variable is measured by $\ln \frac{\texttt{GSearch}+1\times10^{-7}}{100-\texttt{GSearch}+1\times10^{-7}}$. All variables except `Holi` are described in Section 3. `Holi` is described in Section 4.2. All models include week, state, and firm fixed effects among regressors. The inference is based on unit-cluster standard errors. t-statistics are reported in brackets. Significance code: * p<0.10, ** p<0.05, *** p<0.01.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
`SameState`	23.46***	21.15***	20.98***	2.99***	19.75***	17.86***	18.25***	2.84***
	[15.52]	[17.04]	[16.94]	[16.80]	[6.51]	[6.88]	[6.99]	[7.03]
`Holi`			0.09				0.08	
			[1.04]				[1.00]	
`SameState` × `Holi`			-4.53***				-4.04***	
			[-4.61]				[-3.99]	
`News`					0.20**	0.20**	0.20***	0.05***
					[2.13]	[2.57]	[2.63]	[4.84]
`SameState` × `News`					1.38**	1.43**	1.23**	0.12
					[1.97]	[2.55]	[2.22]	[1.35]
`LocalNews`					2.05**	3.20***	3.05***	0.37**
					[2.28]	[2.63]	[2.60]	[2.45]
`SameState` × `LocalNews`					-4.84	-3.99	-3.37	-0.77
					[-1.05]	[-0.93]	[-0.79]	[-1.08]
`Vol`					2.4	5.45***	5.32***	1.91***
					[1.21]	[3.37]	[3.32]	[8.96]
`SameState` × `Vol`					70.81***	61.00***	62.15***	8.33***
					[2.78]	[3.12]	[3.19]	[2.73]
`SameState` × `Advertising`					-69.98	-84.24*	-83.82*	-12.06*
					[-1.57]	[-1.96]	[-1.95]	[-1.72]
firm FEs	yes	yes	yes	yes	yes	yes	yes	yes
state FEs	yes	yes	yes	yes	yes	yes	yes	yes
week FEs	yes	yes	yes	yes	yes	yes	yes	yes
N	893800	1218800	1244800	1244800	893800	1218800	1244800	1244800
adj. R^2	0.478	0.456	0.488	0.492	0.478	0.456	0.489	0.493

Table A2
Short-term changes in attention around out-of-state acquisitions

This table presents the estimated coefficients of regressions whose dependent variable is the number of web searches regarding the bidder company in its own state (column 1) or in the target company's state (column 2) and those regarding the target company in its own state (column 3) or in the bidder's state (column 4) in a 3-weeks event window bracketed around an out-of-state company acquisition in 2017. The $t = -1$, $t = 0$, and $t = +1$ dummy variables take the value 1 in the pre-acquisition week, in the acquisition week, and in the post-acquisition week, respectively, for the relevant company and set of investors. Their respective coefficients are the estimated changes in attention by the relevant group of investors for the bidder company (in columns 1 and 2) or the target company (in columns 3 and 4) in the pre-acquisition week, in the acquisition week, and in the post-acquisition week, respectively. The constant measures the estimated average level of attention by the relevant group of investors for the bidder company (in columns 1 and 2) or the target company (in columns 3 and 4). The inference is based on unit-cluster standard errors. t-statistics are reported in brackets. Significance code: * p<0.10, ** p<0.05, *** p<0.01.

attention	(1)	(2)	(3)	(4)
from →	bidder state	target state	target state	bidder state
to →	bidder	bidder	target	target
$t = -1$	2.20	6.47*	21.16***	12.09***
	[0.93]	[1.94]	[4.44]	[3.18]
$t = 0$	2.93	4.83*	8.93***	7.22**
	[1.30]	[1.73]	[2.73]	[2.26]
$t = +1$	4.33*	0.39	9.43***	7.86*
	[1.93]	[0.16]	[2.65]	[1.81]
constant	41.70***	38.82***	35.02***	29.91***
	[15.45]	[12.89]	[21.11]	[15.33]
N	4182	4182	1122	1122

Table A3
Long-term changes in attention around out-of-state acquisitions

This table presents the estimated coefficients of regressions whose dependent variable is the number of web searches regarding the bidder company in its state (column 1) or in the target company's state (column 2) and those regarding the target company in its state (column 3) or in the bidder's state (column 4) in a 105-weeks event window bracketed around an out-of-state company acquisition in 2017. The `PostEvent` dummy variable takes value 1 in the year following the acquisition for the relevant company and set of investors. Its coefficient is the estimated change in attention by the relevant group of investors for the bidder company (in columns 1 and 2) or the target company (in columns 3 and 4) in the post-acquisition year, respectively. The constant measures the estimated average level of attention by the relevant group of investors for the bidder company (in columns 1 and 2) or the target company (in columns 3 and 4). The inference is based on unit-cluster standard errors. t-statistics are reported in brackets. Significance code: * p<0.10, ** p<0.05, *** p<0.01.

attention	(1)	(2)	(3)	(4)
from →	bidder state	target state	target state	bidder state
to →	bidder	bidder	target	target
`PostEvent`	2.02***	1.26*	-4.41***	-1.66**
	[2.90]	[1.79]	[-8.23]	[-4.97]
constant	41.75***	38.95***	33.46***	29.51***
	[21.71]	[18.30]	[31.14]	[29.56]
N	8200	8200	1486	1486

Table A4
Long-term changes in attention around out-of-state acquisitions, broken down by size of the target company

This table presents the estimated coefficients of regressions in which the dependent variable is the number of web searches from the target company state (Panel A) to the bidder and target company and from the bidder company state (Panel B) to the bidder and target company. The samples are broken down between above-average and below-average acquisition size, considering a 52-weeks event window after an out-of-state company acquisition in 2017. The `PostEvent` dummy variable takes value 1 in the year following the acquisition for the relevant company and set of investors. The inference is based on unit-cluster standard errors. t-statistics are reported in brackets. Significance code: * p<0.10, ** p<0.05, *** p<0.01.

Panel A				
attention	(1)	(2)	(3)	(4)
from →	target state	target state	target state	target state
to →	bidder	bidder	target	target
acquisition size →	large	small	large	small
`PostEvent`	6.44***	0.78	0.17	-6.52***
	[5.99]	[1.22]	[0.30]	[-7.23]
constant	44.23***	38.45***	31.90***	34.18***
	[21.08]	[18.10]	[30.42]	[29.46]
N	700	7500	462	1024

Panel B				
attention	(5)	(6)	(7)	(8)
from →	bidder state	bidder state	bidder state	bidder state
to →	bidder	bidder	target	target
level of advertising →	large	small	large	small
`PostEvent`	4.69***	1.77**	3.82***	-4.20***
	[7.94]	[2.53]	[9.62]	[-6.33]
constant	50.40***	40.94***	32.32***	28.21***
	[31.63]	[21.20]	[17.08]	[20.29]
N	700	7500	462	1024

Table A5
Long-term changes in attention around out-of-state acquisitions, broken down by advertising of the target company

This table presents the estimated coefficients of regressions in which the dependent variable is the number of web searches from the target company state (Panel A) to the bidder and target company and from the bidder company state (Panel B) to the bidder and target company. The samples are broken down between above-average and below-average levels of advertising, considering a 52-weeks event window after an out-of-state company acquisition in 2017. The `PostEvent` dummy variable takes value 1 in the year following the acquisition for the relevant company and set of investors. The inference is based on unit-cluster standard errors. t-statistics are reported in brackets. Significance code: * p<0.10, ** p<0.05, *** p<0.01.

Panel A				
attention	(1)	(2)	(3)	(4)
from →	target state	target state	target state	target state
to →	bidder	bidder	target	target
level of advertising →	high	low	high	low
`PostEvent`	1.93***	0.17	-1.53**	-3.59***
	[2.87]	[0.30]	[-2.08]	[-3.63]
constant	37.46***	42.58***	33.09***	39.26***
	[19.30]	[18.18]	[46.79]	[25.43]
N	3500	3800	655	349

Panel B				
attention	(5)	(6)	(7)	(8)
from →	bidder state	bidder state	bidder state	bidder state
to →	bidder	bidder	target	target
level of advertising →	high	low	high	low
`PostEvent`	2.07***	1.61**	1.38***	2.67***
	[2.64]	[2.51]	[3.83]	[5.91]
constant	40.99***	45.19***	35.63***	27.38***
	[22.79]	[22.08]	[19.79]	[24.12]
N	3500	3800	655	349