Asymmetric Attention and Stock Returns*

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Abstract

This paper constructs a new measure of attention allocation by local investors relative to nonlocals using aggregate search volume from Google. We first present a conceptual framework in which local investors optimally choose to focus their attention on local stocks when they receive private news, leading to an asymmetric allocation of attention between local and nonlocal investors. Consistent with the main prediction of this framework, we find that firms attracting abnormally high asymmetric attention from local relative to nonlocal investors earn higher returns. A portfolio that goes long in stocks with high asymmetric attention and short in stocks with low asymmetric attention has an alpha of 32 basis points per month. The results are stronger for stocks with a greater degree of information frictions. The new measure of asymmetric attention allows one to infer the arrival of unobservable private information by observing investors' attention allocation behavior.

Keywords: Limited attention, Geography, Asymmetric Information, Stock Returns.

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1 Introduction

This paper brings together two strands of the literature in finance that study the role of *i)* geography and *ii)* limited attention in financial decisions. There is substantial evidence suggesting that investors possess local information advantages and supporting the role of geography in finance. It is also well documented that investors have limited attention and need to choose what to learn. Our contribution to both literatures is to construct a measure of the attention allocation decisions of local retail investors relative to nonlocals and study its asset pricing implications.

The challenge when taking attention allocation theories to the data is to find direct measures of information processing efforts. Previous research used different indirect measures of attention such as advertising expenses (Lou, 2008), media coverage (Fang and Peress, 2009), abnormal trading volume (Hou, Peng, and Xiong, 2008), extreme returns (Barber and Odean, 2008) and the state of the business cycle (Kacperczyk, van Nieuwerburgh, and Veldkamp, 2016). Recent work by Mondria, Wu, and Zhang (2010), Da, Engelberg, and Gao (2011), and Drake, Roulstone, and Thornock (2012) overcame this challenge by using measures of aggregate search frequency from AOL and Google search engines, respectively, as direct measures of attention. As argued by Da, Engelberg, and Gao (2011), if a search engine user is searching for a company ticker, it is highly likely that this user is interested in financial information about the company. Notwithstanding, the distinction between the effort exerted by locals relative to nonlocals remains a challenge to the evaluation of current attention allocation theories.

We obtain direct measures of such efforts by exploring a feature of Google Trends that allows us to distinguish the location, by U.S. state, in which searches are performed. We construct a measure of abnormal asymmetric attention, which captures unusual patterns in the attention allocated to a stock by locals relative to nonlocals, and explore its asset pricing implications. An increase in abnormal asymmetric attention means that local retail investors are allocating an unusually large amount of their attention budget to learning public information about a local stock and, more importantly, that such unusual behavior is not observed for nonlocal retail investors. We focus on stocks included in the S&P 500 between January 2004 and December 2016.

Google searches capture the information acquisition choices of only retail investors, since institutional investors use Bloomberg terminals to search for information as postulated by Da, Engelberg, and Gao (2011) and Ben-Rephael, Da, and Israelsen (2016). In this paper, we rely on the argument that retail investors perform searches mainly for buying decisions. The literature has used two main arguments to rationalize this decision. First, most retail investors cannot short stocks and can only act on positive information to buy stocks. Second, as argued by Barber and Odean (2008), the decisions to buy or sell assets are fundamentally different. When choosing what stocks to buy, retail investors are mostly concerned about future returns, so information processing is an important component of their decision-making. In contrast, when choosing what stocks to sell, most retail investors only focus on past returns (Hartzmark, 2014), so searches are less relevant for their decision-making.

To guide our empirical analysis, we first present a simple conceptual framework in which local and nonlocal investors decide first on allocating their attention to learning about payoffs of local and nonlocal assets, and then decide on their portfolio allocations. The main insight from this framework is that when an investor has a small initial information advantage about a given asset (locals about the local asset, nonlocals about the nonlocal asset), this information advantage will lead them to acquire more information about that asset. Therefore, when locals increase their attention to local assets relative to nonlocals, our conceptual framework implies that locals have received private news. This observation leads to the main empirical prediction that we test using our measure of abnormal asymmetric attention: when we observe locals processing more information about local assets, returns of these assets should increase.

To better understand what drives local investors' search patterns, we examine how our measure of abnormal asymmetric attention is related to news about the firm, earnings announcements, and investors' trading behavior. First, we find that abnormal asymmetric attention is highly correlated with the amount of news about the firm. Search volume of local investors increases more in months with a high number of positive news items than it does in months with a higher number of negative news items. Second, we find that both local and nonlocal investors search more in earnings announcement months, and abnormal asymmetric attention remains unchanged as a result. This pattern is consistent with the predictions from our conceptual framework because earnings announcements are public news that are observable to all investors (locals have no information advantage). Third, we find that buy-sell order imbalance is more tilted towards buy orders in months when the search volume of local investors is higher. Taken together, these results validate our measure of attention allocation by local investors and provide further support for the argument that retail investors perform searches for buying decisions.

Abnormal asymmetric attention predicts future stock returns. In cross-sectional regressions we find that stocks in the top quintile of abnormal asymmetric attention earn future DGTW-adjusted stock returns that are 22 basis points (bps) higher than those of stocks in the bottom quintile. A portfolio that goes long in stocks with high abnormal asymmetric attention and shorts stocks with low abnormal asymmetric attention has a five-factor alpha of 32 bps per month that is statistically and economically significant. To further examine the predictions of our conceptual framework, we study whether our results become more significant for stocks in which asymmetric information is more evident. Indeed, we find that the return differential between stocks with high and low abnormal asymmetric attention is larger for relatively smaller stocks within the S&P500, for stocks with higher bid-ask spreads, higher price impact, and those followed by a lower number of analysts.

We consider the possibility that our measure of abnormal asymmetric attention captures rumors, or more generally attention to a stock that is not backed by fundamentals. We show that the increase in stock returns associated with abnormal asymmetric attention does not reverse over the next month. If anything, there is a slight continuation in the positive correlation between abnormal asymmetric attention and future returns when looking several months ahead. This pattern suggests that the information received by locals is about fundamentals. Finally, we show that our results are robust to controlling for state fixed effects, state characteristics, state-adjusted returns, the probability of informed trading, price impact, analyst coverage, earnings surprises, or the geographic dispersion of the firm's operations.

Our paper is related to the literature that analyzes the role of geography in finance initiated by Coval and Moskowitz (1999, 2001). They provide evidence suggesting that investors possess local information advantages. A growing number of studies support the link between proximity and stock market participants' behavior. Malloy (2005) and Bae, Stulz, and Tan (2008) study the link between geographic proximity and analyst behavior. Portes and Rey (2005) document a close relationship between international capital flows and distance between countries. Ivkovic and Weisbenner (2005) show that individual investors tilt their portfolio towards local assets and earn additional returns. Grote and Umber (2006) and Uysal, Kedia, and Panchapagesan (2008) provide evidence relating proximity with success in mergers and acquisitions deals. Our results are different from previous work in the geography literature. One particular implication from Coval and Moskowitz (1999, 2001) and Ivkovic and Weisbenner (2005) is that companies located in more remote areas suffer from more information asymmetries and, thus, should earn higher returns.

Our paper advances the literature on geography one step further. Specifically, our measure of abnormal asymmetric attention captures asymmetric patterns of information processing between locals and nonlocals. In other words, this measure captures when local investors choose to process more information about local stocks than nonlocal investors. Hence, it allows us to predict whether and when stocks of firms located in a given state will actually suffer from asymmetric information and, thus, earn higher returns. Additionally, this paper also contributes to a growing literature exploring the effects of geography on asset prices (e.g., Pirinsky and Wang (2006), and Garcia and Norli (2012)).

Finally, this paper also contributes to the controversial literature on whether retail investors are informed traders, liquidity providers, or simply noise traders such as Kaniel, Saar, and Titman (2008), Dorn, Huberman, and Sengmueller (2008), Hvidkjaer (2008), Barber, Odean, and Zhu (2009), and Kelley and Tetlock (2013). Our results provide suggestive evidence that local retail investors trade on information.

2 Conceptual Framework

The objective of this section is to use a theoretical framework to predict the arrival of unobservable news to investors. Ideally, we would like to understand the observable actions of investors after receiving unobservable private news. Then, we could infer the arrival of unobservable news by observing the investors' actions. To this end, we will use a simple model of attention allocation behaviour based on van Nieuwerburgh and Veldkamp (2009, 2010). The model presented below is a special case of van Nieuwerburgh and Veldkamp's model with a slight modification in the initial priors of local investors, who will receive exogenous unobservable private news.

2.1 Model Description

For simplicity, we assume a partial-equilibrium model that has two regions with a risky asset in each of them. Each risky asset represents a representative asset of a separate region. The local region's risky asset pays $\tilde{R}_L \sim N\left(\bar{R}, \sigma_R^2\right)$ units of the consumption good. The nonlocal region's risky asset pays $\tilde{R}_N \sim N\left(\bar{R}, \sigma_R^2\right)$ units of the consumption good. For simplicity, the returns of the two assets are independent and identically distributed. There is also a risk free asset with unlimited supply that pays R_f units of the consumption good. There is a continuum of investors of measure one with a limited capacity to analyze the payoffs of both assets. Any investor $i \in [0, 0.5]$ belongs to the local region, while any $i \in (0.5, 1]$ belongs to the nonlocal region. In words, half of the investors belong to the local region and the other half belong to the nonlocal region. The advantage of belonging to the local region is that investors from that region receive an initial private signal at no cost about the payoffs given by

$$\tilde{U}_L = \tilde{R}_L + \tilde{\varepsilon}_L,$$

where $\tilde{\varepsilon}_L \sim N(0, \sigma^2_{\varepsilon L})$ and $\tilde{\varepsilon}_L$ is independent of $\tilde{R}_L$. We will interpret $\tilde{U}_L$ as the arrival of unobservable news to local investors. These news are not observable to nonlocals.

The model has four stages. In the first stage, investors receive an initial wealth, W_0, and limited resources to process information, κ. Also, local investors receive unobservable private news about local payoffs, $\tilde{U}_L$. In the second stage, investors make an attention allocation decision, allocating their limited information resources between the two assets. In the third stage, investors choose the optimal portfolio given the observation of signals, which depends on the amount of information processed about each stock. In the last period, agents consume the payoff of their portfolio. For the rest of the section, we focus on presenting the description and solution of the problem for local investors and explain in words how the problem for nonlocal investors is only slightly different. The only difference between local and nonlocal investors in the model is that local investors receive an initial signal $\tilde{U}_L$ (which nonlocals do not receive).

The attention allocation choice of local investors in the second stage consists of devoting information resources to process and analyze publicly available information about the payoffs. The attention allocation choice of a local investor i will lead to a signal $\tilde{Y}_{ij}$ about each risky asset $j = L, N$ given by

$$\tilde{Y}_{ij} = \tilde{R}_j + \tilde{\eta}_{ij},$$

where $\tilde{\eta}_{ij} \sim N(0, \sigma^2_{\eta ij})$ and $\tilde{\eta}_{ij}$ is independent of $\tilde{R}_j$. The precision of the signals increases with the amount of resources allocated to them. Investors would like signals to provide perfect information about the asset payoffs in order to reduce the uncertainty of their portfolio by setting $\sigma^2_{\eta ij} = 0$. However, they have limited resources to process information, κ, which they allocate among assets. The attention allocation constraint for a local investor i is $\kappa = \kappa_{iL} + \kappa_{iN}$, where κ_{ij} for $j = L, N$ is given by

$$\kappa_{iL} = \log V[\tilde{R}_L \mid \tilde{U}_L] - \log V[\tilde{R}_L \mid \tilde{Y}_{iL}, \tilde{U}_L] \qquad \kappa_{iN} = \log V[\tilde{R}_N] - \log V[\tilde{R}_N \mid \tilde{Y}_{iN}]. \tag{1}$$

A local investor i, with mean-variance preferences, maximizes the following utility function

$$EU_i = E\left[E(W_i' \mid \tilde{Y}_{iL}, \tilde{Y}_{iN}, \tilde{U}_L) - \frac{1}{2} V(W_i' \mid \tilde{Y}_{iL}, \tilde{Y}_{iN}, \tilde{U}_L)\right], \tag{2}$$

where W_i' is the wealth of the local investor in the last period. The objective function of a nonlocal investor is the same as a local investor except that the conditional expectation and variance do not depend on $\tilde{U}_L$. Investors maximize their objective function subject to the following budget constraint

$$W_i' = W_0 \bar{R} + q_{iL}(\tilde{R}_L - R_f P_L) + q_{iN}(\tilde{R}_N - R_f P_N), \tag{3}$$

where q_{iL} and q_{iN} are the asset holdings of investor i, and P_L and P_N are the asset prices of the local and nonlocal asset, which are taken as given.

Assumption (**Behavioral Bias**). *Asset prices P_N and P_L are such that $\bar{R} - R_f P_N \geq 0$ and $E[\tilde{R}_L \mid \tilde{U}_L] - R_f P_L \geq 0$.*

Under this assumption, investors are only considering buying stocks. As argued by Barber and Odean (2008), when deciding to buy a stock, retail investors focus on future returns, so information processing is an important component of their decision-making. In contrast, when deciding to sell a stock, retail investors only focus on past returns, so information processing is an irrelevant component of their decision-making. Additionally, Hartzmark (2014) shows that indeed individual investors focus on past returns when deciding which stocks to sell. Moreover, they tend to apply a particular decision rule: they consider the rank of the stock within their portfolio, and are much more likely to sell stocks with the worst or the best past performance. Since our empirical analysis focuses on retail investors, we add this behavioral assumption to the model.[1]

2.2 Solving the Model

In this section, we describe the main results and implications of the model, leaving all the details of the solution to the Online Appendix. Again, we present the solution for local investors only and explain in words how the solution for nonlocal investors is slightly different. The model is solved using backward induction. First, given an arbitrary attention allocation choice, each agent decides the optimal asset holdings. Second, given the optimal portfolio choice for each signal, each agent decides the optimal attention allocation choice.

The optimal portfolio choice of locals is given by

$$q_{iL} = \frac{E[\tilde{R}_L \mid \tilde{Y}_{iL}, \tilde{U}_L] - R_f P_L}{V[\tilde{R}_L \mid \tilde{Y}_{iL}, \tilde{U}_L]} \qquad q_{iN} = \frac{E[\tilde{R}_N \mid \tilde{Y}_{iN}] - R_f P_N}{V[\tilde{R}_N \mid \tilde{Y}_{iN}]}. \tag{4}$$

The portfolio choice of a nonlocal investor is the same as that of a local investor except that the conditional expectation and variance do not depend on $\tilde{U}_L$. The asset holdings presented in equation (4) show that the investor will buy more of assets that have high expected payoffs and low conditional volatility. Note that mean-variance preferences imply a demand for risky assets that does not depend on wealth.

The attention allocation choice consists of choosing the information resources, κ_{iL} and

[1] Two alternative assumptions would give us similar results, but at the expense of tractability: short-sale constraints as in Yuan (2005) or gamma-distributions for asset payoffs and signals as in Vanden (2007).

κ_{iN}. Taking into account the optimal asset demand given by equation (4), investors maximize their objective function given by equation (2) subject to the attention allocation constraint (1). Substituting q_{iL} and q_{iN} back into the utility function (2), the attention allocation choice problem of a local investor i is given by maximizing

$$EU_i = W_0 \bar{R} - 1 + \frac{1}{2}\frac{V[\tilde{R}_L \mid \tilde{U}_L]}{V[\tilde{R}_L \mid \tilde{Y}_{iL}, \tilde{U}_L]}(1+\theta_L^2) + \frac{1}{2}\frac{V[\tilde{R}_N]}{V[\tilde{R_N} \mid \tilde{Y}_N]}(1+\theta_N^2), \tag{5}$$

where $\theta_L^2 = \frac{\left(E[R_L|\tilde{U}_L]-R_f P_L\right)^2}{V[\tilde{R}_L|\tilde{U}_L]}$ and $\theta_N^2 = \frac{\left(\bar{R}-R_f P_N\right)^2}{\sigma_R^2}$ are the squared Sharpe ratio of the local and nonlocal asset respectively, subject to the information constraint given by

$$\kappa = \log V[\tilde{R}_L \mid \tilde{U}_L] - \log V[\tilde{R}_L \mid \tilde{Y}_{iL}, \tilde{U}_L] + \log V[\tilde{R}_N] - \log V[\tilde{R}_N \mid \tilde{Y}_{iN}]. \tag{6}$$

The attention allocation problem of a nonlocal investor is the same as that of a local investor except that the conditional expectation and variance do not depend on $\tilde{U}_L$ and consequently, they will face different θ_L and θ_N. The solution to the optimization problem is a corner solution. There are two possible corner solutions to the optimization problem: investors optimally choose to allocate all their attention to either the local asset ($\kappa_{iL} = \kappa$) or the nonlocal asset ($\kappa_{iL} = 0$). The first option is to use all information resources to learn about the local asset such that conditional variances are given by $V[\tilde{R}_L \mid \tilde{Y}_{iL}, \tilde{U}_L] = \frac{V[\tilde{R}_L|\tilde{U}_L]}{e^\kappa}$ and $V[\tilde{R}_N \mid \tilde{Y}_{iN}] = \sigma_R^2$, and expected utility equals $EU_i = W_0\bar{R} - 1 + e^\kappa(1+\theta_L^2) + (1+\theta_N^2)$. The second option is to use all information resources to learn about the nonlocal asset such that conditional variances are given by $V[\tilde{R}_L \mid \tilde{Y}_{iL}, \tilde{U}_L] = V[\tilde{R}_L \mid \tilde{U}_L]$ and $V[\tilde{R}_N \mid \tilde{Y}_{iN}] = \frac{\sigma_R^2}{e^\kappa}$, and the expected utility equals $EU_i = W_0\bar{R} - 1 + (1+\theta_L^2) + e^\kappa(1+\theta_N^2)$. The optimal attention allocation choice is to allocate all information resources to learn about the asset j with the highest squared Sharpe ratio θ_j^2. Hence, investors will choose $\kappa_{iL} = \kappa$ if $\theta_L^2 > \theta_N^2$ and choose $\kappa_{iL} = 0$ if $\theta_L^2 < \theta_N^2$. They will be indifferent between one corner or the other when $\theta_L^2 = \theta_N^2$, in which case they would choose one of the two options randomly. Intuitively, a corner solution arises because of the interaction between the portfolio choice and the attention allocation choice. As investors learn more about one asset, they will tilt their portfolios more towards that asset; but the more tilted their portfolios are towards a given asset, the higher the incentives to learn more about that asset.

The model presented above is clearly a simplified model where any investor chooses to allocate all her attention to one asset. One could add complexity to the model to avoid corner solutions, while obtaining the result that local investors tilt most of their attention to local stocks as in Mondria and Wu (2010). Another way to avoid corner solutions would be to allow asset payoffs to have multiple components as in Peng and Xiong (2005) and Kacperczyk, van Nieuwerburgh, and Veldkamp (2016). For our purposes, this modeling choice would complicate the model unnecessarily, without generating additional insights. The empirical implications that we discuss in the next sections would hold also with more complex models.

The behavioral assumption that investors are only considering buying stocks is key to link the model to the data. With this behavioral assumption, local investors will shift all their attention to local stocks only when they receive positive news. Instead, without this behavioral assumption, local investors would also shift all their attention to local stocks whenever they received negative news. In addition, they would also short local stocks. This behavior would not be consistent with the previous literature on retail investors. This literature suggests that retail investors face short-sale constraints (Nagel (2005) and Reed (2013)), hold portfolios that are biased towards local stocks (Ivkovic and Weisbenner (2005)), and process information only when considering which stocks to buy (Barber and Odean (2008) and Hartzmark (2014)).

2.3 Linking the model to the data

To link the model with the data, it is useful to obtain a measure of aggregate attention allocated to a stock to capture the aggregate information capacity allocated to that particular stock. For our purposes, we are interested in a measure of aggregate attention to the local stock. We define *local attention*$=\int_0^{0.5}\kappa_{iL}di$ as the aggregate attention to local stocks by locals. For local investors: *i)* if $\theta_L^2 > \theta_N^2$, then *local attention*$=\int_0^{0.5}\kappa_{iL}di = 0.5\kappa$; *ii)* if $\theta_L^2 < \theta_N^2$, then *local attention*$=\int_0^{0.5}\kappa_{iL}di = 0$; *iii)* if $\theta_L^2 = \theta_N^2$, then locals are split between learning about the two assets and *local attention*$=\int_0^{0.5}\kappa_{iL}di = 0.25\kappa$. We define *nonlocal attention*$=\int_{0.5}^{1}\kappa_{iL}di$ as the aggregate attention to local stocks by nonlocals.

The objective of the model is to provide a framework to predict the arrival of unobservable private news to retail investors. Specifically, we will evaluate the empirical implications of the model when retail investors receive positive unobservable news about the local asset. As a benchmark, we consider the case where no agent has received private news such that $\theta_L^2 = \theta_N^2$, which implies *local attention* $= 0.25\kappa$ and *nonlocal attention* $= 0.25\kappa$.

2.4 Empirical Implications of the Model with Unobservable Private News

The focus of this paper is on the case when locals face $\theta_L^2 > \theta_N^2$, which means that local investors receive positive private news about the local stock. Consequently, if we take $\theta_L^2 > \theta_N^2$ for locals as given, then the main implication of the model is that local investors allocate all their attention to analyze the publicly available information about the local asset when they receive unobservable private news. Hence, *local attention*$=0.5\kappa$. Meanwhile, nonlocals, who have no initial advantage, are indifferent between allocating their attention between local and nonlocal assets. In this case, we would observe that all locals are processing information about the local asset, while nonlocals are split between learning about the two assets. Hence, *nonlocal attention*$=0.25\kappa$. Therefore, if we were to observe the information processing efforts of local investors relative to nonlocals, we could infer the arrival of unobservable private news. Specifically, if there is an increase in *local attention* relative to *nonlocal attention* with respect to the benchmark case, then according to the model, we can infer that there are positive unobservable news about local stocks.

2.5 Empirical Implications of the Model with Public News

Suppose now that the signal $\tilde{U}_L$ of the model is observed by both local and nonlocal investors. Then, the description and solution of the model is the same for both local and nonlocal investors. In this case, we have a model with an initial public signal. One can interpret this public signal as a public announcement by the firm such as an earnings announcement. In this case, both locals and nonlocals have a small initial advantage in investing in local stocks that makes $\theta_L^2 > \theta_N^2$ when the news are positive. As a result, both types of investors would tilt their attention allocation towards local stocks. Hence, *local attention*=0.5κ and *nonlocal attention*=0.5κ. If we observe the information processing efforts of local investors relative to nonlocals, then we can infer the arrival of public news. Specifically, if both *local attention* and *nonlocal attention* increase with respect to the benchmark case, then according to the model, we can infer that there are positive public news about local stocks. Note, however, that in this case there is no change of *local attention* relative to *nonlocal attention*, as the relative attention to publicly available information between local and nonlocal investors would not change.

2.6 Asset Pricing Implications

The model presented above does not have asset pricing implications since it is just a partial equilibrium model, which means that investors are taking prices as given. The purpose of the model is to show that the attention allocation behavior of investors is a good predictor of the arrival of unobservable private news. The main mechanism of the model would survive in a general equilibrium model, where prices would be determined endogenously, but at the expense of adding complexity to the model. Since there is a large literature studying the relationship between information acquisition, asymmetric information, and asset prices, and its implications are well-known, we refrain from modeling the asset pricing implications explicitly.

If the attention allocation decisions were introduced in standard general equilibrium CARA-static models such as Grossman and Stiglitz (1980) and Admati (1985), or dynamic models with slow price adjustments such as Hong and Stein (1999), the effect of attention allocation on asset prices would have a common component. Under asset pricing and attention allocation theories combined, the arrival of unobservable private news about local companies would lead investors to start processing more publicly available information about these local firms. All else equal, the information asymmetry between local and nonlocal investors would be endogenously magnified. Consequently, there would be an increase in the buying pressure by locals and stock prices would increase over a period of time. The empirical implication of these theories combined is that if we observed local investors processing more public information about local stocks relative to nonlocal investors, this would imply that local investors received private information and that stock prices will increase.

3 Data

Our sample consists of the constituents of the S&P 500 that are headquartered in the U.S. The data we use to construct our attention allocation measures are downloaded from Google Trends.[2] Stock prices, return, volume, market capitalization, and related variables are obtained from CRSP; accounting data and headquarter locations are from Compustat; state level data such as population and GDP are from the U.S. Census Bureau. News data are from RavenPack. We obtain measures of buy-sell imbalance and price impact from TAQ, the probability of informed trading (PIN) from Brown and Hillegeist (2007), information on analyst coverage from I/B/E/S, and data on geographic dispersion of the firm's activities from Garcia and Norli (2012). Appendix A provides detailed definitions of all the variables used in the analysis.

[2] https://www.google.ca/trends

3.1 Aggregate search volume index

We obtain aggregate search volume data from Google search engine users using Google Trends as in Da, Engelberg, and Gao, (2011). In our specific case, we are interested in filtering search data at the national and state level. Google Trends uses IP address information to make an educated guess about the location where search queries originated. The data ranges from January 2004 to December 2016 and contains the monthly search volume index (SVI) for any search term. The SVI for a particular term is the query share of that term for a given location and time period, normalized by the highest query share of that term over the time-series. A web search query is the exact phrase a user types into the search engine. Query share for a particular term is the ratio between the number of queries for that term and the total number of queries at a given location and time period. In less technical terms, Google calculates the search traffic for a particular term as the number of searches for this term relative to the total number of searches in Google at a given location and time period. Google then constructs the SVI for a search term by normalizing its search traffic by the highest traffic for that term over the time-series. Hence, SVI data ranges from 0 to 100. A decrease in SVI does not necessarily imply a reduction in the absolute number of web search queries for a particular term. It essentially means that the popularity (or query share) of that particular term is decreasing.

We obtain monthly SVI data for every stock in the S&P 500 headquartered in the U.S. between January 2004 and December 2016.[3] We collect data for all stocks ever included in the index during our sample period and exclude those whose prices are below $5 (to avoid microstructure related biases), which leaves us with a total of 738 stocks. Following Da, Engelberg, and Gao (2011), we collect SVI data for a stock using its ticker. If a search engine user is searching for a company ticker, it is highly likely that this user is interested in financial information about the company.[4] Furthermore, using ticker search volume makes our sample

[3]We focus on S&P 500 stocks and monthly data because Google Trends only returns valid SVI data for web search queries with a significant amount of search volume.

[4]Google searches for a stock ticker might be also capturing the monitoring activity of investors holding

construction less subjective than if we used the company's name.

We then filter the SVI data for each company's ticker by location. Specifically, we define *national attention* as the natural logarithm of a company's ticker SVI among all search engine users in U.S., and *local attention* as the natural logarithm of a company's ticker SVI among search engine users located in the state where the company is headquartered.[5] For each ticker, we collect local and national SVI data simultaneously. Google Trends normalizes both variables by the same constant, which is the highest query share in any of the two time-series. We can then compare the relative popularity of a company's ticker between national and local investors. We define the variable *asymmetric attention* as the natural logarithm of the relative SVI between locals and nationals, or equivalently as the difference between *local attention* and *national attention*. An asymmetric attention larger than zero implies that local investors search information about local stocks more frequently than nonlocal investors.

Searches for shorter tickers are more likely to be contaminated by typos, especially with the appearance of the auto-complete function on Google. Using this intuition, in our main analysis we restrict our sample first to stocks with tickers longer than one character.[6] Also, as in Da, Engelberg, and Gao (2011), Google Trends does not return valid SVI data for tickers with low search volume. This issue is exacerbated in our paper when calculating local attention, as Google Trends only returns data for terms that have a significant amount of search volume. We overcome this obstacle by using monthly data and restricting our sample to stocks with positive national SVI.

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the stock. If one believes that price movements carry information, then monitoring a stock price is a way of processing information about a stock.

[5]Both variables are calculated as $ln(1 + SVI)$.

[6]Section 5.2 shows the robustness of our results to alternative classifications of contaminated tickers, as well as leaving all firms in the sample.

3.2 Main attention measures and independent variables

To analyze the asset pricing implications of our conceptual framework, we need to examine unusual patterns in the attention allocation behavior of retail investors. We measure unusual search volume using the abnormal SVI (ASVI) of a ticker. Following Da, Engelberg, and Gao (2011), ASVI is defined as the natural logarithm of the SVI during the current month less the natural logarithm of the mean SVI during the previous three months. Then, we measure *abnormal national attention* as the ASVI of a company's ticker from all users located in U.S. and *abnormal local attention* as the ASVI of a company's ticker filtered by searches located in the state where the company is headquartered. Finally, we measure *abnormal asymmetric attention* as the relative ASVI of local versus nonlocal investors, that is, the difference between *abnormal local attention* and *abnormal national attention.* In sum, abnormal attention is proxied by unusual search volume relative to the previous three months.[7]

The independent variables we use in the study are defined as follows: *i*) ME is the market capitalization in the previous month $(t-1)$; *ii*) BE/ME is the book-to-market value of equity, where the book value, calculated according to Davis, Fama, and French (2000), is divided by the previous month's market capitalization; *iii*) Ret is the return of the stock during the month; *iv*) Ret[t-12,t-1] is the cumulative return of the stock between months t-12 and t-1; *v*) Amihud is the illiquidity measure constructed according to Amihud (2002); *vi*) Spread is the proportional quoted bid-ask spread; *vii*) Volatility is the standard deviation of the daily stock returns in the current month; *viii*) ΔTurnover is the difference in the natural logarithm of stock turnover between t and $t-1$. In later tests, we also use *ix*) Geographic dispersion is the proxy of Garcia and Norli (2012) capturing the geographic dispersion of the firm's operations and *x*) Price impact is a measure of information asymmetry. Price impact is the change in the current quoted midpoint to the quoted midpoint five minutes in the future (Holden and

[7] All of our results are robust to alternative specifications of ASVI.

Jacobsen, 2014). We use the Lee and Ready (1991) algorithm to identify a trade as a buy or sell. Following Holden and Jacobsen (2014), we aggregate price impact to the daily level by taking the dollar-volume weighted price impact across all trades per day, and then further aggregate it to the monthly level using a similar procedure.

Panel A of Table 1 presents summary statistics for our abnormal local attention, abnormal national attention, and abnormal asymmetric attention variables, as well as the independent variables. The mean and median of the abnormal attention variables are around zero. These measures also have significant variation: the standard deviation of abnormal national attention, abnormal local attention, and abnormal asymmetric attention are 0.21, 0.61, and 0.61, respectively. The average (median) firm in our sample has a market capitalization of $22.9 bn ($9.9 bn). Because our sample period includes the strong market prior to the crisis, the crisis, as well as the subsequent recovery, average returns are relatively high, and there is considerable variation in returns. We verify that the maximum monthly and cumulative returns are due to the crash and recovery of Avis Budget Group in 2009-2010, and financial stocks during the crisis. Winsorizing our return data at the 1^{st} and 99^{th} percentiles to remove these outliers leaves the size and significance of our main results unaffected.

Panel B of Table 1 exhibits the relation of our abnormal asymmetric attention variable to several firm characteristics. Each month, we divide our sample into five quintiles according to the abnormal asymmetric attention variable, where the first quintile consists of stocks with the lowest abnormal asymmetric attention. Stocks in the first quintile experience abnormal increases in the attention allocated by the average U.S. investor, while stocks in the fifth quintile experience abnormal increases in the attention allocated by local investors. From the univariate analysis, we can observe that there is no monotonic relation between abnormal asymmetric attention and any relevant firm characteristic. Panel C of Table 1 shows the pairwise correlation coefficients between abnormal asymmetric attention and firm characteristics used in our regressions. Only firm size, past one-year returns, and the change in turnover are significantly correlated with abnormal asymmetric attention. However, these correlation coefficients are small in magnitude.

4 Understanding search patterns

In this section, we conduct a number of tests to understand the variation in our measures of investors' search behavior.

4.1 News and abnormal asymmetric attention

In this section, we show that local news about a stock, which we define as news about the firm unrelated to earnings announcements, generate an increase in abnormal asymmetric attention, consistent with our conceptual framework in section 2.4. We exclude news about earnings announcements as we interpret them as public news that do not provide an information advantage to local investors. We analyze earnings announcements in the next section.

Table 2 shows regressions of abnormal asymmetric attention on several measures of news, constructed similarly to Da, Engelberg, and Gao (2011). Table 2 column 1 shows that the number of news items from Dow Jones is strongly correlated with our measure of abnormal asymmetric attention, suggesting that local investors search more than national investors in months where there are more news items appearing about a firm. News items from Dow Jones typically also appear with similar information content (and often even with similar wording) in local newspapers. We confirm this by collecting news stories from Factiva, LexisNexis, and Google for a small subsample of randomly selected news events.[8]

The coefficients reported are standardized, implying that a one-standard-deviation increase in the total number of news items is associated with an increase of 0.0165 standard deviations

[8]For example, in October 2007 a coalition of states and environmental groups led by New York and the federal government reached a settlement with American Electric Power (AEP), requiring the company to dramatically cut its emissions in the single greatest reduction of air pollution from a Clean Air Act enforcement action. Dow Jones reported this information, and so did local news sources in Ohio, where the AEP is headquartered, such as the Cincinnati Post, Crain's Cleveland News, the Columbus Dispatch, the Dayton Daily News, or the Lima News.

of our abnormal asymmetric attention measure. News items from Dow Jones may not be the only source of information for investors. As an alternative measure, we also look at press releases and regulatory disclosures that RavenPack collects from newswires and press release distribution networks such as PRNewswire or Business Wire. Column 2 shows that there is no significant correlation between the total number of press releases in a given month and abnormal asymmetric attention.

We now examine what type of news local investors respond to more than nonlocal investors. Column 3 uses the number of Dow Jones news articles as the independent variable. We define news articles following Tetlock (2010) and Da, Engelberg, and Gao (2011), who argue that articles, i.e. longer, more detailed news items, are more likely to capture information that is important and timely.[9] The number of news articles is also positively correlated with abnormal asymmetric attention. The size and statistical significance of the coefficient are similar to that in column 1, suggesting that local investors are more likely to search for the firm's ticker in months when high-quality, thorough news items appear about it.

An idea underlying our empirical predictions is that individual investors are more likely to acquire information when deciding which stocks to buy compared to when deciding which stocks to sell.[10] In columns 4-7 we gauge the validity of this claim in our sample by looking separately at the count of positive and negative news items and press releases. Columns 4 and 5 show that abnormal asymmetric attention is positively correlated with both positive and negative news items. However, the economic magnitude of the coefficient is significantly larger for positive news items. Columns 6 and 7 show that abnormal asymmetric attention is positively correlated with press releases containing positive news, but negatively correlated with those containing negative information. These results are consistent with the idea that locals search more than nonlocals in months with positive information about the firm, but

[9]Da, Engelberg, and Gao (2011) refer to these longer news items as "chunky news", because in their data source a longer article is released in several chunks. We use the indicator of RavenPack which defines news articles to be "composed of both a headline and one or more paragraphs of mostly textual material".

[10]See section 2.3 for a more elaborate discussion.

this difference is smaller, or even negative, in months with negative information.

Finally, we use a measure developed by RavenPack that gauges *ex ante* how much return volatility a given news item is likely to entail. This measure is a prediction based on past data. Column 8 shows that locals search significantly more than nonlocals in months with more news items that are classified ex ante as likely to raise volatility by a large amount. In contrast, Column 9 shows that nonlocals search more than locals in months with many news items that are associated with small changes in volatility.

In sum, the results in Table 2 show that our measure of abnormal asymmetric attention is correlated with several measures of news about the firm. In addition, our results also confirm that locals search more than nonlocals when news about the firm is positive, and when the news is likely to lead to large increases in volatility.

4.2 Earnings announcements and the search patterns of locals and nonlocals

In this section, we show that public news about a stock, which we define as news about the firm related to earnings announcements, generate an increase in abnormal local attention and abnormal national attention, but has an insignificant effect on abnormal asymmetric attention, which is consistent with our conceptual framework in section 2.5.

We consider earnings announcements as public news that do not provide an information advantage to local investors, as they are widely followed by both locals and nonlocals. In Table 3, we regress our measures of investor attention on a dummy variable equal to 1 if there is an earnings announcement in a given month. Columns 1 and 2 show that the search volume of both locals and nonlocals increases in months with earnings announcements. Abnormal asymmetric attention, however, is not significantly higher in earnings announcement months.

We also examine whether Google search volume of locals spikes around earnings announcements with positive surprises. Figure 1 shows abnormal local attention (top left), abnormal national attention (top right), and abnormal asymmetric attention (bottom) in the month before, the month of, and the month after earnings announcements with positive standardized unexpected earnings (SUE). Local investors search more in months with positive earnings surprises, but not in the month before nor the month after. We see the same pattern for national searches. As a result, abnormal asymmetric attention is not significantly different in months with positive earnings surprises, consistent with our prediction that both local and nonlocal investors allocate more attention to the firm after the release of public news about that firm.

4.3 Search patterns of locals and nonlocals and trading behavior

In this section, we show evidence consistent with the existence of a buying pressure by investors after an increase in abnormal local attention and abnormal national attention as we assumed in section 2.6 for our conceptual framework to have asset pricing implications.

To analyze whether local investors perform Google searches before buying stocks, we examine whether months with a higher number of buy-initiated orders, as opposed to sell-initiated orders, are associated with higher search volume by local investors. Table 4 shows regressions of measures of buy-sell imbalance on measures of abnormal attention and firm fixed effects. We calculate buy-sell imbalance from the TAQ database using the algorithm of Lee and Ready (1991) to classify trades. Because both the average and the standard deviation of the buy-sell imbalance may differ across stocks, we standardize the measure to have a mean of 0 and a variance of 1. Column 1 of Table 4 shows that a higher volume of Google searches by local investors is indeed associated with a higher number of buy transactions. The coefficient is statistically significant at the 1% level. Column 2 shows similar patterns for the relation between abnormal national attention and buy-sell imbalance. Finally, column 3 shows that there is a positive and significant relation between abnormal asymmetric attention and buy-sell imbalance. We obtain similar results in columns 4-6 where we use an indicator variable for positive order imbalance. Overall, these results indicate that Google search volume of local investors is associated with more buy-initiated orders. A caveat when using order imbalance data, however, is that we cannot discern whether the trades are placed by individual or institutional investors. Therefore, order imbalance is a noisy measure of individual investors' investment decisions.

5 Attention and stock returns

In this section, we investigate whether stocks that have an abnormal pattern of national and asymmetric attention earn higher future returns. We use two different approaches to investigate the relationship between abnormal SVI and future stock returns. First, we run Fama and MacBeth (1973) cross-sectional regressions. Then, we show that these regressions are robust if we remove from the sample stocks with tickers that have a generic meaning. Second, we form long-short portfolios sorted by abnormal attention.

5.1 Cross-sectional regressions

We first study the relation between abnormal SVI and future stock returns for the S&P 500 stocks included in our sample. We run Fama and MacBeth (1973) cross-sectional regressions each month from January 2004 to December 2016. These results are reported in Table 5. The dependent variable is the DGTW characteristic-adjusted abnormal return from month $t+1$. The DGTW-adjusted returns are constructed using the method developed by Daniel et al. (1997).[11] All regressions control for the following firm characteristics defined in section 3.2: log(ME) is the natural logarithm of the market capitalization in month t; log(BE/ME) is the natural logarithm of the book-to-market value of equity; Ret is the return of the stock during month t; Ret[t-12,t-1] is the cumulative return of the stock between $t-12$ and $t-1$; Amihud is the illiquidity measure constructed according to Amihud (2002) from month t; Spread is the proportional quoted bid-ask spread in month t; Volatility is the standard deviation of the daily stock returns of the current month t; ΔTurnover is the difference in the natural logarithm of

[11] Our results remain robust if we use of future raw excess returns instead of DGTW-adjusted returns.

stock turnover between t and $t-1$.

In the first column of Table 5, we replicate the results from Da, Engelberg, and Gao (2011) at the monthly frequency. We use abnormal national attention as the independent variable. We find no evidence of an empirical relation between abnormal national attention and future DGTW adjusted stock returns. Da, Engelberg, and Gao (2011) argued that abnormal national attention has an effect in the first two weeks of the month, which is then reversed in the future.

In the second column, we study the relation between stock returns and abnormal asymmetric attention. The coefficient of abnormal asymmetric attention is economically and statistically significant. A one standard deviation increase in abnormal asymmetric attention is associated with an increase in next-month DGTW-adjusted stock returns of $(0.61 \times 0.214 =)$ 13 bps. Another way to quantify the economic significance of the coefficient of abnormal asymmetric attention is to take the difference between the fifth and first quintiles of abnormal asymmetric attention from Panel B in Table 1 and multiply it by the regression coefficient: $(0.50 + 0.53) \times 0.214$. All else equal, observations with high abnormal asymmetric attention earn future DGTW adjusted stock returns that are 22 bps higher than observations with low abnormal asymmetric attention. The significant effect of abnormal asymmetric attention is obtained after controlling for firm characteristics that previous studies found to affect stock returns. These results are consistent with the asset pricing implications of our conceptual framework.

5.2 Accuracy of abnormal asymmetric attention

To examine the sensitivity of our results to the accuracy of our measure of asymmetric attention, we eliminate from the sample firms with tickers that may have a generic meaning (other than the ticker symbol of a given stock) or are otherwise prone to appear in searches for reasons other than investor attention to the stock. Table 5 uses several classification algorithms to identify such tickers.

The baseline regression in column 2 is restricted to tickers longer than one character. Column 3 further restricts the sample to stocks with tickers longer than two characters. In columns 4-6, we use the Merriam-Webster Dictionary as well as internet searches to determine whether a word may have a generic meaning either in itself, or as a commonly used abbreviation or jargon. We perform this classification ourselves (Dictionary 1, shown in column 4), and have the same task done independently by a doctoral student research assistant (Dictionary 2, shown in column 5). As a final test, to further enhance the reliability of our classification, we exclude from the sample all firms whose tickers are classified as having a generic meaning using either of the two approaches (Dictionary 1 and 2, shown in column 6).

Moving from column 2 to column 6 in Table 5, the statistical significance of our coefficient estimate of abnormal asymmetric attention remains the same, significant at the 1% level, while its size increases from 0.214 to 0.278. This pattern is consistent with the idea that Google searches for firms with ticker symbols that have a generic meaning are a noisier measure of investor attention than Google searches for firms with ticker symbols that do not have a generic meaning. Once this additional noise is cleaned from the data, the pattern we show in the baseline analysis persists, and becomes stronger.

Finally, we also show the results from a regression where we use all of the sample, without any regard for whether tickers have a generic meaning or not. Estimates from this model, shown in Table 5 column 7, are very similar in size and significance to those shown in our main specification.

5.3 Long-short portfolios

We now examine the relationship between abnormal asymmetric attention and future returns of equal- and value-weighted portfolios formed using S&P 500 stocks. Each month, we sort stocks based on their abnormal asymmetric attention. We then form three different portfolios: *i*) the *high-asymmetry* portfolio consists of stocks that, in a given month, have abnormal asymmetric attention above the 80th percentile; *ii*) the *low-asymmetry* portfolio consists of stocks that, in a given month, have abnormal asymmetric attention below the 20th percentile *high-asymmetry* portfolio; *iii*) the *long-short* portfolio is a zero-investment portfolio that, in a given month, goes long in *high-asymmetry* stocks and shorts *low-asymmetry* stocks. We form and calculate the following month's return for each of these three portfolios in every month. We then regress the time-series returns on the five-factor model, which includes three factors from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor from Pastor and Stambaugh (2003). The market portfolio, size factor, book-to-market factor, momentum factor, and liquidity factor are all downloaded from WRDS.

The first three columns of Panel A in Table 6 report the raw excess returns for each of the three portfolios sorted by abnormal asymmetric attention. The low-asymmetry portfolio earns excess returns of 0.74% per month and the high-asymmetry portfolio earns excess returns of 1.00% per month. The long-short portfolio earns statistically significant excess returns of 26 bps. We find similar results when using value-weighted portfolios. The excess returns on the long-short portfolio increase to 30 bps, statistically significant at the 5% level.

In the last three columns of Panel A in Table 6, we look at the alphas estimated using the five-factor model. When we look at equally-weighted portfolios, the high-asymmetry portfolio has an average alpha of 0.88% in the following month, while the low-asymmetry portfolio has an average alpha of 0.58% in the following month. The long-short portfolio shows a 30 bps difference between the high- and low-asymmetry portfolios that is statistically and economically significant.

Looking at value-weighted returns, we find that the individual alphas are higher, at 1.03% for the high-asymmetry portfolio and 0.71% for the low-asymmetry portfolio. The return on the long-short portfolio is 32 bps, which is statistically and economically significant, and is similar to the alpha observed for the equal-weighted case. The difference in magnitude for equal-weighted and value-weighted returns between the high-asymmetry and low-asymmetry portfolios is higher than the value obtained in the cross-sectional regressions – although we note that the two magnitudes are not directly comparable.

In sum, the previous three sections present empirical evidence supporting a robust relation between abnormal asymmetric attention and future returns for S&P 500 stocks. Stocks that attract an abnormal amount of attention from local relative to nonlocal investors earn higher future returns. This result holds for excess returns and after adjusting for risk factors.

Panel B of Table 6 examines whether the long-short portfolio strategy based on abnormal asymmetric attention entails high exposures to any of the five factors in our model. We show the factor loadings of both the equal-weighted and the value-weighted long-short portfolios. All factor loadings are small, and statistically insignificant with one exception. The equal-weighted long-short portfolio has a market beta of –0.13, significant at the 10% level. We conclude that the long-short portfolio strategy based on abnormal asymmetric attention generates statistically and economically significant alphas without taking on significant factor exposures.

6 Robustness

6.1 State characteristics

We now examine the robustness of our regressions to the inclusion of characteristics of the states in which firms are headquartered. The motivation is to check whether our results are driven by a small group of stocks that are headquartered in a particular state. In Table 7, we introduce additional variables to control for state fixed effects and state characteristics. In the first column, we add state fixed effects to our Fama-MacBeth regressions. In column 2, we change the dependent variable to state-portfolio adjusted returns, and in column 3 we add state fixed effects to this specification. Seasholes and Zhu (2010) highlight that many studies on local bias may suffer from a cross-sectional sampling error as neither firms, nor industries, nor investors are uniformly distributed across the U.S. To mitigate this issue, we construct state portfolios in the spirit of the local portfolios used in Seasholes and Zhu (2010), but using states instead of ZIP codes as the level of aggregation. For each U.S. state in each month, we calculate the return of a value-weighted portfolio of the stocks of S&P 500 firms headquartered in the state, and call this the return on the state portfolio in that month. We then calculate the state-portfolio adjusted return as the return on a given stock minus the return on the corresponding state portfolio.[12]

In column 4, we introduce state characteristics such as GDP per capita, to control for more developed states, and population, to control for the size of the state. In a further attempt to rule out that our results are due to incorrect benchmarking and variation in returns across states, we also control directly for the return on the state portfolio. We find that the coefficient of GDP per capita is negative and statistically significant, population size and the return on the state portfolio are statistically insignificant, and that the magnitude and significance of the coefficient of abnormal asymmetric attention remains virtually unchanged compared to previous specifications. Column 5 controls for the geographic dispersion proxy of Garcia and Norli (2012) to rule out the possibility that our measure of abnormal asymmetric attention is correlated with the geographic dispersion of the firm's operations. The intuition is that firms with operations in many states may attract more searches from nonlocals (i.e. investors outside the headquarter state). Our results are similar in size and in significance to the baseline regression in Table 5 after controlling for geographic dispersion of the firm's operations.

In sum, the results are robust to the inclusion of state fixed effects, controlling for state characteristics, controlling for the geographic dispersion of a firm's operations, and changing the return benchmark to a local portfolio.

[12]We use S&P 500 firms to form the portfolios for two reasons. First, we would like to avoid benchmarking S&P 500 firms against smaller firms as their characteristics and sensitivities to factors may be quite different. Second, this approach is conservative as it may attenuate the adjusted returns towards zero in states with few S&P 500 firms. Suppose that there is a state in which only one S&P 500 is headquartered. By construction, this firm will be the state portfolio for itself, leading to adjusted returns of zero. This attenuation issue is more severe in states with few S&P 500 firms.

6.2 Industry effects

We also check the robustness of our results to industry effects. Hou and Robinson (2006) report a relation between industry concentration and stock returns. In column 6 of Table 7, we add industry fixed effects to our baseline regression. We define industries using 2-digit SIC codes. We could potentially use more SIC digits to define an industry, but since we have few firms, increasing the number of digits would essentially control for firm fixed effects. The significance of the coefficient of abnormal asymmetric attention remains unaltered with respect to results reported in Table 5, although its magnitude decreases from 0.214 to 0.170.

6.3 Alternative measure of returns

In column 7 of Table 7, we show that our main result in Table 5 is robust to the use of future raw stock returns instead of future DGTW-adjusted stock returns. We use next-month raw stock returns as the dependent variable and abnormal asymmetric attention as the independent variable. We find that the coefficient of abnormal asymmetric attention is also statistically and economically significant.

6.4 Measures of informed trading

In columns 8 and 9 of Table 7, we show the robustness of our results to alternative proxies of informed trading. In column 8, we repeat our main regression from Table 5 using price impact (e.g. Brogaard et al. (2015)) instead of bid-ask spreads. In column 9, we use both price impact and the probability of informed trading (PIN) measure of (Easley et al. (1996)), computed using the method of Brown and Hillegeist (2007). Our data on price impact are available for 2004-2014, and the PIN data are available for 2004-2010. Columns 8 and 9 show that our results remain robust to controlling for these proxies of informed trading instead of the bid-ask spread.[13]

6.5 Analyst coverage and earnings surprises

We perform two additional robustness tests of our main regression. First, in column 10 in Table 7, we show that our results do not change if we control for analyst coverage. Second, column 11 in Table 7 shows that our results are also unaltered if we control for earnings surprises in the regression. These tests add further support to the idea that that local investors have information that is incremental to other information that is publicly available.

7 Information frictions

Our conceptual framework relies on investors having an initial information advantage. This assumption can be justified on several grounds: *i)* the existence of asymmetric information at the local level has been extensively discussed by the literature on geography and finance, which argues that investors are better informed about local assets; *ii)* behavioral explanations such as local distraction bias in which local investors read local newspapers, listen to local radio stations, and watch local TV channels may lead to the existence of asymmetric information; *iii)* local media is, on average, positively biased towards local stocks.

In this section, we examine whether the abnormal return associated with abnormal asymmetric attention is arising from information frictions. According to our conceptual framework, we should observe a more pronounced effect of abnormal asymmetric attention for stocks with higher information frictions.

We use cross-sectional regressions similar to those in Table 5 to test for information frictions. We split our sample according to several variables that may be correlated with the degree of information frictions and examine whether our results become stronger in the sub-

[13]The change in the coefficient of abnormal asymmetric attention could be due either to the introduction of the new control variable, or to the change in the sample period. In additional tests, we verify that the majority of the change in the coefficient is due to the latter effect and not to the former.

sample with higher information frictions. For all of these tests, we use the median to separate the sample into two halves. Table 8 column 1 repeats our baseline estimates from Table 5 to facilitate comparisons. First, we examine whether the relation between abnormal asymmetric attention and future returns varies between small versus large firms – keeping in mind that these differences in size are interpreted within the S&P 500. Table 8 column 2 reports estimates of the same regression as column 1, but restricting the sample to relatively smaller firms, defined as those with a below-median market capitalization. We find that the relation between our measure of abnormal asymmetric attention and stock returns becomes more economically significant. For these smaller firms within the S&P 500, a one standard deviation increase in abnormal asymmetric attention is associated with an increase in next-month DGTW abnormal stock return of 20 bps. Comparing the lowest and the highest quintile of abnormal asymmetric attention, the difference in DGTW abnormal stock returns is 33.9 bps.[14]

An alternative measure of information frictions is liquidity. As argued by Frieder and Subrahmanyam (2005) and Loughran and Schultz (2005), information frictions are a major determinant of liquidity. Hence, we can also investigate our information frictions hypothesis using price impact or bid-ask spreads. Columns 3 and 4 in Table 8 show that the coefficient of abnormal asymmetric attention also increases for stocks with high trading costs, defined as having bid-ask spreads above the median and for stocks with high price impact. These patterns are consistent with the idea that private information of local investors is more valuable in stocks with relatively higher information frictions. Again, we emphasize that these differences are relative within the S&P 500.

Security analysts play an important role in generating and interpreting new information about securities. To further examine whether the effect of abnormal asymmetric attention is higher for stocks with high information frictions, column 5 in Table 8 shows results for firms

[14]We verify that the average values of abnormal asymmetric attention across its quintiles are similar in the overall distribution and for small (large) firms.

with below-median analyst coverage. We find that the coefficient of abnormal asymmetric attention increases to 0.246, lending further support to the idea that abnormal asymmetric attention is a better predictor of one-month-ahead stock returns for stocks with higher information frictions.

Finally, as an overview, Figure 2 compares the coefficient estimates of abnormal asymmetric attention in subsamples of stocks with high information frictions to those in subsamples of stocks with low information frictions. The coefficient estimate is consistently higher and more statistically significant for stocks with high information frictions as compared to stocks with low information frictions for all the measures of information asymmetry we use.

In column 6 of Table 8 we use the geographic dispersion proxy of Garcia and Norli (2012) to provide further evidence that local investors' information acquisition behavior predicts stock returns. Their measure is increasing in the geographic dispersion of the firm's operations. Therefore, if it is local investors' information acquisition that predicts stock returns, this pattern should be stronger for firms whose operations are concentrated in few U.S. states so that it is easy to interpret the notion of 'local'. We find that our coefficient estimate increases from 0.214 to 0.364 once we restrict the sample to firms with a below-median geographic dispersion of operations.

8 Alternative Stories

This section discusses the interpretation of our results. We consider whether our empirical evidence is consistent with alternative stories such as the price-pressure hypothesis, the view that only locals matter, and rumors.

8.1 Public News

The price-pressure hypothesis studied in papers such as Barber and Odean (2008) and Da, Engelberg, and Gao (2011) is based on the idea that limited attention affects asset prices because investors have a large set of available assets when making buying decisions. This implies that when investors choose to allocate attention to a particular stock, there will be an increase in buying pressure that leads to an increase in the holdings and price of the stock.

The empirical implication of these theories is that if we observe investors processing more public information about a certain stock, this means that this particular stock grabbed the attention of investors and its price should increase. Thus, the prediction of the price-pressure hypothesis is that an increase in investor attention is associated with higher future returns. This prediction relates to changes in investor attention, and not to changes in the difference between national and local attention (i.e. asymmetric attention). The common prediction of these models is that it is abnormal national attention that is associated with higher future returns instead of abnormal asymmetric attention.

The results in columns 1 of Table 5 are not consistent with this explanation: we show that abnormal national attention does not predict one-month ahead stock returns. Indeed, our results confirm the findings of Da, Engelberg, and Gao (2011) at the monthly frequency. They show that there is an increase in asset prices over the two weeks following the attention-grabbing event, which is then reversed in the future. One potential explanation for this finding is related to the data frequency. The empirical evidence supporting the price-pressure hypothesis is mostly based on daily and weekly data.

8.2 Only Locals Matter

Another possibility is that the attention behavior of just local investors is driving the results as opposed to abnormal asymmetric attention. This finding would also be consistent with the price-pressure hypothesis described in the previous section. We could interpret an increase in abnormal local attention to indicate a rise in the amount of public information processed by local investors who are considering buying a local stock. This would imply that this particular stock grabbed the attention of local investors and its stock price should increase.

To test this alternative hypothesis, we examine the relationship between abnormal local attention and future returns of equal- and value-weighted portfolios. Panel C of Table 6 presents Jensen's alphas for three portfolios sorted by abnormal local attention. The *high-local* portfolio includes stocks that have a local ASVI above the 80th percentile in a given month, while the *low-local* portfolio includes those below the 20th percentile. The *long-short-local* portfolio is constructed by taking a long position in *high-local* stocks and short position in *low-local* stocks. We then calculate the following-month's returns for each of these three portfolios. We show excess returns, as well as alphas from a five-factor model.

Using equal-weighted portfolios, the high-local portfolio experiences an average 0.87% following-month excess return, while the low-local portfolio had an average 0.79% following-month excess return. However, the long-short portfolio has an alpha that is small, and not statistically different from zero. We find similar results using value-weighted portfolios. The right three columns of Panel C show alphas from a five-factor model. When looking at equal-weighted portfolios, the alpha of the high-local portfolio is 74 bps, while the alpha of the low-local portfolio is 64 bps. Similarly to excess returns, we find that the long-short portfolio has an alpha that is close to zero and statistically insignificant. We find similar results for value-weighted portfolio alphas.

Our results suggest that neither abnormal national attention nor abnormal local attention predicts future returns. Rather, it is the *difference* between abnormal local attention and abnormal national attention that predicts stock returns one month ahead. Thus, our results are not consistent with the hypothesis that it is just the search behavior of locals that is driving our results.

8.3 Rumors

Our conceptual framework and discussion throughout the paper relies on investors allocating attention to information about the fundamentals of the firm. It is possible that the search behavior of agents responds to rumors about the firm. In this section, we examine whether our measure of abnormal asymmetric attention is capturing the arrival of news about fundamentals. To this end, we now perform two tests to analyze whether the predictability using abnormal asymmetric attention reverses at longer horizons.

First, we repeat the Fama-MacBeth regressions shown in Table 5, but regress cumulative DGTW benchmark-adjusted returns in months (t+1) through (t+2), (t+1) through (t+3), . . . , (t+1) through (t+12) on our investor attention measure in month t. These tests are shown in Table 9 Panel A. For comparison, we include the result of our main regression in column 1. For later months, we find that the relation between abnormal asymmetric attention in month t and cumulative returns over months (t+1) through (t+k) generally becomes stronger economically, while its statistical significance decreases. We estimate the largest coefficient, 0.466 (compared to 0.214 in the main analysis) for cumulative returns in the period of months (t+1) to (t+12), although the statistical significance of this effect is smaller.

Second, we repeat the regressions shown in Table 5, but regress returns in month (t+2), (t+3), . . . , (t+12) on abnormal asymmetric attention in month t. We summarize these tests in Table 9 Panel B. We find that regression coefficients are insignificant in all later months. Coefficients are initially positive in months (t+2) and (t+4), but insignificant, with t-statistics ranging between 0.16 and 1.01. The highest point estimate is 0.092 in month t=7, with a t-statistic of 1.58. We find a negative relation for months (t+5) and (t+11), although the coefficients are not statistically significant.

The results from both of these tests suggest that abnormal asymmetric attention predicts one-month-ahead returns. We do not observe a significant reversal over the next months. If anything, from the analysis of the cumulative returns, it appears that there is a slight continuation in the positive correlation between abnormal asymmetric attention and future returns. However, the month-by-month analysis highlights that this is because abnormal asymmetric attention predicts one-month-ahead returns, not because it is a statistically significant predictor of returns in individual months past the first.

Another way of analyzing the dynamics of the effect we document is to look at momentum. Boguth et al. (2016, Figure 1) show that information is incorporated faster into prices for stocks with positive momentum (winners) than for stocks with negative momentum (losers). In column 7 of Table 8, we split stocks into winners and losers based on their past returns (Ret[t-12,t-1]), and examine whether the relation is stronger for winners, defined as stocks with past returns above the median. The coefficient estimate increases significantly relative to the full sample; however, it is now only marginally statistically significant at the 10% level. Therefore, this test suggests that abnormal asymmetric attention is a stronger predictor of returns for stocks with strong past performance, for which prior research suggests that information is incorporated quicker into prices. Considering the decrease in statistical significance, however, this piece of evidence is not completely conclusive.[15]

Overall, our findings are consistent with abnormal asymmetric attention capturing the arrival of news about fundamentals. The information that local investors receive gradually diffuses to nonlocal investors and has permanent effects on asset prices, suggesting the information received by locals is information about fundamentals.

9 Conclusion

In this paper, we use data from Google Trends to construct a new measure, abnormal asymmetric attention, that captures asymmetric patterns in the search behavior of local investors relative to nonlocals. Using a simple conceptual framework, we posit that an increase in information processing by local investors relative to nonlocals predicts higher future stock returns. Consistent with this prediction, we find that stocks earn higher returns when they attract

[15]To further test the role of abnormal asymmetric attention in momentum, we run horse-race regressions to compare the return predictability of past returns with and without abnormal asymmetric attention. We find that controlling for any of these momentum measures does not drive out the predictive power of abnormal asymmetric attention and vice-versa. These tests are unreported for brevity.

abnormally high asymmetric attention from local investors. Portfolios consisting of stocks with high abnormal asymmetric attention obtain following-month risk-adjusted returns that are 32 bps higher than portfolios consisting of stocks with low abnormal asymmetric attention. Further, we provide evidence suggesting that the asymmetric attention effect exists due to the presence of local information frictions. Our results become stronger for stocks of relatively smaller firms within the S&P 500, stocks with high bid-ask spreads, and stocks with a lower analyst coverage.

Unfortunately, we are not able to increase the sample size of this study to include other stocks due to lack of SVI data at the local level for stocks outside the S&P 500. We conjecture that the asymmetric attention effect will increase in its magnitude because S&P 500 stocks are widely followed at the national level.

We hope to encourage more work exploring attention allocation theories in the future. Previous work has focused on the existence of information asymmetries to tackle many finance and macroeconomic topics. The novel measure of asymmetric attention allows us to predict the arrival of private information by observing investors' behavior. Thus, given that we can infer the arrival of private news at any moment in time, we can now provide more accurate evidence in favor of or against asymmetric information as the explanation to many puzzles.

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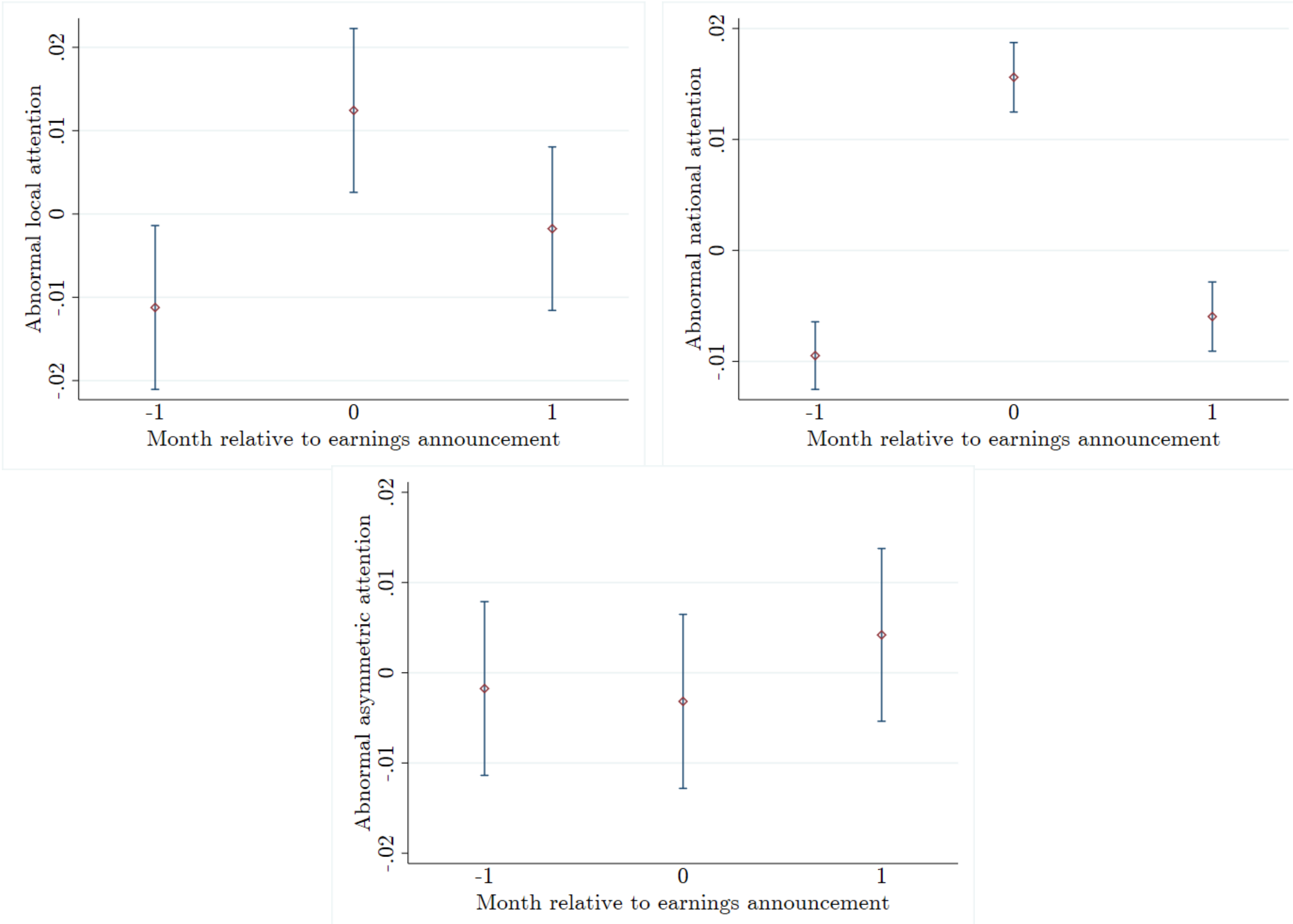
Appendix A: Variable definitions

Variable	Definition
Attention measures	
Abnormal national attention	The natural logarithm of a company's ticker ASVI among all search engine users in the U.S. Search volume index (SVI) of a company is the aggregate search volume for the company's ticker obtained from Google Insights for Search. We define abnormal search volume index (ASVI) as the natural logarithm of SVI during the current month minus the natural logarithm of the median SVI during the previous quarter (previous three months).
Abnormal local attention	The natural logarithm of a company's ticker ASVI among search engine users located in the state where the company is headquartered. Search volume index (SVI) of a company is the aggregate search volume for the company's ticker obtained from Google Insights for Search. We define abnormal search volume index (ASVI) as the natural logarithm of SVI during the current month minus the natural logarithm of the median SVI during the previous quarter (previous three months).
Abnormal asymmetric attention	The difference between *abnormal local attention* and *abnormal national*
Main independent variables	
ME	Market capitalization in the previous month (t-1), measured in $ millions
BE/ME	Book-to-market value of equity, where the book value, which is calculated according to Davis, Fama, and French (2000), is divided by the previous month market capitalization
Ret	Return of the stock during the month
Ret[t-12,t-1]	Cumulative return of the stock between t-12 and t-1
Amihud	Illiquidity measure constructed according to Amihud (2002)
Spread	The proportional quoted bid-ask spread
Volatility	Standard deviation of the daily stock returns of the current month
ΔTurnover	The difference in the natural logarithm of stock turnover between t and t-1
Measures of news	
DJ newsitems	The number of financial news items about the firm in Dow Jones Newswires, regional editions of the Wall Street Journal, Barron's and MarketWatch. We include news items that are directly relevant to the firm (RavenPack relevance score of 90/100 or above). Source: RavenPack
PR newsitems	The number of press releases, regulatory, and corporate disclosures about the firm. We include items that are directly relevant to the firm (RavenPack relevance score of 90/100 or above). Source: RavenPack
DJ article	The number of full articles, defined as "a news article composed of both a headline and one or more paragraphs of mostly textual material" about the firm in Dow Jones Newswires, regional editions of the Wall Street Journal, Barron's and MarketWatch. We include news items that are directly relevant to the firm (RavenPack relevance score of 90/100 or above). Source: RavenPack
DJ positive	The number of financial news items about the firm in Dow Jones Newswires, regional editions of the Wall Street Journal, Barron's and MarketWatch that have a positive sentiment as measured by a composite sentiment score (CSS) above 50/100. We include news items that are directly relevant to the firm (RavenPack relevance score of 90/100 or above). Source: RavenPack
DJ negative	The number of financial news items about the firm in Dow Jones Newswires, regional editions of the Wall Street Journal, Barron's and MarketWatch that have a negative sentiment as measured by a composite sentiment score (CSS) below 50/100. We include news items that are directly relevant to the firm (RavenPack relevance score of 90/100 or above). Source: RavenPack

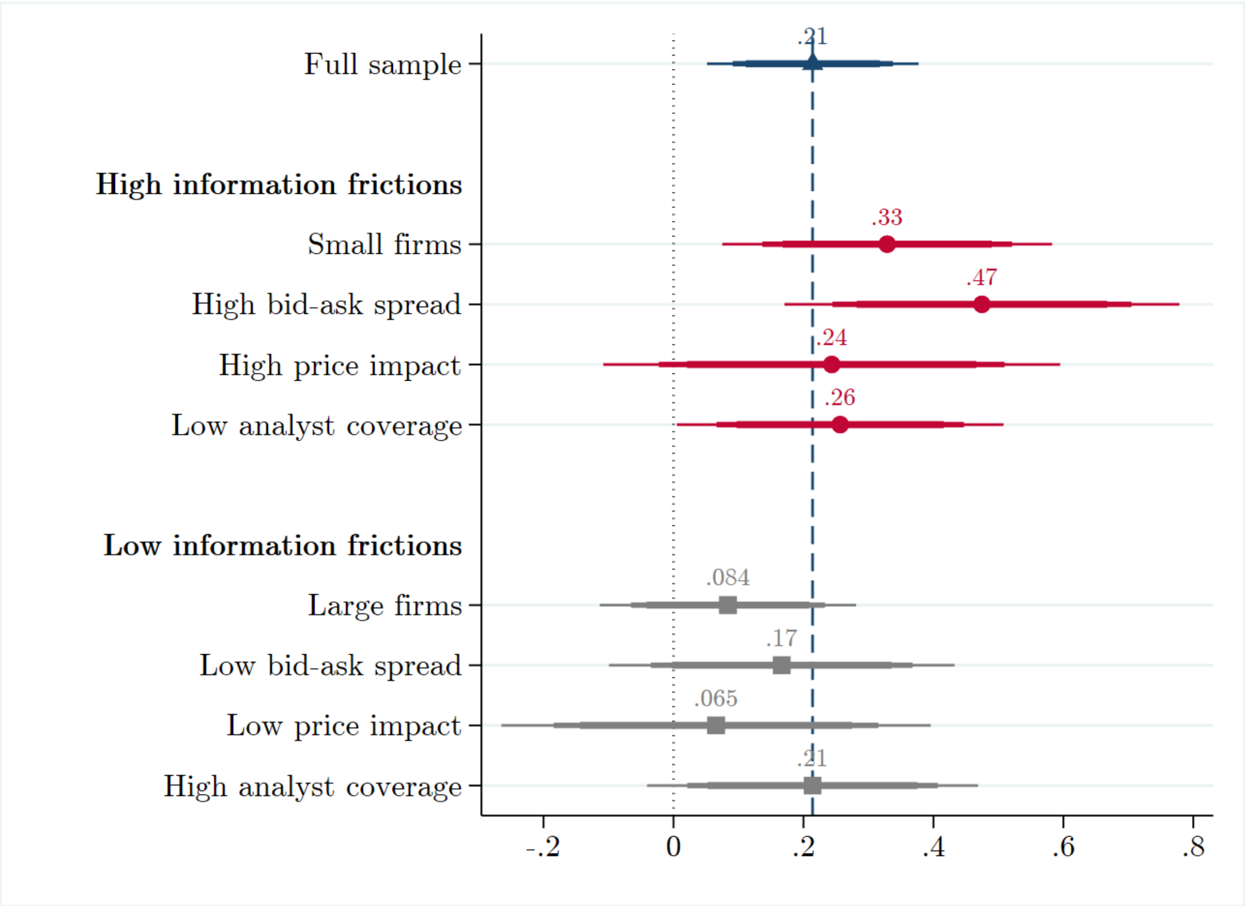
PR positive	The number of press releases, regulatory, and corporate disclosures that have a positive sentiment as measured by a composite sentiment score (CSS) above 50/100. We include news items that are directly relevant to the firm (RavenPack relevance score of 90/100 or above). Source: RavenPack
PR negative	The number of press releases, regulatory, and corporate disclosures that have a negative sentiment as measured by a composite sentiment score (CSS) below 50/100. We include news items that are directly relevant to the firm (RavenPack relevance score of 90/100 or above). Source: RavenPack
PR hivol	The number of press releases, regulatory, and corporate disclosures that are expected to have a high impact on volatility as measured by a news impact projection (NIP) score above 50/100. We include news items that are directly relevant to the firm (RavenPack relevance score of 90/100 or above). Source: RavenPack
PR lovol	The number of press releases, regulatory, and corporate disclosures that are expected to have a low impact on volatility as measured by a news impact projection (NIP) score below 50/100. We include news items that are directly relevant to the firm (RavenPack relevance score of 90/100 or above). Source: RavenPack
Measures related to earnings announcements	
EA month	A month in which the firm announces quarterly earnings (dummy). Source: I/B/E/S and Compustat
Earnings surprise (SUE)	Realized quarterly earnings per share minus the consensus (median) analyst forecast, scaled by the lagged share price. Source: I/B/E/S and CRSP
Measures of buy-sell imbalance and informed trading	
Order imbalance	The number of buy-initiated orders less the number of sell-initiated orders divided by the sum of total orders. We use the Lee and Ready (1991) algorithm to identify an order as a buy or sell. Source: TAQ
Order imbalance positive	Dummy equal to 1 if the firm-month observation has more buy-initiated orders than sell-initiated orders. Source: TAQ
Price impact	The change in the current quoted midpoint to the quoted midpoint five minutes in the future. We use the Lee and Ready (1991) algorithm to identify a trade as a buy or sell. Following Holden and Jacobsen (2014), it is aggregated to the daily level by taking the dollar-volume weighted price impact across all trades per day, and then aggregated to the monthly level using a similar procedure.
PIN	The Probability of Informed Trading measure constructed according to Easley, Kiefer, O'Hara, and Paperman (1996)
Measures related to geographic location	
Geographic dispersion	The proxy of geographic dispersion of the firm's operations from Garcia and Norli (2007). Source: Diego Garcia's website
Population	The population of the state where the firm is headquartered. Source: U.S. Census Bureau
GDP per capita	The GDP per capita of the state where the firm is headquartered. Source: U.S. Census Bureau
State portfolio return	State portfolios are constructed as value-weighted portfolios of the stocks of S&P 500 firms headquartered in each U.S. state.
State-adjusted return	The return on the stock minus the return on the corresponding state portfolio
Measure of analyst coverage	
Analyst coverage	The number of analysts covering the stock, measured as the number of analysts with estimates of current-year EPS listed in the I/B/E/S Summary file in the month prior to the fiscal year end.

Figure 1: Abnormal attention measures around positive earnings surprises



Note: Residuals from a regression of abnormal attention measures on firm and month fixed effects in the months around earnings announcements with positive surprises. The horizontal axis measures event time. Month 0 is the month of the announcement. The vertical axis measures abnormal local attention in the top left graph, abnormal national attention in the top right graph and abnormal asymmetric attention in the bottom graph. The circles represent the average of the residuals and the bars show the upper and lower end of the 95% confidence interval. Months with positive earnings surprises are ones in which the realized quarterly earnings per share is higher than the median analyst forecast of quarterly earnings per share.

Figure 2: Regression coefficients of abnormal asymmetric attention in stocks with high vs. low information frictions



Note: Coefficient estimates from Monthly Fama-MacBeth (1973) regressions from January 2004 to December 2016. The dependent variable is the DGTW characteristic-adjusted abnormal return in month t+1. The graph shows the point estimates and standard errors of the coefficient of abnormal asymmetric attention in various samples. The point estimate is shown above each marker. The triangle marker shows the coefficient estimate for the full sample, from Table 5 column 2. The point estimate is also marked with a dashed line to facilitate comparison. The circle markers show the coefficient estimates for subsamples of stocks with high information frictions, from Table 8 columns 2-5. The square markers show the coefficient estimates for subsamples of stocks with low information frictions. We sort observations into subsamples using the median of the variable noted on the vertical axis.

Table 1: Summary statistics and quintiles by asymmetric attention

Panel A: Descriptive Statistics						
	Mean	Std. Dev.	Min	Median	Max	No. Stocks
Abnormal national attention	-0.010	0.21	-3.40	0	2.29	738
Abnormal local attention	-0.016	0.61	-4.58	0	4.62	738
Abnormal asymmetric attention	-0.006	0.61	-4.72	0	4.96	738
ME	22,860	42,653	94	9,873	750,710	738
BE/ME	0.44	0.43	-26.93	0.37	15.96	738
Ret	1.03	8.80	-26.01	1.10	29	738
Ret[t-12,t-1]	14.93	36.23	-68.28	12.73	154	738
Amihud	0.009	0.012	0.000	0.006	0.08	738
Spread	0.073	0.112	-0.068	0.037	0.73	738
Volatility	1.915	1.270	0.537	1.546	7.984	738
ΔTurnover	0.002	0.318	-0.781	-0.009	0.887	738
Geographic dispersion	12.79	11.19	1	9	50	670
Price impact	0.0003	0.001	-0.117	0.0002	0.113	722

Panel B: Averages by Abnormal Asymmetric Attention (Relative ASVI) Quintiles					
	Q1	Q2	Q3	Q4	Q5
Abnormal asymmetric attention	-0.53	-0.08	0.002	0.09	0.50
ME	19,743	25,833	27,468	25,903	19,111
BE/ME	0.43	0.43	0.45	0.44	0.44
Ret	0.97	0.99	1.03	1.07	0.99
Ret[t-12,t-1]	14.7	14.19	13.5	13.74	13.85
Amihud	0.009	0.009	0.008	0.009	0.009
Spread	0.073	0.072	0.070	0.072	0.076
Volatility	1.96	1.90	1.89	1.91	1.96
ΔTurnover	0.002	-0.002	0.002	0.003	-0.0004
Geographic dispersion	12.97	12.82	12.79	12.81	12.91
Price impact	0.0003	0.0003	0.0003	0.0003	0.0003

Table 1 – continued

Panel C: Correlation matrix of the main variables												
	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Abnormal asymmetric attention	1											
2. ME	0.01***	1										
3. BE/ME	0.00	-0.11***	1									
4. Ret	0.00	0.01	0.08***	1								
5. Ret[t-12,t-1]	0.01**	0.00	-0.21***	0.00	1							
6. Amihud	0.00	0.03***	-0.01*	0.00	0.00	1						
7. Spread	0.00	-0.08***	0.09***	-0.08***	-0.08***	0.24***	1					
8. Volatility	0.00	-0.15***	0.27***	-0.11***	-0.18***	0.00	0.25***	1				
9. ΔTurnover	0.02***	-0.01	-0.02***	-0.09***	0.02***	-0.01**	0.03***	0.20***	1			
10. Geographic dispersion	0.00	-0.06***	0.12***	-0.01**	-0.02***	0.09***	0.02***	0.02***	0.00	1		
11. Price impact	0.00	-0.03***	0.04***	-0.01	-0.01**	0.00	0.04***	0.07***	0.01	-0.01*	1	
12. PIN	0.01	-0.26***	0.03***	0.05***	0.06***	0.29***	0.12***	-0.19***	0.00	0.00	0.01*	1
13. Earnings surprise (SUE)	-0.01	0.01	-0.05***	0.09***	0.05***	0.00	-0.06***	-0.06***	0.00	-0.01	0.00	0.04***

Note: Variables are defined in Appendix A. Panel A provides summary statistics of the variables used in the analysis of the paper. Panel B exhibits the relation of our *abnormal asymmetric attention* variable to firm characteristics. Each month, we divide our sample into five quintiles according to the asymmetric attention variable, where the first quintile consists of stocks with the lowest asymmetric attention. Panel B reports the averages of the firm characteristics for each of the five quintiles. Panel C reports pairwise correlation coefficients between the main variables used in the paper. The symbols ***, **, and * denote that the individual correlation coefficient is significant at the 1%, 5%, and 10% significance level, respectively.

Table 2: News and abnormal asymmetric attention

	Abnormal asymmetric attention								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DJ newsitems	0.0163***								
	(3.447)								
PR newsitems		0.0004							
		(0.035)							
DJ article			0.0146***						
			(3.528)						
DJ positive				0.0151***					
				(2.737)					
DJ negative					0.0078**				
					(2.481)				
PR positive						0.0024**			
						(2.099)			
PR negative							-0.0011***		
							(-3.108)		
PR hivol								0.0079***	
								(12.084)	
PR lovol									-0.0014**
									(-2.384)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84,635	84,635	84,635	84,635	84,635	84,635	84,635	84,635	84,635

Note: Regressions of abnormal asymmetric attention on measures of news and firm fixed effects. Each column reports standardized coefficient estimates with heteroscedasticity-robust standard errors clustered at the firm level underneath. Variables are defined in Appendix A. News data are from RavenPack. We only include news items that are directly relevant to the firm (relevance of 90 or above). The symbols ***, **, and * denote that the individual coefficient is significant at the 1%, 5%, and 10% significance level, respectively.

Table 3: Earnings announcements and search patterns of locals and nonlocals

	Abnormal local attention	Abnormal national attention	Abnormal asymmetric attention
	(1)	(2)	(3)
EA month	0.0271**	0.0171***	0.0100
	(2.416)	(4.602)	(0.910)
Firm FE	Yes	Yes	Yes
Observations	84,635	84,635	84,635
Adjusted R-squared	-0.003	0.001	-0.003

Note: Regressions of investor attention measures on dummy variables for earnings announcement months and firm fixed effects. The dependent variable is indicated in the column heading. Each column reports coefficient estimates with heteroscedasticity-robust standard errors clustered at the firm level underneath. Variables are defined in Appendix A. Data on earnings announcements are from I/B/E/S and Compustat. We follow DellaVigna and Pollet (2009) and take the earlier of the two dates in cases where the two data sources disagree. The symbols ***, **, and * denote that the individual coefficient is significant at the 1%, 5%, and 10% significance level, respectively.

Table 4: Trading behavior and local searches

	Order imbalance			Order imbalance positive		
	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal local attention	0.0204***			0.0136***		
	(3.724)			(4.790)		
Abnormal national attention		0.0847***			0.0489***	
		(5.045)			(5.601)	
Abnormal asymmetric attention			0.0115**			0.0085***
			(2.099)			(3.052)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84,635	84,635	84,635	84,635	84,635	84,635
Adjusted R-squared	0.004	0.004	0.004	0.036	0.036	0.036

Note: Regressions of investor attention measures on measures of buy-sell order imbalance and firm fixed effects. The dependent variable is indicated in the column heading. Each column reports coefficient estimates with heteroscedasticity-robust standard errors clustered at the firm level underneath. Variables are defined in Appendix A. Data on order imbalance are from the TAQ database. We classify transactions into buy and sell orders using the algorithm of Lee and Ready (1991). The symbols ***, **, and * denote that the individual coefficient is significant at the 1%, 5%, and 10% significance level, respectively.

Table 5: Abnormal asymmetric attention and stock returns

Observations	Length above 1	Length above 1	Length above 2	Dictionary 1	Dictionary 2	Dictionary 1 and 2	No selection
Month	t+1	t+1	t+1	t+1	t+1	t+1	t+1
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Abnormal national attn.	-0.239						
	(-1.563)						
Abnormal asymmetric attn.		0.214***	0.226***	0.262***	0.265***	0.278***	0.213***
		(3.435)	(3.559)	(3.571)	(3.671)	(3.762)	(3.417)
log(ME)	-0.240***	-0.241***	-0.244***	-0.210***	-0.206***	-0.206***	-0.241***
	(-6.359)	(-6.419)	(-6.415)	(-5.248)	(-5.302)	(-5.205)	(-6.508)
log(BE/ME)	-0.016	-0.016	-0.001	-0.021	-0.014	-0.017	-0.014
	(-0.257)	(-0.262)	(-0.011)	(-0.313)	(-0.222)	(-0.254)	(-0.229)
Ret	0.000	-0.000	-0.000	0.000	-0.001	-0.001	0.000
	(0.028)	(-0.032)	(-0.014)	(0.036)	(-0.209)	(-0.173)	(0.055)
Ret[t-12,t-1]	-0.000	-0.000	-0.000	-0.001	-0.001	-0.001	-0.000
	(-0.086)	(-0.086)	(-0.086)	(-0.344)	(-0.293)	(-0.364)	(-0.079)
Amihud	0.291	0.316	0.264	0.724	0.756	0.687	0.305
	(1.023)	(1.142)	(0.924)	(1.174)	(1.213)	(1.064)	(1.083)
Spread	1.269	1.268	1.191	2.078**	1.550*	2.063**	1.322
	(1.559)	(1.562)	(1.502)	(2.055)	(1.836)	(2.049)	(1.634)
Volatility	-0.002	-0.006	-0.020	-0.031	-0.051	-0.040	-0.011
	(-0.015)	(-0.062)	(-0.183)	(-0.277)	(-0.462)	(-0.353)	(-0.106)
ΔTurnover	0.012	-0.000	0.000	0.054	0.065	0.045	0.006
	(0.074)	(-0.003)	(0.003)	(0.285)	(0.345)	(0.233)	(0.034)
R-squared	0.055	0.054	0.057	0.064	0.063	0.065	0.054

Note: Monthly Fama-MacBeth (1973) regressions from January 2004 to December 2016. The dependent variable is the DGTW characteristic-adjusted abnormal return in month t+1. Columns 1-2 show the main model, which excludes firms with a ticker symbol consisting of one character. Column 3 shows model estimates excluding firms with a ticker symbol consisting of one or two characters. In column 4, we exclude firms whose tickers we classify as having a generic meaning based on the Merriam-Webster Dictionary and internet searches. In column 5, we exclude firms whose tickers were classified by our research assistant as having a generic meaning using the same search algorithm. In column 6, we exclude all firms that either we or the research assistant classified as having a generic meaning. In column 7, we show estimates using all of the S&P 500 firms, irrespective of the length of their ticker symbol, and whether their ticker symbol has a generic meaning or not. Variables are defined in Appendix A. The symbols ***, **, and * denote that the individual coefficient is significant at the 1%, 5%, and 10% significance level, respectively.

Table 6: Portfolios sorted by abnormal asymmetric attention

Panel A: Portfolios Sorted by Abnormal Asymmetric Attention

	Excess returns			Five-factor alphas		
	Low-asym	High-asym	High-Low	Low-asym	High-asym	High-Low
EW excess	0.74*	1.00**	0.26**	0.58	0.88	0.30**
returns	(0.42)	(0.42)	(0.13)	(0.55)	(0.56)	(0.13)
VW excess	0.88***	1.18***	0.30**	0.71*	1.03***	0.32***
returns	(0.32)	(0.32)	(0.13)	(0.38)	(0.39)	(0.12)

Panel B: Factor loadings of long-short portfolios sorted by abnormal asymmetric attention

	Alpha	Mkt-Rf	SMB	HML	MOM	LIQ
EV excess returns	0.29**	-0.13*	-0.06	-0.0004	0.01	-0.003
	(0.13)	(0.07)	(0.06)	(0.06)	(0.06)	(0.05)
VW excess returns	0.32***	-0.07	-0.05	-0.10	-0.03	-0.03
	(0.12)	(0.09)	(0.10)	(0.13)	(0.08)	(0.46)

Panel C: Portfolios Sorted by Abnormal Local Attention

	Excess returns			Five-factor alphas		
	Low-local	High-local	High-Low	Low-local	High-local	High-Low
EW excess	0.79*	0.87**	0.08	0.64	0.74	0.10
returns	(0.44)	(0.42)	(0.12)	(0.60)	(0.55)	(0.12)
VW excess	1.03***	1.00***	-0.03	0.89**	0.89**	0.00
returns	(0.34)	(0.33)	(0.13)	(0.42)	(0.40)	(0.11)

Note: Excess returns and alphas for portfolios sorted by *abnormal asymmetric attention* and portfolios sorted by *abnormal local attention*. Variables are defined in Appendix A. Panel A shows excess returns and alphas for the three portfolios sorted by *abnormal asymmetric attention*. Each month, we form three different portfolios: i) the high-asymmetry portfolio consists of stocks with Relative ASVI above the 80th percentile; ii) the low-asymmetry portfolio consists of stocks with Relative ASVI below the 20th percentile; iii) the long-short portfolio is a zero-investment portfolio that longs high-asymmetry stocks and shorts low-asymmetry stocks. We show the following-month excess return over the risk free rate for each portfolio and alphas from a five-factor model that includes the three Fama and French (1993) factors, the Carhart (1997) momentum factor and the Pastor and Stambaugh (2003) liquidity factor. Panel B exhibits factor loadings for the long-short portfolios of Panel A. Panel C presents excess returns and alphas for three portfolios sorted by *abnormal local attention*. The numbers in parentheses are Newey-West standard errors robust to heteroscedasticity and autocorrelation of up to 4 lags. The symbols ***, **, and * denote that the individual coefficient is significant at the 1%, 5%, and 10% significance level, respectively.

Table 7: Abnormal asymmetric attention and stock returns – robustness

Dependent variable	DGTW adj. ret.	State adj. ret.	State adj. ret.	DGTW adj. ret.	DGTW adj. ret.	DGTW adj. ret.	Raw return	DGTW adj. ret.	DGTW adj. ret.	DGTW adj. ret.	DGTW adj. ret.
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Abnormal asymmetric attention	0.202***	0.134**	0.156**	0.206***	0.233***	0.170***	0.190***	0.174***	0.183**	0.218***	0.219***
	(3.088)	(2.035)	(2.253)	(3.310)	(3.682)	(3.055)	(2.954)	(2.942)	(2.294)	(3.391)	(3.495)
Population				0.005*							
				(1.663)							
GDP per capita				-0.004**							
				(-2.171)							
State portfolio return				0.018							
				(1.211)							
Geographic dispersion					-0.006**						
					(-2.000)						
Price impact								182.415	610.515*		
								(0.729)	(1.856)		
PIN									-3.686*		
									(-1.766)		
Analyst coverage										0.009	
										(1.226)	
Earnings surprise (SUE)											24.405
											(0.672)
Controls from Table 5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation procedure	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB
Fixed effects	state	no	state	no	no	industry	no	no	no	no	no
R-squared	0.137	0.097	0.161	0.064	0.059	0.275	0.115	0.055	0.065	0.063	0.057

Note: Fama-MacBeth (1973) regressions in which the dependent variable is the DGTW characteristic-adjusted abnormal return in columns 1, 4-6, and 8-11, the state-portfolio adjusted return in regressions 2-3 and the raw return on the stock in 7, all evaluated in month t+1. This table checks the robustness of the main results of the paper to state and industry effects, geographic dispersion, benchmarking returns against state portfolios, the use of raw returns, and controlling for geographic dispersion, measures of informed trading, analyst coverage, and earnings surprises. Variables are defined in Appendix A. State portfolios are constructed as value-weighted portfolios of the stocks of S&P 500 firms headquartered in each U.S. state. The state-portfolio adjusted return is the return on the stock minus the return on the corresponding state portfolio. In column 6 we control for industry (2-digit SIC) fixed effects. Column 7 checks the robustness of regression 2 in Table 5 to the use of raw returns as a dependent variable. Data on price impact (PIN) are available for 2004-2014 (2004-2010). The symbols ***, **, and * denote that the individual coefficient is significant at the 1%, 5%, and 10% significance level, respectively.

Table 8: Information frictions

Observations	All	Small firms	High spread	High price impact	Low analyst coverage	High geo. dispersion	Winners
Month	t+1	t+1	t+1	t+1	t+1	t+1	t+1
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Abnormal asymmetric attn.	0.214***	0.329***	0.475***	0.244*	0.246**	0.364***	0.914*
	(3.435)	(3.380)	(4.075)	(1.812)	(2.517)	(3.877)	(1.663)
log(ME)	-0.241***	-0.543***	-0.251***	-0.363***	-0.254***	-0.138***	-0.348*
	(-6.419)	(-5.442)	(-4.539)	(-4.802)	(-4.092)	(-2.830)	(-1.813)
log(BE/ME)	-0.016	-0.108	0.008	-0.026	-0.039	0.027	-0.215
	(-0.262)	(-1.389)	(0.094)	(-0.289)	(-0.497)	(0.395)	(-0.703)
Ret	-0.000	0.003	0.002	-0.003	0.005	-0.002	0.017
	(-0.032)	(0.390)	(0.305)	(-0.435)	(0.651)	(-0.319)	(0.514)
Ret[t-12,t-1]	-0.000	0.003	0.001	0.003	-0.003	0.001	-0.016
	(-0.086)	(0.879)	(0.231)	(0.671)	(-0.711)	(0.329)	(-0.511)
Amihud	0.316	0.931*	0.135	0.261	6.150**	13.035*	14.445
	(1.142)	(1.710)	(0.366)	(0.152)	(2.559)	(1.804)	(1.256)
Spread	1.268	1.780	2.456*	-0.376	0.950	1.774	0.307
	(1.562)	(1.561)	(1.880)	(-0.246)	(0.631)	(1.295)	(0.182)
Volatility	-0.006	0.050	-0.026	0.108	0.100	0.053	0.017
	(-0.062)	(0.416)	(-0.217)	(0.854)	(0.816)	(0.466)	(0.101)
ΔTurnover	-0.000	-0.112	-0.182	-0.142	0.144	0.155	0.426
	(-0.003)	(-0.519)	(-0.799)	(-0.627)	(0.786)	(0.714)	(0.471)
R-squared	0.054	0.074	0.083	0.084	0.085	0.083	0.132

Note: Monthly Fama-MacBeth (1973) regressions from January 2004 to December 2016. This table presents results our main model from column 2 of Table 5 re-estimated for different subsamples. We sort observations into subsamples using the median of the variable noted in the column heading. The dependent variable is the DGTW characteristic-adjusted abnormal return in month t+1. Variables are defined in Appendix A. The symbols ***, **, and * denote that the individual coefficient is significant at the 1%, 5%, and 10% significance level, respectively.

Table 9: Abnormal Asymmetric Attention and Reversals in Stock Returns

Panel A: Abnormal asymmetric attention and cumulative returns

Return measurement period	t+1	(t+1, t+2)	(t+1, t+3)	(t+1, t+4)	(t+1, t+5)	(t+1, t+6)	(t+1, t+7)	(t+1, t+8)	(t+1, t+9)	(t+1, t+10)	(t+1, t+11)	(t+1, t+12)
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Abnormal asymmetric attention	0.214***	0.224***	0.279***	0.305**	0.274**	0.312**	0.376**	0.407**	0.389**	0.430**	0.409**	0.466**
	(3.435)	(2.673)	(2.936)	(2.586)	(2.019)	(2.167)	(2.438)	(2.363)	(2.035)	(2.181)	(2.072)	(2.228)
Controls from Table 5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.054	0.060	0.062	0.063	0.065	0.068	0.068	0.070	0.073	0.075	0.078	0.079

Panel B: Abnormal asymmetric attention and monthly returns

Month	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Abnormal asymmetric attention	0.214***	0.010	0.053	0.049	-0.016	0.046	0.092	0.070	0.053	0.004	-0.006	0.038
	(3.435)	(0.160)	(1.006)	(0.889)	(-0.255)	(0.811)	(1.579)	(1.089)	(0.803)	(0.076)	(-0.098)	(0.601)
Controls from Table 5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.054	0.060	0.059	0.054	0.056	0.057	0.052	0.054	0.054	0.052	0.053	0.055

Note: Monthly Fama-MacBeth (1973) regressions from January 2004 to December 2016. Panel A shows regressions of cumulative returns on abnormal asymmetric attention and Panel B shows regressions of monthly returns on abnormal asymmetric attention. The dependent variable in Panel A is the cumulative DGTW characteristic-adjusted abnormal return from month t+1 to the month shown in the column heading (t+2, t+3, etc.). The dependent variable in Panel B is the DGTW characteristic-adjusted abnormal return in the month shown in the column heading (t+1, t+2, t+3, etc.).All regressions in both Panels A and B also contain the control variables used in Table 5. We omit the coefficients of these control variables for brevity. Variables are defined in Appendix A. The symbols ***, **, and * denote that the individual coefficient is significant at the 1%, 5%, and 10% significance level, respectively.

Online Appendix to

Asymmetric Attention and Stock Returns

Any investor $i \in [0, 0.5]$ belongs to the local region, has an ex-ante information set $\Omega_i = \{U_L\}$, and has an ex-post information set $I_i = \{\tilde{U}_L, \tilde{Y}_{iL}, \tilde{Y}_{iN}\}$. Any $i \in (0.5, 1]$ belongs to the nonlocal region, has an ex-ante information set $\Omega_i = \emptyset$, and has an ex-post information set $I_i = \{\tilde{Y}_{iL}, \tilde{Y}_{iN}\}$. Any investor i, with a constant risk aversion parameter equal to one, maximizes the utility function

$$EU_i = E\left[E(W_i' \mid I_i) - \frac{1}{2}V(W_i' \mid I_i) \mid \Omega_i\right], \tag{1}$$

where W_i' is the wealth of the investor in the last period, subject to the budget constraint

$$W_i' = W_0\bar{R} + q_{iL}(\tilde{R}_L - \bar{R}P_L) + q_{iN}(\tilde{R}_N - \bar{R}P_N), \tag{2}$$

where q_{iL} and q_{iN} are the asset holdings of the investor, and P_L and P_N are the asset prices of the local and nonlocal asset, which are taken as given. The attention allocation choice of investor i will lead to a signal $\tilde{Y}_{ij}$ about each risky asset $j = L, N$ given by

$$\tilde{Y}_{ij} = \tilde{R}_j + \tilde{\eta}_{ij},$$

where $\tilde{\eta}_{ij} \sim N(0, \sigma^2_{\eta ij})$.

We solve the model using backward induction. First, given an arbitrary information choice, each investor decides her optimal asset holdings. Second, given the optimal risky asset demand for each signal, each investor decides her optimal information choice.

1 Portfolio Choice

First, the investor chooses the optimal risky asset demand taking the signals as given. After observing the signals, the investor derives her posterior beliefs for each asset $j = L, N$ and maximizes the following utility function

$$E(W_i' \mid I_i) - \frac{1}{2}V(W_i' \mid I_i).$$

Substituting in the budget constraint (2), we obtain

$$\left[W_0\bar{R} + q_{iL}(E[\tilde{R}_L \mid I_i] - \bar{R}P_L) + q_{iN}(E[\tilde{R}_N \mid I_i] - \bar{R}P_N)\right] - \frac{1}{2}\left[q_{iL}^2 V[\tilde{R}_L \mid I_i] + q_{iN}^2 V[\tilde{R}_N \mid I_i]\right].$$

Taking the first-order condition with respect to q_{ij} for $j = L, N$, we obtain

$$q_{ij} = \frac{E[\tilde{R}_j \mid I_i] - \bar{R}P_j}{V[\tilde{R}_j \mid I_i]}. \tag{3}$$

This equation tells us that the investor will buy more of assets that have high expected payoffs and low conditional volatility. Note that mean-variance preferences imply a demand for risky assets that does not depend on wealth.

2 Information Choice

Second, the investor chooses the optimal allocation of information resources, κ_{iL} and κ_{iN}. Taking into account the optimal asset demand given by equation (3), investors maximize their objective function given by equation (1) subject to the information constraint.

Substituting q_{ij} back into the utility function (1), we obtain:

$$EU_i = W_0\bar{R} + \frac{1}{2}E\left[\frac{\left(E[\tilde{R}_L \mid I_i] - \bar{R}P_L\right)^2}{V[\tilde{R}_L \mid I_i]} + \frac{\left(E[\tilde{R}_N \mid I_i] - \bar{R}P_N\right)^2}{V[\tilde{R}_N \mid I_i]} \mid \Omega_i\right] \tag{4}$$

We have to take the expectation of a squared random variable. Recall that for any random variable x, we can calculate $E[x^2] = V(x) + [E(x)]^2$. In this particular case, for any investor i and asset j,

$$x = \frac{E[\tilde{R}_j \mid I_i] - \bar{R}P_j}{(V[\tilde{R}_j \mid I_i])^{1/2}},$$

where the expectation is given by

$$E(x) = \frac{E[\tilde{R}_j \mid \Omega_i] - \bar{R}P_j}{(V[\tilde{R}_j \mid I_i])^{1/2}},$$

and the variance is given by

$$V(x) = \frac{V\left[E[\tilde{R}_j \mid I_i] \mid \Omega_i\right]}{V[\tilde{R}_j \mid I_i]} = \frac{V[\tilde{R}_j \mid \Omega_i] - V[\tilde{R}_j \mid I_i]}{V[\tilde{R}_j \mid I_i]}.$$

We apply the law of total variance $V[E(X \mid Y)] = V(X) - E[V(X \mid Y)]$ is applied in the second equality. Therefore, for $j = L, N$, we obtain

$$E[x^2] = E\left[\frac{\left(E[\tilde{R}_j \mid I_i] - \bar{R}P_j\right)^2}{V[\tilde{R}_j \mid I_i]}\right] = \frac{V[\tilde{R}_j \mid \Omega_i] - V[\tilde{R}_j \mid I_i]}{V[\tilde{R}_j \mid I_i]} + \frac{\left(E[\tilde{R}_j \mid \Omega_i] - \bar{R}P_j\right)^2}{V[\tilde{R}_j \mid I_i]}.$$

Applying this result to the investor's expected utility for any posterior belief in equation (4), we obtain

$$EU_i = W_0\bar{R} - 1 + \frac{1}{2}\frac{V[\tilde{R}_L \mid \Omega_i]}{V[\tilde{R}_L \mid I_i]}(1 + \theta_{iL}^2) + \frac{1}{2}\frac{V[\tilde{R}_N \mid \Omega_i]}{V[\tilde{R}_N \mid I_i]}(1 + \theta_{iN}^2), \tag{5}$$

where $\theta_{ij}^2 = \frac{\left(E[\tilde{R}_j|\Omega_i] - \bar{R}P_j\right)^2}{V[\tilde{R}_j|\Omega_i]}$ is the squared Sharpe ratio of asset $j = L, N$ for investor i. The information constraint is given by

$$\kappa = \log V[\tilde{R}_L \mid \Omega_i] - \log V[\tilde{R}_L \mid I_i] + \log V[\tilde{R}_N] - \log V[\tilde{R}_N \mid I_i],$$

which can be rewritten as

$$\frac{e^\kappa}{V[\tilde{R}_L \mid \Omega_i]V[\tilde{R}_N \mid \Omega_i]} = \frac{1}{V[\tilde{R}_L \mid I_i]}\frac{1}{V[\tilde{R}_N \mid I_i]}. \tag{6}$$

Hence, investors maximize their objective function given by equation (5) subject to the information constraint (6). Since every signal variance $\sigma_{\eta iL}^2$ and $\sigma_{\eta iN}^2$ has a unique posterior belief variance $V[\tilde{R}_L \mid I_i]$ and $V[\tilde{R}_N \mid I_i]$ associated with it, we can economize on notation and optimize over the inverse of posterior variances. Thus, the problem simplifies to maximizing a weighted sum subject to a product constraint. Note that a posterior variance can never exceed a prior variance:

$$V[\tilde{R}_j \mid I_i] \leq V[\tilde{R}_j \mid \Omega_i].$$

We can write our optimization problem as

$$\max_{x_1, x_2} a_1 x_1 + a_2 x_2$$

subject to

$$a_3 = x_1 x_2,$$

where a_1, a_2 and a_3 are positive constants and $x_1 \geq 0$ and $x_2 \geq 0$. If we substitute the constraint into the objective function, then we get the following unconstrained optimization problem

$$\max_{x_1} a_1 x_1 + a_2 \frac{a_3}{x_1}.$$

The objective function is a convex function since the second-order condition is given by $2a_2 a_3 x_1^{-3} \geq 0$ as long as $x_1 \geq 0$, hence the solution to the optimization problem is a corner solution. There are two corner solutions to the optimization problem. The first solution is to use all information resources to learn about the local asset such that conditional variances are given by $V[\tilde{R}_L \mid I_i] = \frac{V[\tilde{R}_L | \Omega_i]}{e^\kappa}$ and $V[\tilde{R}_N \mid I_i] = \sigma_R^2$, and expected utility equals $EU_i = W_0 \bar{R} - 1 + e^\kappa (1 + \theta_{iL}^2) + (1 + \theta_{iN}^2)$. The second solution is to use all information resources to learn about the nonlocal asset such that conditional variances are given by $V[\tilde{R}_L \mid I_i] = V[\tilde{R}_L \mid \Omega_i]$ and $V[\tilde{R}_N \mid I_i] = \frac{\sigma_R^2}{e^\kappa}$, and expected utility equals $EU_i = W_0 \bar{R} - 1 + (1 + \theta_{iL}^2) + e^\kappa (1 + \theta_{iN}^2)$. The optimal information choice by investor i is to allocate all information resources to learn about the asset j with the highest squared Sharpe ratio θ_{ij}^2.