Measuring Investor Attention using Google Search

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While investor attention is fundamental to the efficient functioning of capital markets, it is also an elusive construct that researchers struggle to measure. In recent years, the search volume index ("SVI") of ticker searches on Google has become a ubiquitous measure of investor attention, but the amount and effects of measurement error in ticker SVI are unknown. We investigate measurement error in ticker SVI using a dataset of 2.7 billion website visits following S&P 500 firms' ticker searches. We find that 69% of searches are unrelated to investing, that this measurement error is highly correlated with firm characteristics, and that this measurement error can easily generate false-positive or false-negative results in common settings. We go on to show that a modified version of SVI using both a firm's ticker and the word "stock" (e.g., searches for "CAT stock," which we label "ticker-stock SVI") not only better captures the search terms that investors typically use, but also has considerably less measurement error that is largely uncorrelated with observable firm characteristics. Ticker-stock SVI produces better-specified tests and while researchers must still carefully consider the effects of measurement error, we recommend that ticker-stock SVI is used in place of ticker SVI in most settings. We provide a dataset of ticker-stock SVI to facilitate future work.

KEYWORDS: Google ticker search; SVI; investor attention; measurement error.

JEL CLASSIFICATION: C13, C15, M41.

DATA: TS-SVI for the Russell 3000 is available for download at: github.com/robinlitjens/GoogleTickerStock-SVI and will be updated annually.

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1. Introduction

Investor attention is integral to effective capital markets, given it is a key mechanism through which information is processed and priced (Blankespoor et al., 2020). Despite the widespread adoption of algorithmic trading in the past decade, which would suggest less of a need for investor attention, research still demonstrates the important role that human investor attention plays in stock selections and the processing of financial news (e.g., Barber and Odean 2008; Engelberg and Parsons 2011; Drake et al. 2012; deHaan et al. 2015; Lawrence et al. 2018). Given its fundamental role in the capital markets, a large body of academic literature aims to study the importance, determinants, and effects of investor attention.

The main challenge in studying investor attention is that it is an elusive and difficult construct to measure with observational data. Earlier research typically measures investor attention using indirect proxies such as extreme returns, trading volume, and the assumed salience of events or settings (e.g., Chen et al. 2002; Barber and Odean 2008; Lehavy and Sloan 2008; DellaVigna and Pollet 2009; Hirshleifer et al. 2009; Aboody et al. 2010). As reviewed by Blankespoor et al. (2020), using indirect proxies raises concerns about whether the proxies are, in fact, highly correlated with investor attention and to the exclusion of other forces.

Modern research uses more direct measures of investor attention that leverage data on investors' acquisition of stock-relevant information. For example, proxies such as ticker searches on Google, financial report downloads from EDGAR, or activity on Yahoo Finance. Because an investor's information acquisition requires her attention, observing more widespread acquisition activities is indicative of more widespread investor attention. Among these proxies, Google's ticker search volume index ("SVI") has emerged as among the most popular. For example, as of the date of this writing, at least 100 published studies have used Google ticker SVI since Da et al.

(2011) and Drake et al. (2012) first illustrated how it can be used as a proxy for attention.[1]

Google ticker SVI has permitted an exciting wave of research on investor attention, but an important caveat is that SVI contains measurement error because searches for tickers such as "CAT" are conducted by both investors searching for Caterpillar Inc. and by internet users searching for felines.[2] Measurement error in SVI has the potential to cause types 1 or 2 errors (i.e., false-positive or false-negative results), depending on how it relates to the parameters of data generating processes and regression models. The prior literature acknowledges the existence of measurement error in SVI and makes efforts to mitigate measurement error by dropping expected noisy tickers and by creating measures of abnormal SVI. However, without data on true Google ticker searches, prior research has been unable to quantify the extent or effects of measurement error in ticker SVI.

Our study aims to quantify and investigate the effects of measurement error in Google ticker SVI as a proxy for investor attention. We estimate the extent of measurement error in ticker SVI using a dataset of roughly 2.7 billion website visits resulting from Google searches for S&P 500 tickers over 2016 – 2017. Our investigation proceeds in four parts.

First, we analytically detail the sources and forms of measurement error in ticker SVI and explain why it is ex-ante difficult to predict how measurement error positively versus negatively biases regression estimates. A key problem with SVI is that measurement error from non-investor searches has complex, non-additive relations to true investor search, which means that measurement error in SVI can drive types 1 or 2 errors even when other simplifying assumptions

[1] Blankespoor et al. (2020) review various measures of investors' information processing activities. Google ticker SVI has several advantages over other proxies, including that it is more widely available and captures a broader range of information acquisition. For example, EDGAR downloads data are not available in the late 2010's, and capture only attention to SEC filings. A list of published studies using Google ticker SVI is available in our Supplementary Materials.

[2] Measurement error is the difference between an observed variable and the underlying variable of interest (Wooldridge 2012, p852). Measurement error is not necessarily "random noise."

hold. We intuitively illustrate the potential for types 1 and 2 errors using two simple use-cases from Drake et al. (2012, hereafter "DRT") and explain why "abnormal" SVI transformations and other ad hoc methods for eliminating measurement error are unlikely to be fully effective.

Second, we descriptively analyze estimated measurement error in SVI and show that it is both considerable and non-random across firms. On average, 69% of Google ticker searches result in users clicking-through to non-investing websites, indicating that these searches are measurement error in SVI as a proxy for investor attention. Moreover, this measurement error varies systematically across industries and is highly correlated with firm characteristics such as size, book-to-market, analyst following, and volatility. We find that ad hoc guesses at ambiguous tickers are partially correct, but that considerable measurement error exists among tickers that are typically not considered ambiguous; e.g., four-letter tickers that are not common words or brands still average 47% non-investor search.

Third, we empirically examine the effects of measurement error in SVI using the forementioned two use-cases from DRT. The first use-case investigates investor attention to earnings announcements using regressions in which SVI is the dependent variable. We find that measurement error in SVI attenuates regression estimates and can therefore produce type 2 errors, even for extreme increases in true investor search around events. The second use-case investigates cross-sectional variation in investor attention to earnings announcements. Because measurement error in SVI is lower among firms that are larger, have more analysts, and have wider spreads, we show that cross-sectional regressions that partition on these characteristics can easily generate type 1 errors even when true investor search does not differ across firms. For example, simulations find that for a modest doubling of true investor search for all tickers on a randomly selected event day, 71% of trials find that increases in SVI are significantly greater for larger firms, amounting to a type 1 error rate of 71%.

The take-away from our two use-cases is that measurement error in SVI can easily cause both types 1 and 2 errors when used as a dependent variable in simple analyses, and so SVI likely has even more complex effects when used as an independent variable of interest. For example, measurement error in SVI as an independent variable can bias the coefficient on SVI itself and the coefficients on all other regressors that correlate with SVI, and the signs of those biases are model-specific and extremely difficult to guess ex-ante.

Fourth and finally, given the foregoing issues with SVI, we introduce and examine a modified version of SVI that is constructed using both a firm's ticker and the word "stock." For example, investor attention to Caterpillar would be captured by searches for "CAT stock."[3] We label this modified version as "ticker-stock SVI" or "TS-SVI," and find that it both has less measurement error and better reflects the way investors search for stock information. Specifically, we estimate that just 20% of TS-SVI searches are by non-investors, and that the average gross volume of investor searches using "[ticker] stock" is about three times that of using "[ticker]."[4] Moreover, measurement error in TS-SVI is largely uncorrelated with observable cross-sectional firm characteristics, and our simulation analyses using TS-SVI as a dependent variable find no evidence that TS-SVI leads to unacceptable levels of type-1 errors.

We conclude that TS-SVI produces better-specified tests and more robust inferences than similar analyses using SVI, and while still maintaining appropriate diligence, we recommend that researchers use TS-SVI in place of ticker SVI in future studies. Appropriate diligence should

[3] We thank one of our referees for guiding us to this modified measure. Google constructs its search volume index the same way for any keyword(s), so our analytical discussion from Section 2 pertains to both ticker SVI and ticker-stock SVI. The difference is that we expect searches for "[ticker] stock" to contain fewer non-investor searches than searches for just "[ticker]".

[4] For Caterpillar, for instance, we estimate that just 6% of searches for "CAT" are by investors versus 83% of searches for "CAT stock." In terms of search volume, we estimate that there are 71,447 investor searches for "CAT" per month versus 107,716 for "CAT stock."

include using our discussion from Section 2 to carefully consider how measurement error in TS-SVI likely affects estimates and inferences in each study's particular setting.[5] We provide a dataset of TS-SVI for the Russell 3000 to support future studies, and we provide ticker-level estimates of measurement error in TS-SVI to help facilitate considerations about measurement error in those studies' settings.

2. The Sources and Effects Measurement Error in Google Ticker SVI

This section details how SVI is constructed, its sources of measurement error, and how that measurement error likely affects regression results.

2.1 Sources of Measurement Error

Google calculates SVI for the keyword *i* in a specified geography in period *t* is as follows:

$$SVI_{i,t} = \left(\frac{Keyword\_Search_{i,t} / Geo\_Search_t}{max_w \left[Keyword\_Search_{i,t} / Geo\_Search_t \right]_w} \right) * 100 \qquad \textbf{(1)}$$

Keyword_Search is the number of searches for the keyword *i* in period *t*. For our purposes, the keywords are firms' tickers on a daily basis. Geo_Search_t is the total searches for all keywords in the selected geographic area during period *t*. The geographic area is typically set to the United States in studies of U.S. firms and totals billions of searches per day.[6] The denominator is the maximum scaled search for firm *i* observed for any period *t* over time window *w*, such that SVI represents the within-firm relative keyword search on a scale of 0 to 100. The time window *w* is chosen by the researcher when requesting the data from Google.

Ambiguous tickers mean that *Keyword_Search* includes actual ticker searches by investors

[5] TS-SVI is constructed identically to SVI as detailed in Section 2, but the *Keyword_Search* includes "[ticker] stock" instead of just "[ticker]".
[6] Google scales by *Geo_Search* to facilitate comparisons of "relative popularity" of keywords across geographies, "otherwise places with the most search volume would always be ranked highest." https://support.google.com/trends/answer/4365533?hl=en&ref_topic=6248052. Accessed March 2018.

(*Investor_Search*) as well as searches for the same word but for non-investing purposes (*Noise_Search*). *Noise_Search* is, therefore, measurement error in SVI as a proxy for investor attention. Together, SVI can be rewritten as follows:

$$SVI_{i,t} = \left(\frac{\left(Investor\_Search_{i,t} + Noise\_Search_{i,t}\right) \big/ Geo\_Search_t}{max_w \left[\left(Investor\_Search_{i,t} + Noise\_Search_{i,t}\right) \big/ Geo\_Search_t \right]_w} \right) * 100 \tag{2}$$

Prior research recognizes that the levels of *Investor_Search* and *Noise_Search* likely differ across tickers, so studies often attempt to mitigate biases by using abnormal transformations of SVI. One common abnormal transformation, ASVI, is calculated as the percentage change between SVI in period *t* and the average SVI observed over a pre-event control window (Drake et al. 2012).[7] For conciseness, we use IS, NS, and GS as shorthand for investor, non-investor, and geo search, and represent the control window as just a single period:

$$ASVI_{i,t} = \frac{SVI_{i,t} - SVI_{i,t-1}}{SVI_{i,t-1}} = \frac{\left(\frac{\frac{IS_{i,t}+NS_{i,t}}{GS_t}}{max_w \left[\frac{IS_{i,t}+NS_{i,t}}{GS_t} \right]_w} \right) - \left(\frac{\frac{IS_{i,t-1}+NS_{i,t-1}}{GS_{t-1}}}{max_w \left[\frac{IS_{i,t-1}+NS_{i,t-1}}{GS_{t-1}} \right]_w} \right)}{\left(\frac{\frac{IS_{i,t-1}+NS_{i,t-1}}{GS_{t-1}}}{max_w \left[\frac{IS_{i,t-1}+NS_{i,t-1}}{GS_{t-1}} \right]_w} \right)} \tag{3}$$

Da et al. (2011) use an alternate abnormal specification based on the difference between logged event-window SVI minus the logged median SVI from a pre-event control window (ASVI2). For simplicity, we again represent the pre-event control window as just a single period:[8]

$$ASVI2_{i,t} = ln\left(1 + SVI_{i,t}\right) - ln\left(1 + SVI_{i,t-1}\right)$$

$$= ln\left[1 + \frac{\frac{IS_{i,t}+NS_{i,t}}{GS_t}}{max_w \left[\frac{IS_{i,t}+NS_{i,t}}{GS_t} \right]_w} \right] - ln\left[1 + \frac{\frac{IS_{i,t-1}+NS_{i,t-1}}{GS_{t-1}}}{max_w \left[\frac{IS_{i,t-1}+NS_{i,t-1}}{GS_{t-1}} \right]_w} \right]$$

[7] For example, specifying the pre-event control window to be the same weekday over the trailing ten weeks helps to eliminate systematic variation in search across weekdays.
[8] Adding 1 before logging is done to avoid losing observations for which SVI is zero.

(4)

Equations (3) and (4) show that *Noise_Search* has complex, non-linear roles in both ASVI and ASVI2. While the abnormal transformations likely eliminate some portion of *Noise_Search*, their effectiveness is unclear.

Recognizing the limits of abnormal transformations, some studies further attempt to mitigate *Noise_Search* by dropping tickers that are thought to be especially ambiguous. Ambiguous tickers usually include those that are one- or two-letters long, brand names, and common words such as CAT (e.g., DRT). Da et al. (2011) note that a drawback of this approach is that it introduces subjectivity into the sample construction. Another problem is that papers often do not report the excluded tickers (e.g., deHaan et al. 2015), complicating replication and comparisons across papers.

Another approach to mitigating *Noise_Search* is to include only tickers where a Google search produces a stock market summary box as the first result (i.e., a box showing the stock price and other information). Madsen & Niessner (2019) explain that this approach also has several weaknesses, including: (i) Google changes its search results over time, so it is difficult to know what a ticker search would have produced during a study's sample period; (ii) Google can tailor search results to specific users; and (iii) it is not clear that the presence of a stock summary box means that the searcher was interested in stock information (for example, even if a "CAT" search produces a stock summary box, the searcher may still click on a lower link for felines).

In sum, Equations (2), (3), and (4) show that SVI, ASVI, and ASVI2 are complex functions of *Noise_Search*, and the effectiveness of ad hoc approaches to dropping noisy tickers is unclear. While the three equations also contain measurement error from *Geo_Search*, *Geo_Search* is not firm-specific so is unlikely to be a major concern in most studies, at least for firms within the same geography.[9] We therefore focus on the effects of measurement error due to *Noise_Search*.

2.2. The effects of Noise_Search on regression estimates

It is difficult to predict how measurement error from *Noise_Search* biases regression coefficient estimates. As always, the effects of measurement error depend on a multitude of factors, including whether measurement error is in the dependent or independent variables (or both), how measurement errors relate to the true variables, and the correlations between regressors. For SVI, ASVI, and ASVI2, a particular challenge is that *Noise_Search* is not an additive function of *Investor_Search*, which means that *Noise_Search* can negatively or positively biases coefficient estimates even when other simplifying assumptions hold.

We illustrate the potential effects of *Noise_Search* on both types 1 and 2 errors using two cases from DRT in which SVI is the dependent variable. We choose these two cases because they are simple and because they are from one of the earliest studies using ticker SVI as a proxy for investor attention. We follow with a brief discussion of additional complications when using SVI as an independent variable.

2.2.1. Case 1: SVI as a dependent variable in pooled tests

The first case investigates investor search around earnings announcements relative to days without earnings announcements.[10] The panel dataset includes an observation for each firm *i* on day *t*, but we drop the subscripts for brevity going forward. A researcher would ideally start with a univariate model such as:

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[9] Bias due to systematic variation in *Geo_Search* is likely rare but is conceivable. As one potential example, Huang et al. (2019) examine whether investor attention declines around jackpot lotteries in Taiwan. They find large increases in Google SVI for words like "lottery" and decreases in SVI for firms' names on lottery days. If lottery-related searches have a sufficiently large impact on *Geo_Search*, then SVI for firms' names on lottery days could be biased. A separate concern is that *Geo_Search* likely has time trends (e.g., weekdays have more search than weekends), but such trends can likely be reduced by carefully selecting the control window in ASVI and ASVI2 (e.g., the same day over the last several weeks) and by using time fixed effects.

[10] DRT also examine search around other announcements. We focus on earnings announcements for simplicity but the same econometric issues would apply to search around any event.

$$SVI' = \beta_0 + \beta_1 EA + \mu \quad \textbf{(5)}$$

Where SVI′ is perfectly measured investor search, EA is an indicator for earnings announcement days, μ is the unexplained residual, and we assume that all of the usual OLS conditions hold. In practice, though, the researcher must use an observable proxy SVI instead of SVI′.

Introductory textbooks (e.g., Wooldridge 2012, Chapter 9) explain that measurement error in SVI will not bias estimated β_0 and β_1 from equation (5) under the following conditions: (i) the relation between noise search (NS) and SVI is additive; (ii) NS has a zero mean; and (iii) NS is uncorrelated with SVI′, EA, and μ. In such cases, the only effect of NS is to increase the error variance and, therefore, the risk of type 2 errors.[11]

The discussion in Section 2.1 indicates that the first two forementioned conditions do not hold for SVI′. Specifically: (i) the relation between true investor search and noise search is not additive; and (ii) noise search cannot be negative, so it likely has a positive mean. Relaxing these conditions means that NS can produce either positively or negatively biased estimates of β_1. As a simple demonstration, consider a non-additive form SVI=(SVI′/NS). Substituting into (5) yields:

$$(SVI'/NS) = (\beta_0/NS) + (\beta_1/NS)EA + (\mu/NS) \quad \textbf{(6a)}$$

$$SVI = (\beta_0/NS) + (\beta_1/NS)EA + (\mu/NS) \quad \textbf{(6b)}$$

$$SVI = \gamma_0 + \gamma_1 EA + \eta \quad \textbf{(6c)}$$

Equation (6c) will estimate γ_1, which differs from β_1 by $[(\beta_1/NS) - \beta_1]$. The sign of the bias depends on both β_1 and NS, so is ambiguous without further knowledge.

The effects of NS in (6c) are further complicated if we relax assumption (iii) and allow NS and EA to be correlated, in which case the bias in γ_1 relative to β_1 would also depend on the sign

[11] Adding measurement error to the dependent variable increases the variance of the dependent variable, even if the measurement error is random and mean-zero. Specifically, $Var(Y+NS) = Var(Y) + Var(NS) + 2\times Cov(Y,NS)$.

and strength of that correlation. As an applied example, Madsen & Niessner (2019) examine the effects of product advertisements (the independent variable) on investor search (proxied by ticker SVI). Madsen & Niessner explain that, because some firms' product names are similar to their tickers, product searches are noise search that likely increases around advertisements. Thus, NS is correlated with the independent variable of interest, which likely biases inferences about the effects of advertisements on investor attention.

The effects of NS are also further complicated if allow the independent variable of interest to be measured with error. For example, exploratory analyses in Ben-Rephael et al. (2017) examine SVI around news articles, with the latter proxied by articles broadcast over Dow Jones newswire. The news proxy has measurement error because Dow Jones newswire also contains firm-issued press releases, which (by many definitions) are not true news articles (Blankespoor et al. 2018). Firm-issued press releases likely include product announcements that cause consumers to Google search for product names. When product names are similar to tickers, NS correlates with measurement error in the independent variable of interest.

Finally, the effects of NS are again further complicated if we expand (6c) to include a control variable, γ_2Z. If NS is correlated with the measured value of Z, then estimated γ_2 can be biased. Bias in estimated γ_2 can affect estimated γ_1, with the sign and magnitude depending on both the bias in γ_2 and the correlation structures between NS, EA, and Z. In practice, archival studies tend to include numerous control variables, so correlations between NS and controls are plausibly common.

In sum, even in relatively simple cases, noise search can produce positively or negatively biased coefficient estimates in models with SVI as a dependent variable.

2.2.2 Case 2: SVI as a dependent variable in cross-sectional tests

The second case builds on the first by examining cross-sectional predictions about which types of firms have greater increases in investor search around earnings announcements. Specifically, DRT examine whether increases in search are greater for firms that are larger, have more analysts, and have higher bid-ask spreads. They partition firms into high/low groups of each characteristic using a binary partitioning variable, *Partition*.

Simple cross-sectional tests can compare coefficients across models of sub-populations or, equivalently, use an $EA \times Partition$ interaction variable:

For *Partition* = 0: $$SVI = \beta_0 + \beta_1 EA + \eta \qquad \textbf{(7a)}$$

For *Partition* = 1: $$SVI = \Omega_0 + \Omega_1 EA + \eta \qquad \textbf{(7b)}$$

Pooled: $$SVI = \phi_0 + \phi_1 EA + \phi_2 Partition + \phi_3 EA \times Partition + \eta \qquad \textbf{(7c)}$$

Where the test of interest is that ($\Omega_1 > \beta_1$) or, equivalently, ($\phi_3 > 0$).

Non-additive NS can cause both type 1 and 2 errors in cross-sectional tests, depending on how it varies across tickers with *Partition*=0 versus 1. For example, assume that β_1 and Ω_1 are positive and that NS biases estimates of both towards zero. If firms in *Partition=1* tend to have less noise search than firms with *Partition=0*, then we could find that estimated ($\Omega_1 > \beta_1$) even for firms with identical increases in investor search around earnings announcements, resulting in a type 1 error.

In practice, it is hard to speculate about how noise search correlates with common partitioning variables. We instead leave correlations as an empirical question to examine below.

2.2.3 Other cases: SVI as an independent variable

Measurement error in an independent variable is generally more problematic than measurement error in a dependent variable. In a multiple regression, even random, additive measurement error in an independent variable can not only positively or negatively bias the coefficient on the measured variable itself, but can also positively or negatively bias the coefficients on all other regressors. Thus, the effects of noise search on false-positive or -negative results when SVI is used as an independent variable are again difficult to predict. Studies including Brown et al. (1987), Easton and Zmijewski (1989), Jennings et al. (2022), and Roberts and Whited (2013) further discuss the complications of measurement error in independent variables.

3. Data, Sample Construction, and Estimating *Noise_Search*

3.1 Sample selection

Table 1, Panel A details our sample selection. Our sample includes S&P 500 firms as of January 1st, 2016. We include tickers for all share classes, yielding 511 tickers. Our sample spans 2016 through 2017. We download SVI data from Google for each ticker and construct a daily series using the procedures in the definition for SVI in Appendix A. We drop two tickers for which SVI is unavailable and 19 firms with ticker changes during our sample period. Lastly, we require each firm to have the necessary variables in Compustat, CRSP, I/B/E/S, and FactSet. Our final sample includes 481 firms, 490 tickers, and 245,015 trading days.[12] Summary statistics are provided in Panel B of Table 1, and variable definitions are in Appendix A.

3.2 Method for estimating Investor_Search versus Noise_Search

We estimate *Noise_Search* in SVI by assessing whether ticker keyword searches are made by investors searching for current information about the ticker versus non-investors searching ticker homonyms. We make this determination using a dataset of roughly 2.7 billion website visits following Google searches for S&P 500 tickers during our sample period, which we label ticker "click-throughs." We obtain the dataset from SimilarWeb, which sells web traffic data for commercial purposes and reports an accuracy rate of over 99%. These web traffic data include

[12] Three tickers do not have the full two years available in CRSP/Compustat/IBES. Tickers with missing SVI are because Google does not provide SVI for keywords with minimal search. See Table 1 for details.

click-throughs for each website as a fraction of total click-throughs and are obtained by SimilarWeb from a variety of sources, including internet service providers, browser trackers, and data sharing agreements with websites. SimilarWeb discloses that "two billion digital signals are analyzed, consisting of 2 terabytes of data by 200 data scientists, ensuring a statistically representative dataset" from 100 million websites across 190 countries.[13] Moreover, it mentions that approximately 50% of the S&P 500 firms rely on SimilarWeb for decision-making. Hence, SimilarWeb does not appear to have any obvious coverage biases.

We identify *Investor_Search* versus *Noise_Search* based on the contents of the website visited after each ticker search. If a searcher clicks through to a website containing investment-related information, we designate that search as *Investor_Search*. We designate click-throughs to other websites as *Noise_Search*. We start by using SimilarWeb's website classifications to assess whether each click-through website has investment-related content. As shown in column (ii) of Table 2 Panel A, 35.3% of all click-throughs go to websites that are categorized by SimilarWeb as "Shopping." The next highest categories are "Unknown" at 17.0% and "Finance" at 9.6%. Thus, it appears that many ticker searches are likely *Noise_Search*.

Rather than relying solely on SimilarWeb's categorizations, we also manually review websites to determine whether they contain investor-related information. This determination requires subjectivity, and we applied the coding rules below. Incorrect classifications of *Investor_Search* introduces some measurement error, the effects of which we discuss in Section 3.4. Except for the first rule, we use the same website classifications for all firms (e.g., wsj.com is designated as investor-related for all tickers), which helps mitigate the risk that measurement error from misclassifications varies systematically across firms.

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[13] https://www.similarweb.com/corp/ourdata/ (accessed September 10, 2021)

1) Firms' investment-specific domains are classified as *Investor_Search* (e.g., investor.fb.com). Commercial homepages are *Noise_Search* (e.g., facebook.com). While investors could perform visits to commercial webpages, the volume of visits indicates that most visits to commercial websites are not by investors (e.g., 97% of all ticker searches for "CVS" go to cvs.com).[14] Still, reperforming our analyses in Tables 4 and 5 while classifying commercial homepage visits as *Investor_Related* produces unchanged inferences.
2) News and media websites are classified as *Investor_Search* if they contain primarily financial news (e.g., marketwatch.com). News and media websites primarily containing general-interest news are classified as *Noise_Search* (e.g., people.com and espn.com).
3) Trading websites such as wfadvisors.com or fidelity.com are classified as *Investor_Search*. Visits to retail bank websites such as wellsfargo.com are classified as *Noise_Search*.

Reviewing every click-through website is costly, so we take a sampling approach. We start by reviewing the top ten click-through websites for each ticker. If the top ten websites do not comprise at least 70% of the total traffic, we review additional websites until at least 70% of traffic is covered. To ensure that we have good coverage across SimilarWeb's categories, we also review a minimum of 70% of traffic within each website category. As shown in column (iii) of Table 2 Panel A, following these procedures means that we review 94% of all website traffic. For unreviewed websites, we use the category's average *Investor_Search* to estimate investor-related searches. Panel B of Table 2 lists the top 20 website domains that are designated as *Investor_Search*, which together comprise roughly 80% of all click-throughs.

After classifying investor and non-investor search at the ticker level, we calculate each ticker's *Investor_Search* and *Noise_Search*. Our estimates of *Investor_Search* and *Noise_Search*

[14] Untabulated tests find insignificant differences in firm characteristics between those that have a separate investor relations domain versus those that do not (e.g., investor.company.com versus company.com/investor).

are averages over the two-year sample, and we do not attempt time-varying estimates for two reasons. First, Google only provides search frequencies in round buckets per month (e.g., 110,000 clicks, 135,000 clicks, etc.) rather than as a continuous number, which eliminates much of the month-over-month variation in search levels.[15] Second, while SimilarWeb can provide click-through data on a monthly basis, the data are unpopulated in months when a ticker does not reach a minimum threshold of clicks. We, therefore, examine SimilarWeb's click-through data for the two-year period and do not analyze the possibility of time-varying measurement error, which is a limitation that we further discuss below.

3.3 Descriptive analysis of Investor_Search and Noise_Search

Table 1, Panel B, shows that our sample average *Investor_Search* is 0.311, indicating that 31% of ticker searches are performed by investors. The remaining 69% of searches are *Noise_Search*. Figure 1 provides a histogram of *Noise_Search* by ticker and shows that it is highly skewed, with 125 tickers having *Noise_Search* of over 90%. SM1 in the Supplementary Materials section reports estimated *Investor_Search* for each of the tickers in our sample.

As mentioned, some studies attempt to mitigate *Noise*_Search by dropping ambiguous tickers that are one- or two-letters long, common words, and brand names. Panel A of Table 3 shows that these intuitions are correct. For example, firms with ambiguous tickers have an average of 2,441,110 searches per month, of which an average of 84.9% are *Noise_Search*.[16] Calculated by firm, the average non-investor (true investor) searches for ambiguous tickers are 2,424,661

[15] While we obtained search frequency data from SimilarWeb, SimilarWeb obtains the data from Google. The search frequency buckets are how Google provides data to AdWords subscribers.
[16] We use the list of 20 ambiguous tickers provided by Drake et al. (2009). As an additional test, we updated the list to include ambiguous tickers added to the S&P 500 between 2009 and 2016 (AMG, CERN, DAL, FOX, LEG, LUV, MAC, O, SIG, V). Untabulated results show comparable average *Noise_Search* of 86.2% for the 30 ambiguous tickers.

(16,449) per month.[17] One- through five-letter tickers have average *Noise_Search* that declines monotonically from 93.4% to 38.7%. However, the ticker-level data in SM1 of the Supplementary Materials show many deviations from these trends. For example, of the 30 tickers with more than 99% *Noise_Search*, 28 tickers have three or more letters. Moreover, VZ has only 43% *Noise_Search* despite being only two letters.

Also as mentioned, another approach to mitigating *Noise_Search* is to include only tickers where a Google search produces a stock market summary box as the first result. Panel A of Table 3 also shows the tickers that produce a market summary box on Google as of August 2018 have *Noise_Search* of 56.8%, relative to 88.8% for tickers that do not produce a market summary box on Google.

Panel B of Table 3 shows substantial variation in *Noise_Search* across industries. Panels C and D of Table 3 show that *Noise_Search* is correlated with firm characteristics that are common control variables or partitioning variables in cross-sectional tests.[18] For example, univariate correlation coefficients in Panel C are significantly negative for market value, return on assets, analyst following and bid-ask spread. Panel D considers these firm characteristics together in an OLS regression. Column (i) shows that common firm characteristics explain 11.9% of the variation in *Noise_Search*, with market value, momentum, and stock beta being individually significant. Column (ii) adds industry fixed effects and controls for ticker length and finds that explanatory power increases to 26.3%, and that leverage and trading volume also become statistically

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[17] 2,424,661 is the average of estimated firm i's non-investor search: $\frac{1}{I}\sum_{i=1}^{I}(Total\_Search_i \times \%Noise\_Search_i)$. This number differs from the pooled average estimated non-investor search of 2,438,237 x 84.9% = 2,070,063 searches. The difference is because the average of a product is not equal to the product of averages.

[18] We examine a handful of firm characteristics that commonly appear as covariates in regression analyses. Results may differ for other firm characteristics or in different samples. Section SM1 of our Supplementary Materials provides *Noise_Search* estimates for each ticker, which can be used to examine variation in *Noise_Search* in other datasets.

significant. Explanatory power of 26% indicates that cross-ticker variation in *Noise_Search* is far from random.

In sum, we find that measurement error from *Noise_Search* in SVI is extensive and highly correlated with many firm characteristics.

3.4 Measurement error in our estimate of Noise_Search

Our estimates of *Noise_Search* have their own measurement error. First, as discussed above, our data only allow us to estimate each firm's *Noise_Search* over the pooled two-year period, while actual *Noise_Search* varies over time. Second, our classifications of websites as *Investor_Search* versus *Noise_Search* require subjectivity and are imperfect. Third, we cannot observe ticker searches that did not result in a website click-through, e.g., if an investor learns solely from the stock information boxes that Google returns for some tickers.[19] These sources of measurement error mean that our assignments of observations to *Noise_Search* deciles below are noisy unto themselves, but we have no reason to believe that measurement error in our estimate of *Noise_Search* systematically confounds our inferences. Still, the extent and effects of measurement error are unobservable, so they may cause unanticipated confounds.

4. Investigating the effects of noise search in SVI in regression analyses

As discussed in Section 2, it is difficult to ex ante predict the effects of *Noise_Search* on regression estimates. This section empirically explores the effects of *Noise_Search* using the two cases from DRT and explained in Section 2.2.

4.1. Case 1: SVI as a dependent variable in pooled tests

We first investigate pooled tests of investor attention around earnings announcements, as motivated in Section 2.2.1. Our regressions resemble (6c):

[19] That said, as discussed in relation to Table 4, our results are very similar when we include/exclude tickers that produce a market summary box in Google.

$$Search = \gamma_0 + \gamma_1 EA + \gamma_{2 \ldots n} Controls + \eta \qquad \textbf{(8)}$$

Search is one of SVI, ASVI, or ASVI2 for firm *i* on day *t*. *EA* is an indicator variable for earnings announcement days. *Controls* follow DRT and include: *News Articles*, *Abs Return, MVE, Analyst Following, Trading Volume, Spread, Fourth Qtr, Total EAs, Institutional Ownership, BTM,* and *year-week fixed effects*. Standard errors are clustered by the firm.

Panel A of Table 4 provides the results of a univariate version of equation (8), excluding controls and fixed effects. The leftmost column presents results for the pooled sample. The upper rows display results for SVI, the middle rows for ASVI, and the lower rows for ASVI2. All three measures find highly significant increases in search around earnings announcements.[20] That said, the *t*-statistic on ASVI is more than double that of SVI, consistent with the ASVI transformation removing some measurement error. ASVI2 is less statistically significant than ASVI but more than SVI. Focusing on ASVI, the coefficient of 0.674 indicates that ticker search increases by roughly 67% around earnings announcements.

Columns (iii) through (xii) of Panel A rerun a univariate equation (8) by decile of ticker-level *Noise_Search*. Both the magnitude and statistical significance of estimated γ_1 tend to decrease across deciles of *Noise_Search*, becoming insignificant by the highest decile. These results are consistent with *Noise_Search* biasing univariate regression coefficient estimates and test statistics towards zero. The trends for SVI, ASVI, and ASVI2 are similar, indicating that the abnormal transformations in ASVI and ASVI2 do not fully eliminate measurement error from *Noise_Search*.

In terms of magnitudes and again focusing on ASVI**,** the coefficient on ASVI of 2.764 in column (iii) of Panel A indicates that search increases by roughly 276% around earnings announcements for tickers with the least *Noise_Search*. Hence, the finding in the pooled sample

[20] The coefficient magnitudes cannot be compared across SVI, ASVI, and ASVI2 due to different functional forms.

estimating a 67% increase in search in column (ii) appears to substantially understate investor attention to earnings announcements. The coefficient on ASVI of -0.008 in column (xi) for the highest decile of *Noise_Search* indicates that investor attention does not increase at earnings announcements, which is plausibly a type 2 error driven by *Noise_Search*.[21]

Ex ante, the effects of adding covariates in Panel B of Table 4 are unclear. On the one hand, because the covariates likely control for some of the variation in search around earnings announcements, the magnitude of estimated γ_1 plausibly declines compared to Panel A. However, as shown in Section 3, *Noise_Search* correlates with several of the controls, so the estimated γ_1 could be positively or negatively biased relative to Panel A. What we observe is that the estimated γ_1 are uniformly smaller and less statistically significant in Panel B relative to Panel A, and that the declining trend in estimated γ_1 across deciles of *Noise_Search* is still evident. Section SM2 of the Supplementary Materials presents the fully tabulated results and shows that control coefficient estimates also tend to attenuate across columns. For example, the coefficient on *News_Articles* for ASVI is 0.054 (t=5.38) for the least noisy decile but is -0.001 (t=-1.01) for the noisiest decile.

Section SM3 of the supplementary materials investigates the effectiveness of additional attempts to mitigate measurement error. We first drop the ambiguous tickers identified by DRT and one- and two-letter tickers. The dropped tickers tend to concentrate in the upper deciles of *Noise_Search,* but the regression coefficients still decline sharply across the deciles. Second, we repeat the prior test after dropping ten additional ambiguous tickers that were added to the S&P 500 after DRT's sample period, and again find similar results. Third, we find similar results when retaining only tickers for which Google returns a stock information box. Finally, we find that

[21] Untabulated regressions of *Search* on *EA* and the interaction of *EA*×*Noise_Search_Decile* finds highly significant negative coefficients on the interaction terms for SVI, ASVI, and ASVI2, which further supports an attenuating effect across deciles of *Noise_Search*.

adding firm fixed effects produces marginally stronger results in the middle deciles of *Noise_Search*, but the declining trend in estimated γ_1 across deciles still persists.[22] Overall, none of the additional attempts to mitigate measurement error appears particularly effective.

In sum, the results in Table 4 indicate measurement error from *Noise_Search* produces downward biased coefficients and *t*-statistics in a simple use-case with SVI as a dependent variable.

4.1.1 Simulation tests

A weakness with the analyses in Table 4 is that it is possible that true investor search around earnings announcements is lower for firms that have higher *Noise_Search*, in which case it is impossible to isolate the effects of measurement error. We address this concern using simulations in which we induce specified increases in *Investor_Search* around random dates.

Section SM4 of our Supplementary Materials details our simulation procedures. In brief, we induce specified increases in *Investor_Search* around random dates (*Random_Day)*, and then estimate equation (8) to see whether it rejects the null that estimated γ_1 on *Random_Day* is zero. We iterate the simulation for 1,000 different *Random_Day* to arrive at an estimated rejection rate. We then repeat the whole process for induced increases of *Investor_Search* ranging from 5% to 500%, and for each of SVI, ASVI, and ASVI2.

Simulation results tabulated in SM4 produce similar inferences to the real data in Table 4. When pooling all firms, model (8) reliably identifies increases in SVI, ASVI, and ASVI2 around *Random_Day* for induced increases in search of 10% or more. When running regressions by decile of *Noise_Search*, results get progressively weaker for the higher deciles. In the highest decile of

[22] Fixed effects that can either mitigate or exacerbate the effects of measurement error depending on: (i) the magnitude of the within-firm variation in the perfectly measured variable relative the within-firm variation in the observable variable's measurement error; and (ii) the correlation structure between the firm fixed effects and both the dependent and independent variables. See Breuer & deHaan (2023) and Jennings et al. (2022) for further discussion.

Noise_Search, model (8) does not reliably identify increases in true search, even for increases as large as 500%.

In sum, the simulation results indicate that the declining coefficients across deciles of *Noise_Search* observed in Table 4 are driven by measurement error as opposed to differences in true investor search.

4.2. Case 2: SVI as a dependent variable in cross-sectional tests

Following DRT, we investigate the cross-sectional effects by creating three binary partitioning indicators for firms in the highest quartile of firm size, analyst following, and bid-ask spread (variables *Large_Firms*, *High_Following*, and *Large_Spread*). Table 3, Panel C shows that *Noise_Search* is correlated with these three characteristics, indicating that measurement error in SVI could confound inferences. We test for cross-sectional differences in search using the following model:

$$Search = \gamma_0 + \gamma_1 EA + \gamma_2 Partition + \gamma_3 EA \times Partition + \gamma_{4 \ldots n} Controls + \varepsilon \qquad \textbf{(9)}$$

Columns (i), (v), and (ix) of Table 5, Panel A investigate the partition *Large_Firms* for SVI, ASVI, and ASVI2. Estimated γ_3 is significantly positive in all specifications, indicating that increases in search around earnings announcements are greater for large firms. We find similar results for *High_Following* (columns ii, vi, x) and *Large_Spread* (columns iii, vii, xi), except for *Large_Spread* for SVI and ASVI2. Overall, the results in Table 5, Panel A resemble those in DRT.

In column (iv) of Table 5, Panel A, we create a partitioning indicator variable for firms in the lowest quartile of *Noise_Search*, labeled *Low_Noise*. We find that these firms also have a significantly greater increase in SVI around earnings announcements, and we find similar results for ASVI (column viii) and ASVI2 (column xii). In fact, the estimated coefficient magnitudes and *t*-statistics are larger for *Low_Noise* than any of the other partitions. The problem, as shown in

Panel C of Table 3, is that *Noise_Search* is negatively correlated with firm size, analyst following, and spread. As such, the statistically significant cross-sectional tests in Panel A of Table 5 are plausibly type 1 errors.

Without a perfect measure of SVI, it is impossible to know for sure whether the results in Panel A are type 1 errors. However, we can use simulations to gauge how likely they are to be type 1 errors. Similar to the simulations discussed in Section 4.1.1, we induce specific amounts of *Investor_Search* on random days and then run model (9) with partitions for each of the actual values of *Large_Firms*, *High_Following*, and *Large_Spread*. Finding a significant γ_3 estimate will be a type 1 error as we have constructed the increase in *Investor_Search* to be equal across firms.[23]

Panel B of Table 5 tabulates results for SVI. The upper rows are the estimated interaction coefficient γ_3 for *Random_Day* × *Large_Firms*. We start with a 25% induced increase in *Investor_Search*, which is likely a modest increase around corporate information events.[24] 25% of trials reject the null (i.e., generate a type 1 error), which is far above the five-percent level of confidence commonly used to assess significance.[25] The middle and lower rows of Panel B show that cross-sectional tests of *High_Following* and *Large_Spread* perform marginally better, but *High_Following* still exceeds a five percent Type 1 error rate when *Investor_Search* is 25%. As the inducement levels increase, the percentage of trials that exceed a five percent type 1 error rate increases. For example, at a 100% inducement level, 71% of trials generate a type 1 error for the

[23] Our procedure is as follows. First, drop all EA days and replace each with a randomly selected non-EA day (*Random_Day*). Second, randomly replace the ticker's SVI time-series with that from another ticker. Replacing the ticker's SVI time-series ensures the level of SVI is not correlated with the ticker's true *Noise_Search*. Third, induce a specific amount of *Investor_Search* on each *Random_Day*. Fourth, estimate model (9) where *Random_Day* replaces the EA to see whether the model rejects the null that the *Random_Day* × *Partition* is equal to zero. *Partition* is one of firm size, analyst following and bid-ask spread. Fifth, repeat this process 100 times, selecting *Random_Day* and random SVI time-series with replacement.

[24] Recall that results in Panel A of Table 4 estimate a 276% increase in abnormal investor search around earnings announcements for firms with the least noisy tickers.

[25] Rejection rates would be higher at a 10-percent level of confidence.

Random_Day × *Large_Firms* interaction term, 48% for *High_Following*, and 9% for *Large_Spread*.

Panels B and C find similar inferences for ASVI and ASVI2, but with generally lower type 1 error rates. Still, for a 100% increase in investor search, both ASVI and ASVI2 reject the null at more than five percent for all partitioning variables.

In sum, our regressions using real data and simulations find that *Noise_Search* can easily drive nontrivial false positives in cross-sectional analyses. Thus, researchers should be extremely cautious in drawing inferences from cross-sectional tests using SVI or abnormal transformations.

4.3. Discussion

The prior two example use-cases indicate that noise search in SVI, ASVI, and ASVI2 can generate types 1 or 2 errors when SVI is used as a dependent variable. As discussed in Section 2, the effects of noise search are likely even more complex when SVI is used as an independent variable.

Future researchers should carefully consider the potential effects of noise search in SVI when designing tests. Table SM1 of the Supplementary Materials provides ticker-level *Noise_Search* estimates to help facilitate those considerations.

5. "Ticker-Stock SVI," or "TS-SVI," as a Measure of Attention

This section investigates whether adding the word "stock" after a firm's ticker produces a better-specified proxy. We refer to the modified measure as "ticker-stock SVI" or "TS-SVI." A benefit of TS-SVI is that it likely captures fewer searches by non-investors. A potential drawback is that it omits investors who search using only a firm's ticker. We estimate TS-SVI investor search (*TS-Investor_Search*) versus noise search (*TS-Noise_Search*) using the same procedures as for SVI.

Table 6 provides summary information for TS-SVI that is analogous to the information for SVI in Table 3. While *Noise_Search* averages 69.0% for SVI in Panel A of Table 3, Panel A of Table 6 shows that *TS-Noise_Search* only averages 19.9% for TS-SVI. Panel A of Table 6 also shows far less variation in noise search across groups of firms for TS-SVI than for SVI. For example, for TS-SVI, one-letter tickers have 25.7% noise search versus 18.9% for four-letter tickers, while for SVI, the difference was 93.4% versus 46.9%. Figure 2 provides a histogram of estimated *TS-Noise_Search* by ticker, analogous to Figure 1.

Panel A of Table 6 also shows that "[ticker] stock" searches average 65,960 per month, which is far fewer than the 230,497 "[ticker]" searches from Table 3. However, after subtracting out the non-investor portion of those searches, the rightmost column of Table 6 Panel A shows that the average estimated true investor search for "[ticker] stock" is 47,266 searches per month, as compared to just 15,939 in Table 3. Detailed data in SM1 of the Supplementary Materials show that the volume of "[ticker] stock" investor searches is greater than just "[ticker]" searches for 79.4% of all tickers. This finding is critical because it indicates that TS-SVI omits fewer, not more, true investor searches than SVI.

Table 6, Panel B presents *TS-Noise_Search* by industry. The minimum (maximum) is 14.6% (23.4%) across all industries, which is a narrower spread than the minimum (maximum) for SVI of 50.6% (80.6%) in Table 3.

Table 6, Panel C finds few significant correlations between *TS-Noise_Search* and common firm characteristics. While Table 3, Panel C found significant correlations between *Noise_Search* and 10 common firm characteristics, Table 6, Panel C finds just one significant correlation between *TS-Noise_Search* and the same firm characteristics. Panel D finds that only analyst following has a significant coefficient in a multiple regression where *TS-Noise_Search* is the dependent variable.

Moreover, the cross-sectional variables explain just 0.1% of the variation in *TS-Noise_Search* for TS-SVI in column (ii) versus 26.3% in column (ii) of Table 3 Panel D, indicating that there are few systematic differences in *TS-Noise_Search* across tickers.

5.1. Case 1: TS-SVI as a dependent variable in pooled tests

Table 7 investigates the ability of TS-SVI to identify increases in investor attention around earnings announcements, both pooled and by decile of *TS-Noise_Search*. It repeats the analysis in Panel B of Table 4, with regressions including controls and time-fixed effects. The only differences are that the dependent variable and deciles of *TS-Noise_Search* are based on TS-SVI instead of SVI. For brevity, we do not tabulate the results from other specifications discussed in relation to Table 4, but the inferences are similar.

The main takeaway from Table 7 is that TS-SVI performs fairly well across deciles of *TS-Noise_Search*. For example, for TS-ASVI, the coefficient in the highest decile of *TS-Noise_Search* is insignificantly different from that in the lowest decile (1.080 versus 0.925, statistical test untabulated).[26] For SVI in Panel B of Table 4, in contrast, the coefficient in the highest decile of *Noise_Search* is very close to zero. Consistent with TS-SVI having less measurement error, the results in Table 7 indicate that TS-SVI identifies significant increases in search around earnings announcements even among the noisiest tickers. Moreover, complete results in Section SM5 of the Supplementary Materials find that the coefficients on the control variables also exhibit little attenuation across columns. Thus, we expect TS-SVI to generate fewer type 2 errors than SVI in pooled tests.

5.2. Case 2: TS-SVI as a dependent variable in cross-sectional tests

Given the evidence in Panels C and D of Table 6 that *Noise_Search* in TS-SVI is largely

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[26] Untabulated regressions of *Search* on EA and the interaction of *EA×Noise_Search_Decile* also find insignificant coefficients on the interaction terms for SVI, ASVI, and ASVI2.

uncorrelated with firm characteristics, we expect TS-SVI to generate fewer type 1 errors in cross-sectional tests. To further investigate this, we repeat the simulation tests from Panels B through D of Table 5, but replace SVI with TS-SVI.[27] Panels A through C of Table 8 present results for TS-SVI, TS-ASVI, and TS-ASVI2, respectively. Rejection rates are under 5% even for a 500% inducement in search, strongly indicating that measurement error in TS-SVI is unlikely to drive type 1 errors in cross-sectional tests using common partitioning variables.

5.3. Discussion

Our analyses indicate that investors search for information by Googling "[ticker] stock" more often than by Googling just "[ticker]," and that the addition of the word "stock" disambiguates ticker searches from homonyms. Said differently, TS-SVI appears to have significantly less measurement error than standard SVI. Moreover, *TS-Noise_Search* in TS-SVI is relatively uncorrelated with common firm characteristics. Table SM1 of our Supplementary Materials provides ticker-level estimates of *TS-Noise_Search*, so that researchers can investigate systematic variation in other samples and contexts.

6. Conclusion and Guidance for Future Research

This study illustrates the importance of carefully considering measurement error in Google ticker SVI as a proxy for investor attention. We estimate that, on average, 69% of S&P 500 ticker searches are by non-investors and therefore are likely measurement error. We find that this measurement error biases regression estimates towards zero when SVI is used as a dependent variable in pooled tests. Moreover, we find that this measurement error is highly correlated with basic firm characteristics, and so can easily lead to false positives in cross-sectional tests. Measurement error in SVI can likely easily generate types 1 and 2 errors when SVI is used as an

[27] Our cross-sectional simulation tests for TS-SVI use the procedures and identical random replacements as those for SVI, which ensures that the two sets of tests are comparable.

independent variable in regressions with multiple covariates.

We recommend that researchers move away from using ticker SVI as a measure of investor attention and instead use Google searches for “[ticker] stock” (TS-SVI). Our analyses indicate that TS-SVI better reflects the keywords that investors actually use to search for stock information and that TS-SVI captures substantially fewer non-investor searches. While researchers should continue to exercise caution in using TS-SVI as a measure of attention, TS-SVI is likely to produce more robust inferences. We have created a dataset of TS-SVI, available online, to support future investor attention research.

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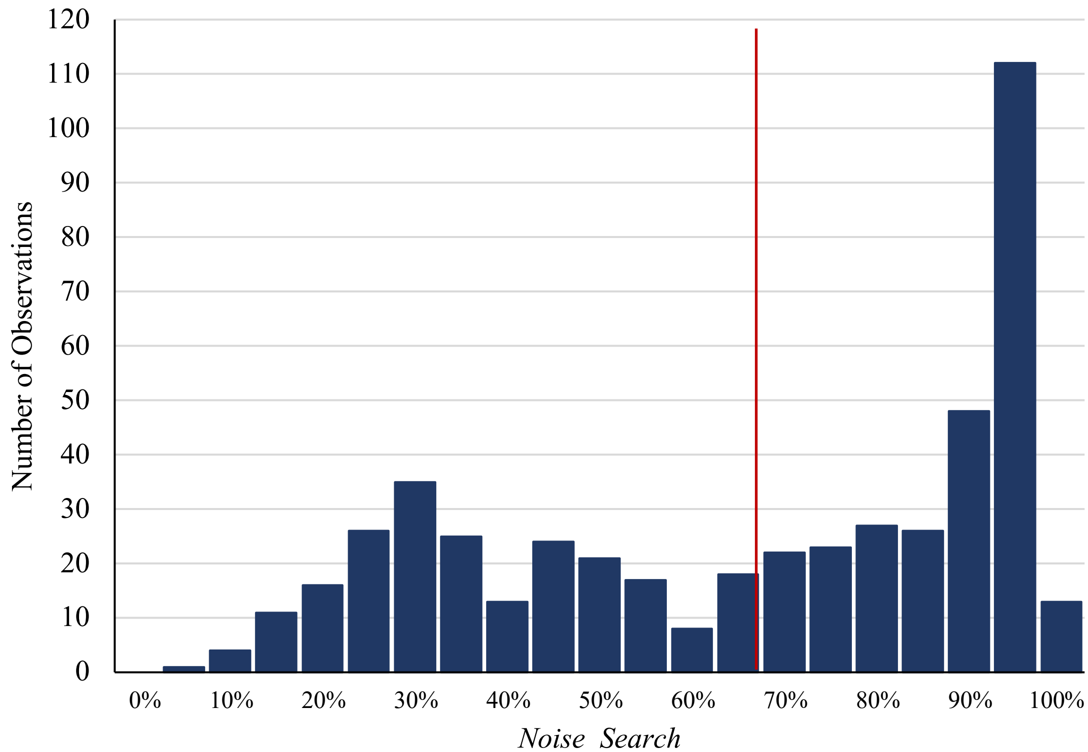
Figure 1 – Histogram of *Noise Search* in SVI Across Tickers

This figure shows the distribution of the variable *Noise_Search* for the 490 tickers in our final sample. The Y-axis is the number of observations (i.e., tickers), and the X-axis is *Noise_Search* variable ranging from 0% to 100%. The reference line represents the mean of *Noise_Search* (at 69%).



<u>Figure 2 – Histogram of *TS-Noise Search* in TS-SVI Across Tickers</u>

This figure shows the distribution of the variable *TS-Noise_Search* for the 490 tickers in our final sample. The Y-axis is the number of observations (i.e., tickers), and the X-axis is *TS-Noise_Search* variable ranging from 0% to 100%. The reference line represents the mean of *TS-Noise_Search* (at 20%).

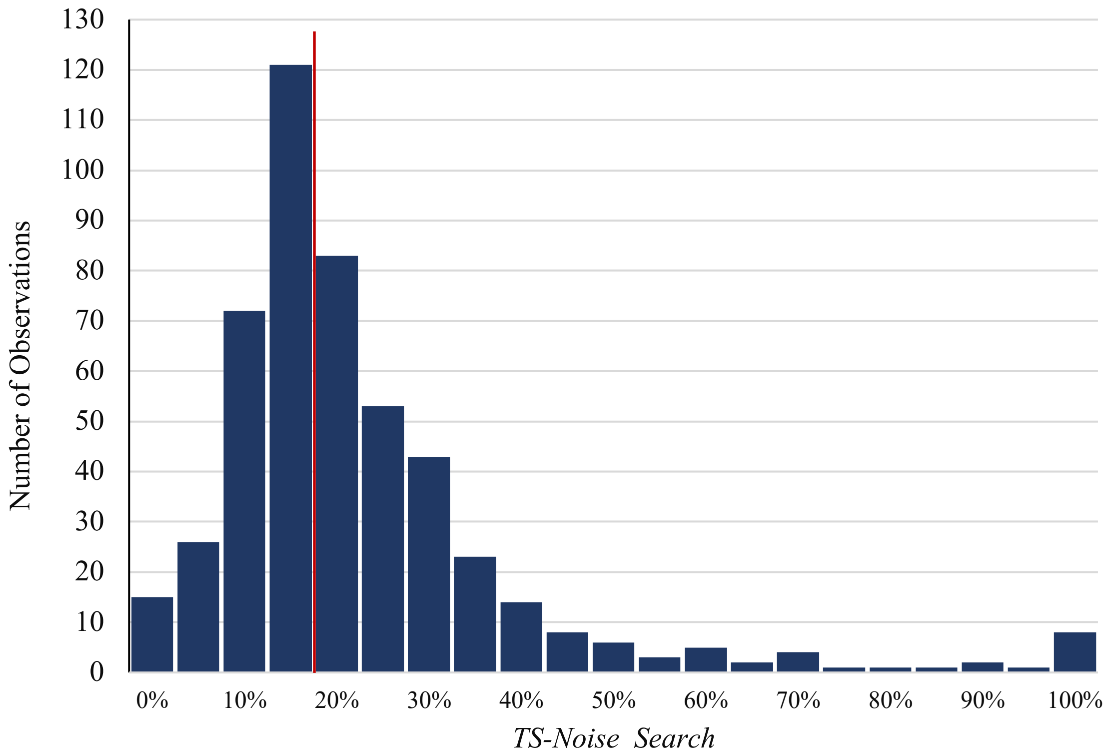


Table 1 – Sample Details

Panel A details our sample selection process. [A] We obtained the S&P 500 list of firms as of January 2016, consisting of 500 firms. In total, 11 firms have two corresponding ticker symbols: Brown-Forman (BFA, BFB), Berkshire Hathaway (BRKA, BRKB), CBS Corp. (CBS, CBSA), Discovery Inc. (DISCA, DISCK), Twenty-First Century Fox (FOX, FOXA), Alphabet Inc (GOOG, GOOGL), Lennar Corp. (LEN, LENB), McCormick & Co. (MKC, MKCV), Constellation Brands (STZ, STZB), and Molson Coors Brewing (TAP, TAPA). We include both tickers for these firms. The dataset covers 2016 and 2017 trading days, totaling 501 days. [B] For two tickers (STZB and MKCV), Google does not provide search volume data due to limited search. [C] 19 tickers have a change in ticker symbol during our sample period due to either a change in firm name (COH, DLPH, TSO, and YHOO) or a merger (BHI, DD, DOW, EMC, HAR, HOT, LVTL, MJN, RAI, SPLS, STJ, SE, LLTC, TYC, and WFM). [D] For tickers SPGI and FTV (Jan-June 2016) and UA (Jan-Jun 2017), the data is not available in CRSP/Compustat/IBES. Panel B presents descriptive statistics per ticker trading day. Variable definitions are provided in Appendix A.

Panel A: Sample selection details

	Firms	**Tickers**	**Trading Days**
[A] Initial Sample of S&P 500 firms as of January 2016	500	511	256,011
[B] Less: firms/tickers without any Google SVI data available	0	2	1,002
[C] Less: firms/tickers with a change in the ticker symbol	19	19	9,519
[D] Less: missing observations in CRSP / Compustat / IBES	0	0	475
Final Sample	481	490	245,015

Panel B: Sample summary statistics

	N	**Mean**	**Std.Dev.**	**p25**	**Median**	**p75**
SVI	245,015	33.484	23.813	12.857	30.186	51.330
ASVI	245,015	0.107	1.928	-0.254	-0.028	0.200
ASVI2	245,015	0.025	0.677	-0.194	0.016	0.268
TS-SVI	245,015	11.302	18.125	0.000	0.000	18.000
TS-ASVI	245,015	0.488	3.728	-1.000	-0.447	0.238
TS-ASVI2	245,015	-0.697	1.443	-1.945	-0.546	0.200
EA	245,015	0.016	0.125	0.000	0.000	0.000
News Articles	245,015	1.647	2.628	0.000	1.000	2.000
Abs Return	245,015	0.100	0.100	0.003	0.007	0.014
Spread	245,015	0.019	0.011	0.011	0.016	0.023
Total EAs	245,015	5.472	2.884	3.000	5.000	8.000
MVE	245,015	5.535	2.877	3.000	6.000	8.000
Analyst Following	245,015	2.841	0.481	2.639	2.908	3.164
BTM	245,015	0.382	0.361	0.166	0.311	0.511
Trading Volume	245,015	1.898	1.102	1.186	1.595	2.291
Institutional Ownership	245,015	0.838	0.1511	0.758	0.856	0.938
Fourth Qtr	245,015	0.248	0.431	0.000	0.000	0.000
Leverage	245,015	0.657	0.208	0.529	0.651	0.794
Momentum	245,015	0.050	0.019	0.037	0.045	0.059
ROA	245,015	0.013	0.025	0.005	0.013	0.022
Stock Volatility	245,015	0.014	0.005	0.010	0.013	0.016
Beta	245,015	0.936	0.654	0.403	0.786	1.332
Investor_Search	245,015	0.311	0.287	0.039	0.218	0.567
Noise_Search	245,015	0.689	0.287	0.433	0.782	0.961
TS-Investor_Search	245,015	0.801	0.167	0.757	0.841	0.895
TS-Noise_Search	245,015	0.199	0.167	0.105	0.159	0.243

Table 2 – Ticker Search Click-Through Website Categorization

Panel A details the types of websites visited after Google ticker searches. Column (i) presents the average total click-throughs per month, pooled across all firms, and Column (ii) shows these click-throughs as a percentage of the average total traffic. Column (iii) is the portion of click-throughs that are to a website included in the review procedure detailed in Section 3.2. In the pooled sample, after typing any of the ticker symbols on Google, individuals clicked on 63,263 different websites. In total, we reviewed 4,460 websites, covering 94% of all clicks. Column (iv) is the fraction of the reviewed traffic that is determined to be "investor-related." Panel B lists the top 20 websites that are identified as investor related.

Panel A: Categories of websites visited

Website Category from SimilarWeb	(i) Avg. Total Clicks per Month	(ii) Percentage of All Traffic	(iii) Percentage of Traffic Reviewed	(iv) Fraction Investor-Related
Adult	168,318	0.1%	72.3%	0.0%
Arts_and_Entertainment	3,892,503	5.7%	92.2%	0.2%
Autos_and_Vehicles	746,802	0.6%	84.5%	1.1%
Beauty_and_Fitness	3,158,182	2.5%	99.6%	0.0%
Books_and_Literature	24,719	0.0%	71.1%	6.1%
Business_and_Industry	6,656,695	5.0%	91.9%	2.3%
Career_and_Education	598,555	0.5%	73.9%	0.7%
Computer_and_Electronics	1,645,274	1.3%	89.6%	0.2%
Finance	7,800,414	9.6%	98.6%	64.8%
Food_and_Drink	351,913	0.3%	72.9%	0.0%
Gambling	40,726	0.0%	83.0%	0.0%
Games	558,790	0.4%	79.4%	0.0%
Health	4,359,264	3.4%	97.0%	0.0%
Home_and_Garden	40,326	0.0%	76.4%	0.0%
Internet_and_Telecom	9,532,860	7.5%	97.6%	0.2%
Law_and_Government	367,407	0.3%	83.1%	1.2%
News_and_Media	6,964,061	7.7%	92.8%	56.0%
People_and_Society	241,284	0.2%	70.3%	0.0%
Pets_and_Animals	163,674	0.1%	78.0%	0.0%
Recreation_and_Hobbies	310,995	0.3%	82.4%	0.0%
Reference	861,556	0.9%	96.2%	8.7%
Science	149,079	0.1%	79.4%	0.0%
Shopping	43,539,718	35.3%	98.5%	0.2%
Sports	186,356	0.2%	73.0%	0.5%
Travel	1,115,030	0.9%	96.4%	4.5%
Unknown	17,395,398	17.0%	84.0%	12.4%
All categories together	**110,869,899**	**100.0%**	**94.0%**	**31.0%**

Panel B: Top 20 investor-related websites

	URL	Percentage of Investor Traffic
1	finance.yahoo.com	28.3%
2	seekingalpha.com	9.0%
3	fool.com	6.4%
4	stocktwits.com	4.9%
5	marketwatch.com	4.9%
6	cnbc.com	3.6%
7	investorplace.com	3.0%
8	thestreet.com	2.8%
9	nasdaq.com	2.8%
10	businessinsider.com	2.3%
11	money.cnn.com	1.9%
12	Bloomberg.com	1.8%
13	invest.ameritrade.com	1.5%
14	stockcharts.com	1.2%
15	investors.com	1.2%
16	barrons.com	1.0%
17	streetinsider.com	0.9%
18	stocknewsjournal.com	0.9%
19	us.etrade.com	0.9%
20	forbes.com	0.8%
21+	All others	19.9%
Total		**100.0%**

Table 3 – Variation in *Noise_Search* across Firms

This table shows cross-sectional variation in variation in non-investor-related clicks (*Noise_Search*) in Google ticker searches. Panel A details the average monthly *Keyword_Search* per ticker by ticker type, as well as the average estimated *Keyword_Search* that is non-investor related and true investor search. The ticker type "Ambiguous" follows Drake et al. (2012) and includes: AA, ABC, ALL, AN, CAT, COST, EBAY, ED, FAST, HAS, HD, HOG, KEY, KO, LOW, MAT, MET, PEG, SEE, TAP. Panel B details the average clicks per firm month by Fama-French 12 industry classification. Panel C presents pairwise correlations of average *Noise_Search* per ticker with average firm characteristics. Panel D provides an OLS regression with *Noise_Search* as the dependent variable and firm characteristics as independent variables. Variable definitions are provided in Appendix A. ∗, ∗∗,∗∗∗ indicates statistical significance at the $p < 0.10, 0.05, 0.01$ level, respectively.

Panel A: Click-throughs by ticker type

Ticker Type	Tickers	Average *Keyword_Search* (per Month)	Average *Noise_Search* (Percent)	Average Estimated Non-Investor Search	Average Estimated True Investor Search
Ambiguous	20	2,441,110	84.9%	2,424,661	16,449
Other One-Letter Tickers	11	1,316,898	93.4%	1,260,060	56,838
Other Two-Letter Tickers	48	283,802	85.6%	116,190	17,612
Other Three-Letter Tickers	303	86,993	72.3%	77,826	8,167
Other Four-Letter Tickers	104	87,265	46.9%	54,546	32,809
Other Five-Letter Tickers	4	144,660	38.7%	113,767	30,984
All tickers	**490**	**230,497**	**69.0%**	**214,558**	**15,939**
Market summary box	304	461,132	56.8%		
No market summary box	186	93,744	88.8%		
All tickers	**490**	**230,497**	**69.0%**		

Panel B: Click-throughs by firm industry

Firm's Industry (FF 12)	Tickers	Average *Ticker Searches* (per Month)	Average *Noise_Search* Percent
Consumer NonDurables	34	82,586	77.6%
Consumer Durables	9	624,934	80.6%
Manufacturing	41	83,002	73.4%
Oil, Gas, and Coal Extraction and Products	27	58,507	69.8%
Chemicals and Allied Products	17	52,297	72.5%
Business Equipment	74	804,373	61.2%
Telephone and Television Transmission	16	244,481	50.9%
Utilities	32	86,151	79.9%
Wholesale, Retail, and Some Services	50	232,726	64.7%
Healthcare, Medical Equipment, and Drugs	39	31,850	50.6%
Finance	99	133,769	75.4%
Other	52	118,712	71.3%
All tickers	**490**	**230,497**	**69.0%**

Panel C: Pairwise correlations of Noise_Search with firm characteristics

	Noise_Search
MVE	-0.171***
	(0.00)
BTM	0.069
	(0.12)
Leverage	0.021
	(0.62)
ROA	-0.071*
	(0.10)
Institutional Ownership	0.027
	(0.54)
Analyst Following	-0.179***
	(0.01)
Momentum	-0.164***
	(0.00)
Stock Volatility	-0.111***
	(0.01)
Trading Volume	-0.092**
	(0.04)
Beta	0.152***
	(0.00)
Spread	-0.101**
	(0.02)
CSR-Rating	-0.031
	(0.48)
News Articles	-0.134***
	(0.00)
Ticker Length	-0.418***
	(0.00)

Panel D: OLS regressions of Noise_Search on firm characteristics

	Noise_Search **(i)**	***Noise_Search*** **(ii)**
MVE	-0.042**	-0.065***
	(-2.57)	(-4.13)
BTM	-0.004	-0.089
	(-0.07)	(-1.64)
Leverage	-0.037	-0.172**
	(-0.54)	(-2.54)
ROA	-1.002	-0.792
	(-0.96)	(-0.76)
Institutional Ownership	-0.025	0.051
	(-0.27)	(0.55)
Analyst Following	-0.029	0.046
	(-0.89)	(1.40)
Momentum	-2.465*	-1.941
	(-1.66)	(-1.38)
Stock Volatility	-7.067	1.477
	(-0.79)	(0.17)
Trading Volume	0.010	-0.039*
	(0.46)	(-1.92)
Beta	0.123***	0.049*
	(5.26)	(1.91)
Spread	-5.825	-0.290
	(-1.14)	(-0.05)
CSR-Rating	0.007	0.003
	(0.46)	(0.22)
News Articles	-0.018	-0.012
	(-1.51)	(-1.06)
Ticker Length		-0.174***
		(-8.74)
Constant	1.776***	2.463***
	(6.07)	(8.58)
Fixed Effects	None	Industry
Observations	490	490
R-squared	0.119	0.263

Table 4 – Regressions of Ticker SVI on Earnings Announcement Days

This table presents the γ_1 coefficient from estimating Equation (8). The dependent variable is *SVI, ASVI,* or *ASVI2*. Panel A (B) tabulates results excluding (including untabulated) control variables: *News Articles, Abs Return, MVE, Analyst Following, Trading Volume, Spread, Fourth Qtr, Total EAs, Institutional Ownership, BTM,* and *Year-Week* fixed effects. Variable definitions are provided in Appendix A. T-statistics are in parentheses. Standard errors are clustered by firm. *, **, *** indicates statistical significance at the p < 0.10, 0.05, 0.01 level, respectively.

Panel A: Without controls or fixed effects

	Pooled	**By Decile of *Noise_Search***									
		1 [Low]	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
Observations	245,015	24,970	24,048	24,549	24,548	25,050	24,283	24,549	24,048	24,922	24,048
Average *Noise_Search*	0.689	0.177	0.311	0.432	0.574	0.729	0.827	0.912	0.960	0.985	0.997
γ_1 for *SVI*	11.430***	20.050***	24.920***	23.570***	16.000***	7.705***	8.687***	6.431***	4.229***	2.203*	0.424
	(29.82)	(26.29)	(28.50)	(25.13)	(14.49)	(6.64)	(7.34)	(5.61)	(3.55)	(1.88)	(0.37)
Adjusted R-squared	0.004	0.027	0.033	0.025	0.008	0.002	0.002	0.001	0.001	0.000	0.000
γ_1 for *ASVI*	0.674***	2.764***	2.461***	2.097***	1.115***	0.404***	0.292	0.282***	0.104	0.095***	-0.008
	(60.99)	(28.28)	(31.87)	(27.50)	(16.95)	(5.42)	(1.50)	(10.25)	(0.65)	(3.61)	(-0.35)
Adjusted R-squared	0.015	0.031	0.041	0.030	0.012	0.001	0.000	0.004	0.000	0.001	0.000
γ_1 for *ASVI2*	0.462***	1.099***	1.052***	0.948***	0.590***	0.299***	0.256***	0.178***	0.114***	0.077***	-0.003
	(42.49)	(21.96)	(23.61)	(23.96)	(14.95)	(8.62)	(8.17)	(6.76)	(4.94)	(3.73)	(-0.21)
Adjusted R-squared	0.007	0.019	0.023	0.023	0.009	0.003	0.003	0.002	0.001	0.001	0.000

Panel B: With controls and year-week fixed effects

	Pooled	**By Decile of *Noise_Search***									
		1 [Low]	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
Observations	245,015	24,970	24,048	24,549	24,548	25,050	24,283	24,549	24,048	24,922	24,048
Average *Noise_Search*	0.689	0.177	0.311	0.432	0.574	0.729	0.827	0.912	0.960	0.985	0.997
γ_1 for *SVI*	7.879***	12.340***	19.330***	14.592***	11.955***	4.801	4.834**	-3.350	-0.221	5.029	4.470**
	(5.17)	(6.60)	(7.73)	(3.98)	(5.31)	(1.60)	(2.09)	(-0.99)	(-0.06)	(1.27)	(2.07)
Adjusted R-squared	0.030	0.132	0.111	0.128	0.064	0.135	0.126	0.105	0.240	0.142	0.147
γ_1 for *ASVI*	0.470***	1.858***	1.901***	1.539***	0.723***	0.186	-0.012	0.168*	0.106	0.046**	0.001
	(13.08)	(6.19)	(5.98)	(5.28)	(4.76)	(1.36)	(-0.06)	(1.86)	(1.58)	(2.03)	(0.04)
Adjusted R-squared	0.037	0.077	0.084	0.065	0.043	0.015	0.018	0.029	0.008	0.027	0.009
γ_1 for *ASVI2*	0.297***	0.702***	0.759***	0.672***	0.379***	0.199***	0.147***	0.073*	0.086***	0.0367*	0.002
	(13.50)	(9.32)	(9.31)	(8.02)	(6.41)	(3.77)	(3.74)	(1.68)	(2.69)	(1.87)	(0.12)
Adjusted R-squared	0.025	0.063	0.066	0.063	0.044	0.017	0.024	0.021	0.021	0.032	0.016

Table 5 – Type 1 Errors in Cross-Sectional Tests

This table presents the results of Equation (9) with high (quartile four) – low (quartiles one to three) partitions on firm size, analyst following, and bid-ask spread. The dependent variable is SVI, ASVI, or ASVI2. Controls and fixed effects are untabulated. Panel A presents regression results using actual data. Panels B through D summarize simulation tests of induced increases in search. Our procedure is as follows. First, drop all EA days and replace each with a randomly selected non-EA day (*Random_Day*). Second, randomly replace the SVI time-series with another firm's time-series. Third, induce a specific amount of *Investor_Search* on each *Random_Day*. Fourth, estimate model (9) where *Random_Day* replaces the EA to see whether the model rejects the null that the *Random_Day* × *Partition* is equal to zero. Fifth, repeat this process 100 times, selecting *Random_Day* and the random SVI time-series with replacement. For each level of induced search, the upper row presents the average coefficient estimate across 100 trials, and the bottom row presents the number of trials that rejected the null of no change in search at a 5% level of confidence. See Section 4.2 for further discussion and Appendix A for variable definitions. Standard errors are clustered by firm. *, **, *** indicates statistical significance at the $p < 0.10$, 0.05, 0.01 level, respectively.

Panel A: Cross-sectional partitions of search on earnings announcement days

	SVI (i)	SVI (ii)	SVI (iii)	SVI (iv)	ASVI (v)	ASVI (vi)	ASVI (vii)	ASVI (viii)	ASVI2 (ix)	ASVI2 (x)	ASVI2 (xi)	ASVI2 (xii)
EA	6.454***	4.426***	6.470***	3.464**	0.408***	0.350***	0.460***	0.255***	0.286***	0.243***	0.398***	0.164***
	(4.33)	(2.89)	(3.60)	(2.31)	(10.14)	(9.57)	(11.31)	(7.24)	(10.43)	(9.57)	(10.34)	(7.19)
Large_Firms	1.512				-0.123*				-0.005			
	(0.68)				(1.74)				(-1.13)			
*EA * Large_Firms*	6.042***				0.348***				0.125**			
	(3.99)				(3.21)				(2.08)			
High_Following		-4.414**				-0.007				-0.007		
		(-2.26)				(-0.96)				(-1.55)		
*EA * High_Following*		8.564***				0.559***				0.282***		
		(5.69)				(5.28)				(4.66)		
Large_Spread			-1.233*				0.001				0.038***	
			(-1.95)				(0.09)				(6.44)	
*EA * Large_Spread*			1.899				0.118*				-0.136***	
			(1.43)				(1.75)				(-3.04)	
Low_Noise				-20.36***				0.498***				0.028***
				(-14.38)				(7.13)				(5.94)
*EA * Low_Noise*				13.79***				1.219***				0.776***
				(9.29)				(10.66)				(11.56)
Controls	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	245,015	245,015	245,015	245,015	245,015	245,015	245,015	245,015	245,015	245,015	245,015	245,015
Adjusted R-squared	0.022	0.025	0.023	0.135	0.023	0.025	0.023	0.032	0.024	0.023	0.024	0.028

Panel B: Simulation results for SVI

Induced Investor_Search of:	25%	50%	100%	200%	500%
Random_Day×Large Firms					
Average Coefficient	0.860	1.967	3.089	4.929	7.158
Interactions rejected at 5% level	25%	46%	71%	92%	99%
Random_Day×High_Following					
Average Coefficient	0.081	1.506	2.408	3.640	4.880
Interactions rejected at 5% level	24%	34%	48%	61%	68%
Random_Day×Large_Spread					
Average Coefficient	0.089	0.294	0.696	0.405	2.076
Interactions rejected at 5% level	4%	6%	9%	16%	28%

Panel C: Simulation results for ASVI

Induced Investor_Search of:	25%	50%	100%	200%	500%
Random_Day×Large Firms					
Average Coefficient	0.031	0.061	0.114	0.191	0.302
Interactions rejected at 5% level	9%	13%	27%	43%	58%
Random_Day×High_Following					
Average Coefficient	0.027	0.048	0.086	0.138	0.212
Interactions rejected at 5% level	2%	13%	21%	29%	32%
Random_Day×Large_Spread					
Average Coefficient	0.016	0.027	0.048	0.086	0.151
Interactions rejected at 5% level	2%	3%	6%	10%	14%

Panel D: Simulation results for ASVI2

Induced Investor_Search of:	25%	50%	100%	200%	500%
Random_Day×Large Firms					
Average Coefficient	0.017	0.037	0.069	0.118	0.208
Interactions rejected at 5% level	11%	22%	61%	82%	100%
Random_Day×High_Following					
Average Coefficient	0.021	0.035	0.057	0.091	0.147
Interactions rejected at 5% level	17%	27%	38%	60%	81%
Random_Day×Large_Spread					
Average Coefficient	0.004	0.009	0.018	0.031	0.058
Interactions rejected at 5% level	3%	3%	8%	15%	22%

Table 6 – Variation in *TS-Noise_Search* across Firms

This table shows cross-sectional variation in non-investor-related clicks-throughs (*TS-Noise_Search*) in Google ticker-stock search (e.g., "AAPL stock"). Panel A details the average monthly *TS-Keyword_Search* per ticker by ticker type, as well as the average estimated *TS-Keyword_Search* that is non-investor related and true investor search. Panel B details the average clicks per firm month by Fama-French 12 industry. Panel C provides correlations between *TS-Noise_Search* and common firm characteristics. Panel D provides an OLS regression with *TS-Noise_Search* as the dependent variable and firm characteristics as independent variables. Variable definitions are provided in Appendix A. ∗, ∗∗, ∗∗∗ indicates statistical significance at the $p < 0.10, 0.05, 0.01$ level, respectively.

Panel A: Click-throughs by ticker type

Ticker Type	Tickers	Average *TS-Keyword_Search* (per Month)	Average *TS-Noise_Search* (Percent)	Average Estimated Non-Investor Search	Average Estimated True Investor Search
Ambiguous	20	46,714	22.9%	8,559	38,155
Other One-Letter Tickers	11	129,743	25.7%	38,826	90,917
Other Two-Letter Tickers	48	100,631	16.8%	27,921	72,710
Other Three-Letter Tickers	303	53,270	20.3%	13,704	39,566
Other Four-Letter Tickers	104	85,007	18.9%	29,324	55,683
Other Five-Letter Tickers	4	36,776	9.3%	4,861	31,915
All tickers	**490**	**65,960**	**19.9%**	**18,694**	**47,266**

Panel B: Click-throughs by firm industry

Firm's Industry (FF 12)	Tickers	Average *TS-Keyword_Search* (per Month)	Average *TS-Noise_Search* (Percent)
Consumer NonDurables	34	21,403	21.8%
Consumer Durables	9	111,245	14.6%
Manufacturing	41	46,994	17.3%
Oil, Gas, and Coal Extraction and Products	27	132,992	20.4%
Chemicals and Allied Products	17	20,920	16.0%
Business Equipment	74	107,364	18.6%
Telephone and Television Transmission	16	68,291	21.1%
Utilities	32	30,400	23.4%
Wholesale, Retail, and Some Services	50	64,445	16.8%
Healthcare, Medical Equipment, and Drugs	39	72,435	16.5%
Finance	99	32,154	22.9%
Other	52	107,090	20.9%
All tickers	**490**	**65,960**	**19.9%**

Panel C: Pairwise correlations of TS-Noise_Search with firm characteristics

	TS-Noise_Search
MVE	0.036
	(0.42)
BTM	0.079*
	(0.07)
Leverage	0.026
	(0.56)
ROA	-0.062
	(0.17)
Institutional Ownership	-0.051
	(0.26)
Analyst Following	0.044
	(0.32)
Momentum	-0.064
	(0.15)
Stock Volatility	-0.068
	(0.132)
Trading Volume	-0.054
	(0.22)
Beta	-0.001
	(0.84)
Spread	-0.067
	(0.13)
CSR-Rating	-0.028
	(0.52)
News Articles	0.073
	(0.11)
Ticker Length	-0.002
	(0.63)

Panel D: Regression analysis of Percent TS-Noise_Search

	TS-Noise_Search (1)	***TS-Noise Search (2)***
MVE	-0.007	-0.009
	(-0.69)	(-0.82)
BTM	0.039	0.012
	(1.15)	(0.32)
Leverage	0.006	-0.015
	(0.15)	(-0.33)
ROA	-0.932	-0.659
	(-1.434)	(-0.93)
Institutional Ownership	-0.035	-0.029
	(-0.59)	(-0.46)
Analyst Following	0.035*	0.050**
	(1.72)	(2.23)
Momentum	-0.151	-0.297
	(-0.16)	(-0.31)
Stock Volatility	-0.862	1.113
	(-0.16)	(0.19)
Trading Volume	0.001	0.003
	(0.10)	(0.23)
Beta	-0.004	0.003
	(-0.26)	(0.16)
Spread	-3.144	-4.190
	(-0.99)	(-1.16)
CSR-Rating	-0.010	-0.013
	(-1.09)	(-1.31)
News Articles	0.007	0.008
	(0.93)	(1.05)
Ticker Length		0.000
		(0.03)
Constant	0.321*	0.341*
	(1.77)	(1.75)
Fixed Effects	None	Industry
Observations	490	490
Adjusted R-squared	0.004	0.001

Table 7 – Regressions using *Google Ticker Stock SVI (TS-SVI)*

This table repeats the analyses from Panel B of Table 4 but uses dependent variables based on Google ticker-stock SVI ("TS-SVI"). Dependent variables *TS-SVI*, *TS-ASVI*, and *TS-ASVI2,* are otherwise constructed analogously to *SVI*, *ASVI*, and *ASVI2* in Table 4. Controls and fixed effects are untabulated. Standard errors are clustered by firm. Variable definitions are provided in Appendix A. *, **, *** indicates statistical significance at the p < 0.10, 0.05, and 0.01 level, respectively.

	Pooled	**By Decile of *TS-Noise_Search***									
		1 [Low]	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
Observations	245,015	24,549	24,549	24,548	24,784	24,549	24,048	24,970	24,047	24,549	24,422
Average *TS-Noise_Search*	0.198	0.024	0.072	0.104	0.126	0.146	0.171	0.199	0.245	0.308	0.591
γ_1 for *TS-SVI*	3.487***	3.887***	2.704*	2.700	1.838	6.553***	4.192**	1.977	5.323***	1.914	5.221**
	(5.52)	(3.34)	(1.67)	(1.37)	(1.12)	(3.53)	(2.12)	(1.14)	(3.24)	(1.36)	(2.17)
Adjusted R-squared	0.078	0.049	0.052	0.087	0.094	0.138	0.063	0.144	0.077	0.110	0.074
γ_1 for *TS-ASVI*	0.928***	1.080***	0.745***	0.666***	0.690***	0.940***	1.218***	1.045***	1.015***	0.812**	0.925***
	(10.24)	(2.89)	(2.80)	(2.88)	(3.47)	(3.31)	(4.49)	(3.55)	(3.49)	(2.36)	(3.05)
Adjusted R-squared	0.008	0.006	0.007	0.007	0.006	0.004	0.007	0.009	0.011	0.007	0.006
γ_1 for *TS-ASVI2*	0.316***	0.307***	0.263***	0.462***	0.254***	0.425***	0.499***	0.264***	0.398***	0.266**	0.216**
	(10.27)	(3.16)	(2.76)	(4.96)	(3.12)	(5.04)	(5.24)	(3.24)	(3.82)	(2.41)	(2.29)
Adjusted R-squared	0.019	0.012	0.016	0.024	0.024	0.030	0.025	0.028	0.024	0.017	0.021

Table 8 – Type 1 Errors in Cross-Sectional Tests using TS-SVI

This table repeats the simulations from Panels B through D of Table 5, but using TS-SVI instead of SVI. All details and random selections are otherwise unchanged from Table 5. Standard errors are clustered by firm. ∗, ∗∗, ∗∗∗ indicates statistical significance at the p < 0.10, 0.05, 0.01 level, respectively.

Panel A: Simulation results for TS-SVI

Induced Investor_Search of:	25%	50%	100%	200%	500%
*Random_Day * Large Firms*					
Average Coefficient	-0.021	-0.037	-0.041	-0.078	-0.198
Interactions rejected at 5% level	4%	3%	3%	3%	1%
*Random_Day * High_Following*					
Average Coefficient	-0.061	-0.087	-0.174	-0.361	-0.227
Interactions rejected at 5% level	1%	1%	1%	1%	1%
*Random_Day * Large_Spread*					
Average Coefficient	0.188	0.277	0.404	0.506	0.568
Interactions rejected at 5% level	2%	2%	3%	5%	4%

Panel B: Simulation results for TS-ASVI

Induced Investor_Search of:	25%	50%	100%	200%	500%
*Random_Day * Large Firms*					
Average Coefficient	-0.008	-0.013	-0.020	-0.037	-0.064
Interactions rejected at 5% level	2%	2%	2%	1%	1%
*Random_Day * High_Following*					
Average Coefficient	-0.002	-0.009	-0.021	-0.032	-0.039
Interactions rejected at 5% level	1%	1%	1%	1%	2%
*Random_Day * Large_Spread*					
Average Coefficient	-0.002	0.000	0.001	-0.004	-0.038
Interactions rejected at 5% level	2%	3%	3%	3%	2%

Panel C: Simulation results for TS-ASVI2

Induced Investor_Search of:	25%	50%	100%	200%	500%
*Random_Day * Large Firms*					
Average Coefficient	-0.010	-0.011	-0.012	-0.013	-0.016
Interactions rejected at 5% level	1%	3%	2%	2%	2%
*Random_Day * High_Following*					
Average Coefficient	0.001	0.001	-0.003	-0.006	-0.001
Interactions rejected at 5% level	4%	4%	4%	3%	2%
*Random_Day * Large_Spread*					
Average Coefficient	0.003	0.010	0.031	0.002	-0.001
Interactions rejected at 5% level	5%	4%	5%	4%	4%

Appendix A: Variable Definitions

All continuous variables are winsorized at 1% and 99%.

Variable	Description	Source
Google Ticker Search Variables:		
Investor_Search$_i$	Percentage of investor-related click-throughs for firm *i* for ticker searches (e.g., "AAPL").	Similar Web
Noise_Search$_i$	Percentage of non-investor-related click-throughs for firm *i* for ticker searches (e.g., "AAPL").	Similar Web
Decile Noise_Search$_i$	Decile rank of *Noise_Search*$_i$	Similar Web
Keyword_Search$_{i,m}$	Monthly absolute Google ticker searches (e.g., AAPL) for firm *i* in month *m*.	Google AdWords
SVI$_{i,t}$	Google ticker search volume index for firm *i* on day *t*. Obtaining daily SVI over a two-year period requires a four-step process. First, we download SVI data for the window of 2004 through 2017. Google provides this data at the monthly level. Second, we downloaded daily SVI for each month in 2016 and 2017. Google provides this data at the daily level. Third, we convert the daily data to a common scale by multiplying the daily data by the monthly SVI scaled by 100. Fourth, we rescale the daily data so that each firm has a maximum value of 100 during our sample period; i.e., we divide each daily value by the maximum value observed for firm *i* over the window of 2016 through 2017.	Google Trends
ASVI$_{i,t}$	SVI for firm *i* on day *t* less the average SVI for firm *i* on the same weekday over the prior 10 weeks, scaled by the average SVI for firm *i* on the same weekday over the prior 10 weeks.	Google Trends
ASVI2$_{i,t}$	Natural log of 1 plus SVI for firm *i* on day *t* less the average of the natural log of 1 plus SVI for firm *i* on the same weekday over the prior 10 weeks.	Google Trends
TS-Investor_Search$_i$	Percentage of investor-related click-throughs for firm *i* for ticker-stock searches (e.g., "AAPL stock")	Similar Web
TS-Noise_Search$_i$	Percentage of non-investor-related click-throughs for firm *i* for ticker-stock searches (e.g., "AAPL stock").	Similar Web
Decile TS-Noise_Search$_i$	Decile rank of *TS-Noise_Search*$_i$.	Similar Web
TS-Keyword_Search$_{i,m}$	Monthly absolute Google ticker-stock searches (e.g., "AAPL stock" for firm *i* in month *m*.)	Google AdWords
TS-SVI$_{i,t}$	Google ticker-stock search volume index (e.g., "AAPL stock") for firm *i* on day *t*. Fixed scaling is employed as in SVI.	Google Trends
TS-ASVI$_{i,t}$	TS-SVI for firm *i* on day *t* less the average TS-SVI for firm *i* on the same weekday over the prior 10 weeks, scaled by the average TS-SVI for firm *i* on the same weekday over the prior 10 weeks.	Google Trends
TS-ASVI2$_{i,t}$	Natural log of 1 plus TS-SVI for firm *i* on day *t* less the average of the natural log of 1 plus TS-SVI for firm *i* on the same weekday over prior 10 weeks.	Google Trends
Events		
EA$_{i,t}$	An indicator variable set equal to one on day *t* if firm *i* announces earnings, and zero otherwise.	Compustat
Determinants of Google Ticker Search:		
News Articles$_{i,t}$	Daily number of news articles for firm *i* on day *t*.	FactSet
Abs Return$_{i,t}$	The absolute raw stock return for firm *i* on day *t*.	CRSP
MVE$_{i,q}$	The decile rank of market capitalization of firm *i* as of most recent fiscal quarter-end *q* (PRCCQ x CSHOQ).	CRSP
Large_Firms$_{i,q}$	Indicator variable set equal to one if the market value of equity of the firm of the most recent fiscal quarter-end is in the highest quartile of the sample, and zero otherwise.	CRSP
Analyst Following$_{i,t}$	Natural log of 1 plus the number of analysts following firm *i* on day *t*.	I/B/E/S
High_Following$_{i,q}$	Indicator variable set equal to one if the average number of analyst following of the most recent fiscal quarter-end is in the highest quartile of the sample and zero otherwise.	I/B/E/S
Trading Volume$_{i,t}$	Daily share volume divided by shares outstanding for firm *i* on day *t*, averaged by month.	CRSP
Spread$_{i,t}$	Bid-ask spread for firm *i* on day *t*. Calculated as [(bid – ask) / price].	CRSP
Large_Spread	Indicator variable equal to one if the average bid-ask spread of the most recent fiscal quarter is in the highest quartile of the sample, and zero otherwise.	CRSP

Variable	Description	Source
Fourth Qtr$_{i,t}$	Indicator variable set equal to one if day *t* is in the fourth fiscal quarter for firm *i* and to zero otherwise.	Compustat
Total EAs$_{t}$	The decile rank of the total number of firms announcing earnings on day *t*, calculated across all of Compustat.	Compustat
Inst. Own$_{i,q}$	Percentage institutional ownership in most recent quarter for firm *i*.	FactSet
BTM$_{i,q}$	The decile rank of the ratio of book value of equity to market capitalization for firm *i* as of the most recent fiscal quarter-end *q*. (CEQQ/[PRCCQ x CSHOQ]).	Compustat/CRSP
Ticker Length	The number of letters of a Google ticker searches (e.g., AAPL has a Ticker Length of 4).	Google Trends
Other Variables		
Leverage$_{i,q}$	The ratio of long-term and short-term debt to total assets for firm *i* as of the most recent fiscal quarter-end.	Compustat
Momentum$_{i,t}$	The absolute buy-and-hold return for firm *i* on day *t*., averaged by month.	CRSP
ROA$_{i,t}$	The ratio of net income to total assets for firm *i* on day *t* for the trailing 4 quarters.	Compustat
Stock Volatility$_{i,t}$	Monthly average of the standard deviation of daily returns for firm *i* on day *t*.	CRSP
Beta$_{i,t}$	The trailing 12-month monthly beta for firm *i* on day *t*.	CRSP
Ambiguous$_{i,}$	Indicator variable set equal to one if the ticker for firm *i* is deemed ambiguous by Drake et al. (2012). Ticker type designations as "Ambiguous" used and obtained from Drake et al. (2011): AA, ABC, ALL, AN, CAT, COST, EBAY, ED, FAST, HAS, HD, HOG, KEY, KO, LOW, MAT, MET, PEG, SEE, TAP.	Drake et al. (2012)
Friday EA$_{i,t}$	An indicator variable set equal to one on day *t* if firm *i* announces earnings is a Friday, and zero otherwise.	Compustat
CSR-Rating	The sum of yearly adjusted community, diversity, employee relations, environment, human rights, and product quality and safety KLD CSR scores. Adjusted CSR is estimated by scaling the raw strength and concern scores of each category by the number of items of the strengths and concerns of that category in the year and then taking the net difference between the strength and concern scores for that category	KLD

Measuring Investor Attention - Supplementary Materials

These Supplementary Materials contain additional discussion and analyses referenced in the main paper.

SM1: Ticker-Level Search Volume and the Fraction of Search Determined to be Investor-Related

SM2: Complete tabulation of Table 4

SM3: Additional specifications of Table 4

SM4: Simulation Results of Induced Increase in Ticker Search on Random Days

SM5: Complete tabulation of Table 7

SM6: Published studies using Google ticker SVI

SM1: Ticker-Level Search Volume and the Fraction Determined to be Investor-Related

This table lists the average ticker searches (e.g., "AAPL") per firm-month (in units of one) for each of the 490 tickers in our sample (*Keyword_Search*) for our sample period (column (i)). Column (ii) lists the percentage of searches determined to be investor-related (*Investor_Search*). "Investor-related" searches are determined based on the contents of the click-through website. Specifically, we designate a website as investor-related if it "likely provides current information for investors about the ticker being searched." See Section 2 for further details. Column (iii) lists estimated ticker search (e.g., "AAPL") that is presumed to be investor-related (i.e., (i)×(ii)). Column (iv) lists the average ticker-stock searches (e.g., "AAPL stock") per firm month (in units of one) for each of the 490 tickers in our sample (*TS-Keyword_Search*) for our sample period. Column (ii) lists the percentage of searches determined to be investor-related (*TS-Investor_Search*). Column (iii) lists estimated ticker-stock search (e.g., "AAPL stock") that is presumed to be investor-related (i.e., (i)×(ii)). *Indicates the ticker search results show a market summary box.

		Ticker Search			Ticker Stock Search		
		(i)	*(ii)*	*(iii)*	*(iv)*	*(v)*	*(vi)*
Ticker	**Name**	***Keyword Search***	***Investor Search***	***Estimated Search (i)×(ii)***	***TS-keyword Search***	***TS-Investor Search***	***Estimated Search (iv)×(v)***
A	Agilent Technologies Inc	1,519,412	0.7%	10,028	6,415	75.4%	4,834
AA	Alcoa Inc	523,333	1.5%	7,955	58,700	78.0%	45,792
AAL	American Airlines Group	41,855*	76.0%	31,797	586,538	85.3%	500,317
AAP	Advance Auto Parts	48,755	17.4%	8,493	9,692	73.6%	7,137
AAPL	Apple Inc.	1,141,600*	70.8%	808,481	1,953,846	80.8%	770,994
ABBV	AbbVie	17,995*	62.9%	11,310	66,538	86.8%	57,775
ABC	AmerisourceBergen Corp	1,192,950	0.1%	716	9,792	41.0%	4,012
ABT	Abbott Laboratories	85,850	7.6%	6,559	69,931	87.0%	60,812
ACN	Accenture plc	33,610	5.6%	1,892	32,500	77.5%	25,188
ADBE	Adobe Systems Inc	22,750*	70.6%	16,055	65,585	79.4%	52,042
ADI	Analog Devices Inc.	41,850	1.3%	527	15,615	73.3%	11,454
ADM	Archer-Daniels-Midland Co	39,845	5.0%	1,980	22,700	77.7%	17,649
ADP	Automatic Data Processing	1,396,000	0.3%	4,048	24,292	91.9%	22,322
ADS	Alliance Data Systems	192,000	2.7%	5,088	12,854	83.0%	10,669
ADSK	Autodesk Inc	121,525*	84.5%	102,701	17,323	87.9%	15,227
AEE	Ameren Corp	18,020*	3.3%	586	4,800	84.4%	4,051
AEP	American Electric Power	138,750*	0.8%	1,096	21,077	85.1%	17,928
AES	AES Corp	165,450	1.0%	1,671	11,862	0.0%	0
AET	Aetna Inc	27,375	6.8%	1,853	566	92.3%	523
AFL	AFLAC Inc	38,440	0.8%	296	26,100	68.5%	17,879
AGN	Allergan plc	23,320*	53.5%	12,465	1,252	94.3%	1,181
AIG	American International Group Inc.	71,600	24.9%	17,800	28,531	65.1%	18,577
AIV	Apartment Investment & Mgmt	1,656*	10.6%	175	18,608	86.0%	16,007
AIZ	Assurant Inc	1,859*	30.0%	557	1,746	69.4%	1,212
AJG	Arthur J. Gallagher & Co.	1,789*	3.9%	70	3,338	78.1%	2,605
AKAM	Akamai Technologies Inc	13,230*	56.2%	7,430	15,800	86.8%	13,711
ALB	Albemarle Corp	247,000*	60.1%	148,447	32,262	89.7%	28,955
ALK	Alaska Air Group Inc	11,575*	48.9%	5,665	44,992	69.0%	31,031
ALL	Allstate Corp	152,625	2.1%	3,175	10,208	20.5%	2,097
ALLE	Allegion	5,824*	30.2%	1,759	883	78.0%	689
ALXN	Alexion Pharmaceuticals	20,240*	69.5%	14,067	8,600	90.8%	7,808
AMAT	Applied Materials Inc	20,305*	74.1%	15,050	89,808	78.9%	70,867
AME	Ametek	25,630*	1.8%	454	7,954	81.8%	6,506
AMG	Affiliated Managers Group Inc	31,370	0.3%	82	2,769	79.7%	2,207
AMGN	Amgen Inc	25,455*	81.6%	20,761	17,508	85.3%	14,936
AMP	Ameriprise Financial	76,300	0.6%	427	5,192	74.2%	3,852
AMT	American Tower Corp A	39,160	25.9%	10,142	32,062	78.1%	25,031
AMZN	Amazon.com Inc	611,450*	66.9%	409,243	1,095,846	73.5%	240,198
AN	AutoNation Inc	143,571	0.6%	818	5,115	93.2%	4,769
ANTM	Anthem Inc.	26,945	1.6%	437	11,723	73.2%	8,585
AON	Aon plc	29,695	5.3%	1,562	12,577	82.9%	10,423

		Ticker Search			Ticker Stock Search		
		(i)	(ii)	(iii)	(iv)	(v)	(vi)
Ticker	**Name**	Keyword Search	Investor Search	Estimated Search (i)×(ii)	TS-keyword Search	TS-Investor Search	Estimated Search (iv)×(v)
APA	Apache Corporation	147,450	0.2%	236	51,054	69.8%	35,641
APC	Anadarko Petroleum Corp	75,800	0.3%	197	467	84.1%	393
APD	Air Products & Chemicals Inc	53,450	3.2%	1,726	12,846	48.8%	6,273
APH	Amphenol Corp A	5,590*	6.8%	382	4,138	70.2%	2,905
ATVI	Activision Blizzard	39,565*	79.3%	31,387	56,208	85.4%	48,018
AVB	AvalonBay Communities Inc.	6,217*	22.0%	1,366	6,508	85.8%	5,586
AVGO	Avago Technologies	23,065*	28.0%	6,447	52,615	85.2%	44,833
AVY	Avery Dennison Corp	1,720*	66.1%	1,137	1,885	90.9%	1,713
AWK	American Water Works Company Inc	16,685	1.2%	207	14,585	85.6%	12,482
AXP	American Express Co	12,960*	80.0%	10,367	31,808	89.5%	28,462
AYI	Acuity Brands Inc	12,686*	7.4%	932	2,538	96.3%	2,444
AZO	AutoZone Inc	66,235	7.3%	4,815	12,215	73.0%	8,912
BA	Boeing Company	181,941*	21.6%	39,226	873,462	78.5%	685,318
BAC	Bank of America Corp	316,300*	59.8%	189,116	379,154	91.1%	345,258
BAX	Baxter International Inc.	5,953*	54.3%	3,230	5,469	83.4%	4,561
BBBY	Bed Bath & Beyond	8,818*	74.1%	6,530	135,892	90.5%	122,928
BBT	BB&T Corporation	2,035,000*	0.2%	3,663	11,908	14.1%	1,677
BBY	Best Buy Co. Inc.	26,015*	53.4%	13,884	48,823	88.9%	43,399
BCR	Bard (C.R.) Inc.	11,506	6.7%	770	82	100.0%	82
BDX	Becton Dickinson	8,415*	49.2%	4,143	11,477	75.7%	8,692
BEN	Franklin Resources	56,100	4.5%	2,530	6,831	70.4%	4,812
BFA	Brown-Forman Corporation	14,425	0.1%	10	215	34.0%	73
BFB	Brown-Forman Corporation	2,650	90.3%	2,394	2,969	43.2%	1,283
BIIB	BIOGEN IDEC Inc.	28,805*	92.2%	26,564	44,585	88.5%	39,471
BK	The Bank of New York Mellon	50,794	3.5%	1,757	14,777	83.0%	12,263
BLK	BlackRock	10,694*	19.7%	2,109	23,346	72.7%	16,970
BLL	Ball Corp	11,900*	63.6%	7,571	7,685	96.3%	7,402
BMY	Bristol-Myers Squibb	41,205*	48.5%	19,980	75,808	87.9%	66,658
BRKA	Berkshire Hathaway	9,550*	80.4%	7,676	7,162	87.5%	6,268
BRKB	Berkshire Hathaway	71,785*	73.4%	52,705	113,115	84.1%	95,107
BSX	Boston Scientific	8,030*	85.4%	6,854	18,215	82.0%	14,945
BWA	BorgWarner	8,770*	1.3%	111	6,815	82.0%	5,588
BXP	Boston Properties	938*	28.0%	263	7,331	72.1%	5,289
C	Citigroup Inc.	1,220,000	8.8%	106,750	146,923	90.5%	133,024
CA	CA Inc.	275,118	0.3%	853	1,312	95.8%	1,257
CAG	ConAgra Foods Inc.	18,545*	2.6%	486	8,531	91.4%	7,796
CAH	Cardinal Health Inc.	17,890	28.6%	5,115	12,831	79.9%	10,255
CAT	Caterpillar Inc.	1,179,000	6.1%	71,447	130,423	82.6%	107,716
CB	Chubb Limited	1,045,588*	3.1%	32,518	10,500	78.3%	8,223
CBG	CBRE Group	9,000	2.3%	209	233	66.7%	155
CBS	CBS Corp.	1,029,200	0.1%	823	10,500	63.2%	6,631
CBSA	CBS Corp.	7,935	0.0%	0	20	63.2%	13
CCI	Crown Castle International Corp.	35,080	5.1%	1,775	32,108	60.0%	19,252
CCL	Carnival Corp.	18,015*	13.5%	2,437	773,615	87.8%	19,746
CELG	Celgene Corp.	38,310*	39.7%	15,224	693	93.5%	648
CERN	Cerner	77,725	7.1%	5,526	9,431	69.5%	6,551
CF	CF Industries Holdings Inc	59,353	7.3%	4,345	6,662	80.5%	5,364
CFG	Citizens Financial Group	9,595*	34.9%	3,350	10,023	80.3%	8,049
CHD	Church & Dwight	22,455	6.4%	1,428	6,338	65.2%	4,133
CHK	Chesapeake Energy	134,250*	70.8%	95,009	28,831	71.7%	20,669
CHRW	C. H. Robinson Worldwide	5,284*	58.5%	3,092	5,185	76.4%	3,963
CI	CIGNA Corp.	60,500*	3.1%	1,894	14,585	72.8%	10,616
CINF	Cincinnati Financial	2,023*	80.1%	1,620	6,669	87.5%	5,837
CL	Colgate-Palmolive	181,941	7.5%	13,646	11,754	76.4%	8,979
CLX	The Clorox Company	4,338*	63.1%	2,737	27,362	88.6%	24,251
CMA	Comerica Inc.	58,130	4.7%	2,720	5,723	88.0%	5,033
CMCSA	Comcast A Corp	28,220*	51.4%	14,508	12,762	93.6%	11,948

		Ticker Search			Ticker Stock Search		
		(i)	(ii)	(iii)	(iv)	(v)	(vi)
Ticker	Name	Keyword Search	Investor Search	Estimated Search (i)×(ii)	TS-keyword Search	TS-Investor Search	Estimated Search (iv)×(v)
CME	CME Group Inc.	52,975	76.2%	40,378	16,454	85.9%	14,129
CMG	Chipotle Mexican Grill	98,075	80.5%	78,911	51,508	84.2%	43,390
CMI	Cummins Inc.	23,465*	14.0%	3,287	18,031	95.8%	17,276
CMS	CMS Energy	202,200	0.1%	121	3,669	94.9%	3,481
CNC	Centene Corporation	37,910	7.4%	2,817	12,092	84.3%	10,189
CNP	CenterPoint Energy	7,890*	24.2%	1,905	8,338	93.7%	7,817
COF	Capital One Financial	27,990*	53.3%	14,905	29,600	83.5%	24,704
COG	Cabot Oil & Gas	39,550	9.2%	3,623	7,392	63.7%	4,710
COL	Rockwell Collins	50,450*	11.4%	5,736	208	97.5%	203
COP	ConocoPhillips	99,350*	31.9%	31,693	58,538	87.8%	51,385
COST	Costco Co.	62,382*	40.1%	25,021	75,231	79.7%	59,997
CPB	Campbell Soup	23,765	4.6%	1,100	11,577	88.8%	10,280
CRM	Salesforce.com	142,750	8.2%	11,648	342,462	85.1%	291,435
CSCO	Cisco Systems	81,975*	47.3%	38,766	94,846	86.3%	81,871
CSRA	CSRA Inc.	22,155	1.8%	401	1,091	100.0%	1,091
CSX	CSX Corp.	56,150	26.6%	14,913	74,115	59.6%	44,173
CTAS	Cintas Corporation	92,750*	27.0%	25,043	6,354	74.2%	4,715
CTL	CenturyLink Inc	19,347*	52.9%	10,236	11,168	86.7%	9,678
CTSH	Cognizant Technology Solutions	67,075*	66.7%	44,719	10,077	46.8%	4,713
CTXS	Citrix Systems	6,055*	84.5%	5,115	5,254	61.0%	3,205
CVS	CVS Health	3,424,000*	0.4%	11,984	247,385	86.0%	212,751
CVX	Chevron Corp.	60,800*	43.0%	26,132	124,231	88.3%	109,696
CXO	Concho Resources	5,160*	6.8%	351	3,556	94.0%	3,342
D	Dominion Resources	823,000	6.2%	51,273	24,292	61.9%	15,037
DAL	Delta Air Lines	39,180	30.3%	11,887	314,231	82.0%	257,764
DE	Deere & Co.	165,000*	33.7%	55,589	37,908	77.9%	29,542
DFS	Discover Financial Services	31,670	3.8%	1,194	34,585	53.3%	18,417
DG	Dollar General	35,276	22.1%	7,796	35,538	85.3%	30,296
DGX	Quest Diagnostics	5,089*	33.4%	1,700	11,262	89.3%	10,057
DHI	D. R. Horton	4,929*	14.6%	721	18,854	78.4%	14,772
DHR	Danaher Corp.	17,935*	21.8%	3,903	17,992	83.6%	15,045
DIS	The Walt Disney Company	136,805*	64.5%	88,294	339,308	77.3%	262,387
DISCA	Discovery Communications-A	1,906*	77.2%	1,471	27,177	89.8%	24,416
DISCK	Discovery Communications-C	1,212*	97.4%	1,180	4,051	94.6%	3,832
DLR	Digital Realty Trust	5,580*	25.7%	1,435	11,285	79.1%	8,924
DLTR	Dollar Tree	5,550*	41.6%	2,307	12,608	100.0%	12,608
DNB	Dun & Bradstreet	14,529	2.3%	340	3,446	80.5%	2,775
DO	Diamond Offshore Drilling	208,941	0.7%	1,358	692	82.0%	567
DOV	Dover Corp.	5,300*	82.8%	4,389	2,200	88.2%	1,940
DPS	Dr. Pepper Snapple Group	131,500	0.2%	237	366	91.8%	336
DRI	Darden Restaurants	42,700	9.3%	3,958	24,185	79.5%	19,222
DTE	DTE Energy Co.	126,500	18.2%	23,048	17,400	81.4%	14,157
DUK	Duke Energy	15,455*	59.7%	9,220	28,192	70.9%	19,982
DVA	DaVita Inc.	44,830*	5.2%	2,318	6,485	89.2%	5,787
DVN	Devon Energy Corp.	10,647*	46.7%	4,976	39,731	89.6%	35,591
EA	Electronic Arts	187,235	16.9%	31,718	39,608	86.2%	34,126
EBAY	eBay Inc.	44,300,000	0.0%	0	92,731	71.9%	66,646
ECL	Ecolab Inc.	7,100*	40.0%	2,836	6,031	67.5%	4,070
ED	Consolidated Edison	245,118	3.6%	8,898	23,008	91.8%	21,114
EFX	Equifax Inc.	11,535*	53.7%	6,193	3,131	77.8%	2,436
EIX	Edison Int'l	4,508*	67.6%	3,046	9,223	57.1%	5,267
EL	Estee Lauder Cos.	90,676	5.8%	5,232	10,338	85.2%	8,806
EMN	Eastman Chemical	5,706*	82.3%	4,693	4,831	94.1%	4,548
EMR	Emerson Electric Company	35,390	13.6%	4,817	11,908	88.2%	10,499
ENDP	Endo International	64,588*	59.2%	38,243	14,062	56.3%	7,917
EOG	EOG Resources	8,665*	24.6%	2,129	27,923	68.6%	19,155
EQIX	Equinix	12,937*	17.7%	2,285	15,277	88.0%	13,442

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EQR	Equity Residential	2,035*	17.0%	346	8,508	90.6%	7,709
EQT	EQT Corporation	17,915*	14.0%	2,499	15,085	82.1%	12,391
ES	Eversource Energy	348,294*	0.3%	1,045	7,200	96.9%	6,976
ESRX	Express Scripts	11,330*	83.4%	9,454	278	90.8%	253
ESS	Essex Property Trust Inc	70,625	2.2%	1,547	5,969	94.5%	5,638
ETFC	E*Trade	6,118*	96.7%	5,913	998	81.8%	816
ETN	Eaton Corporation	18,340	16.0%	2,938	15,262	94.7%	14,459
ETR	Entergy Corp.	10,230*	14.5%	1,485	4,815	100.0%	4,815
EW	Edwards Lifesciences Corp.	170,631	0.9%	1,467	14,938	83.0%	12,403
EXC	Exelon Corp.	18,235*	67.7%	12,351	9,485	55.4%	5,258
EXPD	Expeditors Int'l	4,329*	28.5%	1,233	3,769	70.8%	2,668
EXPE	Expedia Inc.	15,035*	51.5%	7,746	28,431	73.2%	20,811
EXR	Extra Space Storage	3,494*	29.9%	1,044	3,623	88.4%	3,201
F	Ford Motor	3,999,412*	1.1%	45,193	475,923	72.3%	344,283
FAST	Fastenal Co	91,775	1.4%	1,285	10,823	81.5%	8,821
FB	Facebook	5,671,176	1.6%	90,739	949,308	80.8%	767,231
FBHS	Fortune Brands Home & Security	1,456*	5.5%	80	1,815	91.0%	1,652
FCX	Freeport-McMoran Cp & Gld	57,220*	60.2%	34,418	96,423	86.4%	83,348
FDX	FedEx Corporation	13,650*	81.3%	11,093	92,731	12.1%	11,183
FE	FirstEnergy Corp	78,853	1.6%	1,238	25,108	58.4%	14,661
FFIV	F5 Networks	9,795*	65.0%	6,363	5,331	31.8%	1,694
FIS	Fidelity National Information Services	29,500	2.7%	794	13,138	88.0%	11,557
FISV	Fiserv Inc	34,200*	69.9%	23,916	13,808	70.2%	9,697
FITB	Fifth Third Bancorp	8,339*	19.8%	1,652	9,215	84.3%	7,766
FL	Foot Locker Inc	89,265	25.6%	22,807	10,508	80.4%	8,447
FLIR	FLIR Systems	37,990	0.6%	228	13,677	79.8%	10,913
FLR	Fluor Corp.	8,385*	12.6%	1,059	22,300	92.4%	20,607
FLS	Flowserve Corporation	5,178*	3.2%	163	2,262	85.0%	1,922
FMC	FMC Corporation	22,115	9.4%	2,077	6,300	92.4%	5,818
FOX	Twenty-First Century Fox Class B	1,471,250	0.4%	6,179	6,338	84.9%	5,382
FOXA	Twenty-First Century Fox Class A	3,288*	88.3%	2,904	6,723	78.2%	5,255
FRT	Federal Realty Investment Trust	3,950*	47.1%	1,858	10,285	90.3%	9,286
FSLR	First Solar Inc	37,610*	69.0%	25,962	29,231	91.4%	26,723
FTI	FMC Technologies Inc.	4,900	1.8%	89	15,415	90.6%	13,966
FTR	Frontier Communications	33,465*	38.8%	12,998	5,031	81.8%	4,117
FTV	Fortive Corp	52,250	1.6%	826	2,462	54.9%	1,350
GD	General Dynamics	37,453*	38.1%	14,258	46,192	84.0%	38,787
GE	General Electric	170,143	32.6%	55,467	972,923	86.7%	318,831
GGP	General Growth Properties Inc.	6,080*	10.1%	617	387	100.0%	387
GILD	Gilead Sciences	91,700*	61.3%	56,166	104,577	85.6%	89,539
GIS	General Mills	68,600	2.7%	1,873	24,208	80.0%	19,362
GLW	Corning Inc.	14,585*	65.0%	9,473	26,054	91.6%	23,873
GM	General Motors	1,486,471*	2.5%	37,608	459,769	81.6%	375,080
GOOG	Alphabet Inc Class C	1,026,300*	27.7%	283,977	210,769	83.5%	175,950
GOOGL	Alphabet Inc Class A	547,300*	19.5%	106,778	103,115	84.8%	87,462
GPC	Genuine Parts	14,195	10.6%	1,505	7,569	83.7%	6,334
GPN	Global Payments Inc	3,220*	23.1%	743	14,938	92.8%	13,864
GPS	Gap (The)	437,800	1.1%	4,641	53,715	77.7%	41,747
GRMN	Garmin Ltd.	9,340*	52.3%	4,886	4,769	87.7%	4,183
GS	Goldman Sachs Group	118,824*	52.5%	62,347	80,462	84.5%	67,974
GT	Goodyear Tire & Rubber	75,588	5.9%	4,422	31,454	76.7%	24,125
GWW	Grainger (W.W.) Inc.	4,350*	10.7%	464	3,054	74.3%	2,270
HAL	Halliburton Co.	29,680*	31.0%	9,207	1,953,846	83.4%	1,630,289
HAS	Hasbro Inc.	53,200	20.1%	10,688	6,300	97.1%	6,116
HBAN	Huntington Bancshares	10,806*	47.5%	5,132	16,938	88.2%	14,946
HBI	Hanesbrands Inc	10,165*	46.2%	4,693	15,646	85.4%	13,365
HCA	HCA Holdings	40,660	3.7%	1,517	26,892	68.9%	18,523

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HCN	Welltower Inc.	22,476	23.4%	5,259	145	94.5%	137
HCP	HCP Inc.	13,045*	47.3%	6,174	1,173	88.4%	1,037
HD	Home Depot	101,971*	30.3%	30,938	173,077	93.8%	162,364
HES	Hess Corporation	14,275*	8.7%	1,239	9,238	100.0%	9,238
HIG	Hartford Financial Svc.Gp.	10,340*	13.0%	1,344	7,646	91.8%	7,022
HOG	Harley-Davidson	39,470*	7.5%	2,952	21,077	93.1%	19,623
HOLX	Hologic	3,072*	75.1%	2,307	7,685	87.7%	6,737
HON	Honeywell Int'l Inc.	33,060*	12.9%	4,268	35,377	92.0%	32,536
HP	Helmerich & Payne	363,647	0.5%	1,855	19,185	83.0%	15,927
HPE	Hewlett Packard Enterprise	32,465	30.5%	9,895	29,585	70.9%	20,979
HPQ	HP Inc.	16,455*	70.5%	11,606	39,362	90.5%	35,623
HRB	Block H&R	4,915*	52.7%	2,591	12,485	89.8%	11,215
HRL	Hormel Foods Corp.	4,700*	17.4%	816	11,646	68.8%	8,016
HRS	Harris Corporation	10,270	4.4%	448	1,189	63.7%	757
HSIC	Henry Schein	2,446*	81.7%	1,999	1,720	82.4%	1,417
HST	Host Hotels & Resorts	9,650*	4.9%	473	4,200	94.3%	3,960
HSY	The Hershey Company	4,430*	58.3%	2,581	19,738	63.6%	12,547
HUM	Humana Inc.	84,150	1.5%	1,287	7,308	92.3%	6,749
IBM	International Bus. Machines	169,200	21.4%	36,192	311,000	88.2%	274,364
ICE	Intercontinental Exchange	213,450	3.1%	6,574	14,692	0.0%	0
IFF	Intl Flavors & Fragrances	10,030	0.8%	77	6,069	71.4%	4,335
ILMN	Illumina Inc	60,925*	77.3%	47,113	26,285	89.1%	23,417
INTC	Intel Corp.	109,900*	63.6%	69,863	218,462	43.7%	95,490
INTU	Intuit Inc.	6,826*	53.7%	3,662	11,508	85.8%	9,869
IP	International Paper	332,529	0.1%	266	15,785	97.4%	15,370
IPG	Interpublic Group	12,015	1.8%	214	4,769	60.1%	2,865
IR	Ingersoll-Rand PLC	49,682*	3.2%	1,585	3,254	98.5%	3,206
IRM	Iron Mountain Incorporated	9,905*	13.5%	1,340	34,877	92.6%	32,310
ISRG	Intuitive Surgical Inc.	18,410	77.0%	14,168	34,792	91.5%	31,845
ITW	Illinois Tool Works	13,920	4.7%	649	14,262	84.8%	12,098
IVZ	Invesco Ltd.	1,395*	41.9%	585	11,346	85.9%	9,747
JBHT	J. B. Hunt Transport Services	1,671*	100.0%	1,671	2,477	97.7%	2,420
JCI	Johnson Controls	12,775	16.5%	2,104	10,185	70.9%	7,221
JEC	Jacobs Engineering Group	4,119*	26.7%	1,101	365	99.9%	365
JNJ	Johnson & Johnson	32,235	70.8%	22,835	274,154	68.7%	188,371
JNPR	Juniper Networks	8,763*	65.5%	5,741	4,769	100.0%	4,769
JPM	JPMorgan Chase & Co.	124,700*	56.3%	70,206	272,154	0.0%	0
JWN	Nordstrom	11,295*	76.6%	8,654	53,762	83.6%	44,934
K	Kellogg Co.	805,353	0.1%	564	14,492	92.4%	13,391
KEY	KeyCorp	131,500*	1.4%	1,815	20,954	76.4%	16,011
KHC	Kraft Heinz Co	9,425*	42.3%	3,985	41,408	88.4%	36,609
KIM	Kimco Realty	86,800	13.4%	11,623	4,938	86.9%	4,292
KLAC	KLA-Tencor Corp.	5,416*	21.3%	1,153	9,723	98.3%	9,559
KMB	Kimberly-Clark	5,621*	50.2%	2,822	21,415	70.6%	15,123
KMI	Kinder Morgan	27,750*	81.8%	22,697	70,923	89.4%	63,419
KMX	Carmax Inc	6,869*	60.5%	4,158	12,869	86.6%	11,150
KO	The Coca Cola Company	129,118*	48.2%	62,248	164,462	83.5%	137,392
KORS	Michael Kors Holdings	6,540	34.5%	2,257	1,697	90.1%	1,530
KR	Kroger Co.	44,871*	72.6%	32,594	43,492	87.7%	38,142
KSS	Kohl's Corp.	11,570*	12.7%	1,468	59,531	73.0%	43,481
KSU	Kansas City Southern	40,760	1.6%	656	10,154	36.1%	3,667
L	Loews Corp.	1,220,000	2.3%	27,938	1,792	68.1%	1,220
LB	L Brands Inc.	43,865*	24.4%	10,690	23,154	87.3%	20,218
LEG	Leggett & Platt	58,850	0.3%	165	5,285	82.9%	4,383
LEN	Lennar Corp.	16,353	2.3%	376	13,462	86.8%	11,689
LENB	Lennar Corp.	90	0.0%	0	510	100.0%	510
LH	Laboratory Corp. of America Holding	32,641	20.7%	6,770	9,500	34.5%	3,281

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LKQ	LKQ Corporation	160,500	0.3%	514	11,646	94.9%	11,052
LLL	L-3 Communications Holdings	52,800*	17.6%	9,266	402	97.1%	390
LLY	Lilly (Eli) & Co.	14,820*	67.9%	10,066	36,585	90.7%	33,175
LM	Legg Mason	27,100*	2.2%	585	693	96.3%	667
LMT	Lockheed Martin Corp.	49,675*	47.4%	23,531	95,923	83.7%	80,336
LNC	Lincoln National	3,993*	37.9%	1,515	8,177	85.3%	6,978
LNT	Alliant Energy Corp	2,756*	12.2%	335	252,308	80.9%	204,142
LOW	Lowe's Cos.	62,775	29.1%	18,242	69,423	75.7%	52,525
LRCX	Lam Research	14,805*	79.5%	11,764	41,431	87.1%	36,066
LUK	Leucadia National Corp.	5,012	50.4%	2,528	152	100.0%	152
LUV	Southwest Airlines	41,145*	61.3%	25,201	195,769	100.0%	195,769
LYB	LyondellBasell	2,289*	41.4%	947	8,562	78.3%	6,701
M	Macy's Inc.	1,502,941*	2.2%	33,065	119,923	82.4%	98,853
MA	Mastercard Inc.	258,941*	8.7%	22,502	69,654	95.0%	66,192
MAC	Macerich	634,000	0.5%	3,297	55,031	89.1%	49,011
MAR	Marriott Int'l.	197,300	21.2%	41,729	31,877	81.2%	25,897
MAS	Masco Corp.	61,175	0.3%	171	1,938	81.6%	1,582
MAT	Mattel Inc.	53,450*	18.9%	10,123	8,346	74.6%	6,224
MCD	McDonald's Corp.	42,806*	54.1%	23,154	70,462	87.2%	61,471
MCHP	Microchip Technology	5,700*	68.1%	3,883	11,546	86.9%	10,038
MCK	McKesson Corp.	14,720*	74.6%	10,975	14,231	96.4%	13,713
MCO	Moody's Corp	46,225	1.5%	698	5,108	96.0%	4,905
MDLZ	Mondelez International	4,685*	33.8%	1,582	13,723	56.4%	7,747
MDT	Medtronic plc	37,540	17.9%	6,723	35,023	75.9%	26,596
MET	MetLife Inc.	79,775	82.2%	65,583	13,723	88.0%	12,072
MHK	Mohawk Industries	2,426*	9.3%	224	5,077	88.7%	4,503
MKC	McCormick & Co.	5,912	5.7%	339	9,223	73.9%	6,815
MLM	Martin Marietta Materials	32,015	13.0%	4,172	7,331	73.1%	5,359
MMC	Marsh & McLennan	17,110	3.8%	650	6,585	96.6%	6,362
MMM	3M Company	70,100*	21.2%	14,875	72,808	82.8%	60,278
MNK	Mallinckrodt Plc	11,294*	50.6%	5,717	10,867	90.6%	9,849
MNST	Monster Beverage	5,453*	58.7%	3,202	11,631	91.1%	10,595
MO	Altria Group Inc	224,824*	28.1%	63,108	145,538	90.6%	131,930
MON	Monsanto Co.	44,500	30.9%	13,737	630	96.3%	607
MOS	The Mosaic Company	41,130	5.0%	2,052	20,215	92.5%	18,693
MPC	Marathon Petroleum	45,730	8.2%	3,732	95,269	82.2%	78,311
MRK	Merck & Co.	32,241*	47.4%	15,295	72,154	87.3%	62,998
MRO	Marathon Oil Corp.	40,170	27.6%	11,075	193,231	100.0%	193,231
MS	Morgan Stanley	334,500	2.8%	9,466	45,146	83.4%	37,661
MSFT	Microsoft Corp.	191,050*	70.9%	135,359	779,000	78.3%	609,723
MSI	Motorola Solutions Inc.	127,575	0.2%	242	15,254	73.0%	11,138
MTB	M&T Bank Corp.	93,875	0.3%	291	11,192	95.7%	10,707
MU	Micron Technology	188,467*	36.4%	68,527	233,077	89.7%	208,977
MUR	Murphy Oil	7,806	59.5%	4,643	14,908	64.6%	9,629
MYL	Mylan N.V.	14,605*	74.0%	10,814	3,304	84.2%	2,783
NAVI	Navient	27,870	2.8%	775	5,269	86.1%	4,537
NBL	Noble Energy Inc	13,285	1.4%	185	3,635	81.5%	2,963
NDAQ	NASDAQ OMX Group	2,173*	68.3%	1,485	4,131	92.6%	3,823
NEE	NextEra Energy	50,600*	8.3%	4,175	103,885	92.4%	95,990
NEM	Newmont Mining Corp. (Hldg. Co.)	17,465	65.6%	11,459	23,900	86.8%	20,733
NFLX	Netflix Inc.	205,450*	51.2%	105,129	638,000	84.2%	537,196
NFX	Newfield Exploration Co	2,130*	18.4%	393	214	76.1%	163
NI	NiSource Inc.	82,735*	0.3%	248	4,254	73.6%	3,132
NKE	Nike	43,265*	53.0%	22,943	188,538	76.9%	145,061
NLSN	Nielsen Holdings	1,681*	77.8%	1,307	1,835	78.8%	1,446
NOC	Northrop Grumman Corp.	29,625*	14.8%	4,379	30,985	84.1%	26,074
NOV	National Oilwell Varco Inc.	25,765	13.9%	3,568	11,531	0.0%	0

		Ticker Search			Ticker Stock Search		
		(i)	*(ii)*	*(iii)*	*(iv)*	*(v)*	*(vi)*
Ticker	**Name**	***Keyword Search***	***Investor Search***	***Estimated Search (i)×(ii)***	***TS-keyword Search***	***TS-Investor Search***	***Estimated Search (iv)×(v)***
NRG	NRG Energy	47,035	5.4%	2,559	26,631	86.6%	23,049
NSC	Norfolk Southern Corp.	19,715*	9.0%	1,780	15,654	93.3%	14,610
NTAP	NetApp	14,415*	64.7%	9,325	10,323	85.4%	8,812
NTRS	Northern Trust Corp.	3,476*	59.3%	2,061	1,900	72.5%	1,377
NUE	Nucor Corp.	78,275*	21.8%	17,033	33,415	86.8%	28,998
NVDA	Nvidia Corporation	477,150*	73.9%	352,757	1,290,231	87.0%	1,123,017
NWL	Newell Rubbermaid Co.	5,184*	66.3%	3,438	11,408	79.3%	9,043
NWS	News Corp. Class B	410,500	0.0%	41	633	51.3%	325
NWSA	News Corp. Class A	3,115	1.9%	59	1,335	71.0%	949
O	Realty Income Corporation	658,529	7.4%	48,665	72,385	84.5%	61,129
OI	Owens-Illinois Inc.	7,113*	4.9%	351	3,662	78.4%	2,872
OKE	ONEOK	7,089*	21.0%	1,487	62,308	85.9%	53,516
OMC	Omnicom Group	10,890	1.2%	135	5,708	97.1%	5,545
ORCL	Oracle Corp.	137,730*	73.3%	100,997	59,169	81.1%	48,016
ORLY	O'Reilly Automotive	10,815*	13.3%	1,441	15,762	85.3%	13,442
OXY	Occidental Petroleum	21,255*	18.1%	3,843	267,615	0.0%	0
PAYX	Paychex Inc.	2,919*	47.2%	1,377	71,892	89.9%	64,652
PBCT	People's United Financial	2,331*	72.2%	1,682	25,392	42.8%	10,860
PBI	Pitney-Bowes	14,540*	8.4%	1,214	16,800	94.8%	15,918
PCAR	PACCAR Inc.	4,144*	22.5%	934	6,231	87.1%	5,426
PCG	PG&E Corp.	10,695*	20.6%	2,201	58,208	81.2%	47,282
PCLN	Priceline.com Inc	40,475*	73.3%	29,676	834	93.9%	783
PDCO	Patterson Companies	3,475*	55.1%	1,913	2,992	65.2%	1,952
PEG	Public Serv. Enterprise Inc.	55,635*	5.2%	2,915	11,600	38.7%	4,495
PEP	PepsiCo Inc.	90,714*	5.9%	5,370	40,500	87.7%	35,510
PFE	Pfizer Inc.	46,190*	78.3%	36,162	1,548,077	81.8%	1,265,863
PFG	Principal Financial Group	15,490*	38.3%	5,934	18,792	74.0%	13,910
PG	Procter & Gamble	52,735*	18.4%	9,709	149,231	85.8%	128,070
PGR	Progressive Corp.	8,130*	30.2%	2,454	13,723	89.2%	12,245
PH	Parker-Hannifin	96,588	0.6%	599	9,715	79.7%	7,742
PHM	Pulte Homes Inc.	23,400*	24.2%	5,656	6,869	83.2%	5,716
PKI	PerkinElmer	10,360	0.1%	7	5,485	84.0%	4,606
PLD	Prologis	7,242*	45.3%	3,284	7,846	86.6%	6,798
PM	Philip Morris International	142,059*	14.0%	19,831	35,485	83.6%	29,680
PNC	PNC Financial Services	1,472,000	0.1%	1,472	28,385	63.6%	18,059
PNR	Pentair Ltd.	6,485	1.1%	74	2,700	94.0%	2,539
PNW	Pinnacle West Capital	21,050	2.2%	457	4,800	97.1%	4,661
PPG	PPG Industries	40,000	61.5%	24,612	24,231	100.0%	24,231
PPL	PPL Corp.	121,250	0.8%	1,019	42,977	77.6%	33,337
PRGO	Perrigo	5,067*	81.0%	4,104	2,177	82.5%	1,796
PRU	Prudential Financial	92,305*	55.1%	50,851	42,131	87.9%	37,042
PSA	Public Storage	122,500	0.5%	662	8,169	81.1%	6,621
PSX	Phillips 66	33,090*	28.5%	9,427	51,431	87.9%	45,228
PVH	PVH Corp.	15,190	6.5%	986	8,846	78.1%	6,905
PWR	Quanta Services Inc.	7,665	2.7%	210	5,608	90.7%	5,087
PX	Praxair Inc.	31,324*	0.9%	273	274	100.0%	274
PXD	Pioneer Natural Resources	5,539*	44.1%	2,445	12,323	66.9%	8,244
PYPL	PayPal	36,355*	77.1%	28,019	196,077	91.6%	179,665
QCOM	QUALCOMM Inc.	165,800*	74.8%	124,085	159,000	81.9%	130,173
QRVO	Qorvo	9,489*	70.5%	6,686	21,900	82.9%	18,159
R	Ryder System	805,353	0.4%	2,980	13,723	50.1%	6,871
RCL	Royal Caribbean Cruises Ltd	15,085	10.9%	1,649	217,538	100.0%	217,538
REGN	Regeneron	27,515*	68.2%	18,754	60,462	86.7%	52,439
RF	Regions Financial Corp.	40,688*	19.3%	7,861	17,462	83.7%	14,621
RHI	Robert Half International	3,973*	23.2%	920	1,406	68.8%	968
RHT	Red Hat Inc.	11,375*	59.0%	6,710	977	72.8%	712
RIG	Transocean	50,450*	50.5%	25,477	116,346	81.2%	94,461

		Ticker Search			Ticker Stock Search		
		(i)	(ii)	(iii)	(iv)	(v)	(vi)
Ticker	**Name**	***Keyword Search***	***Investor Search***	***Estimated Search (i)×(ii)***	***TS-keyword Search***	***TS-Investor Search***	***Estimated Search (iv)×(v)***
RL	Polo Ralph Lauren Corp.	23,159*	25.7%	5,947	6,215	77.4%	4,810
ROK	Rockwell Automation Inc.	15,500*	12.0%	1,854	5,462	68.5%	3,743
ROP	Roper Industries	14,155*	0.8%	112	3,108	72.8%	2,263
ROST	Ross Stores	6,955*	61.6%	4,286	6,892	80.4%	5,543
RRC	Range Resources Corp.	8,870*	28.9%	2,563	14,085	81.9%	11,537
RSG	Republic Services Inc	5,432*	16.7%	905	4,900	49.7%	2,437
RTN	Raytheon Co.	17,245*	83.2%	14,341	3,454	85.9%	2,968
SBUX	Starbucks Corp.	67,750*	49.5%	33,509	86,769	86.0%	74,578
SCG	SCANA Corp	27,920*	1.5%	419	170	71.9%	122
SCHW	Charles Schwab Corporation	8,465*	39.3%	3,330	11,908	87.2%	10,379
SEE	Sealed Air Corp.	84,050	4.7%	3,942	2,808	94.5%	2,653
SHW	Sherwin-Williams Company	17,408*	47.6%	8,284	22,338	94.8%	21,188
SIG	Signet Jewelers	46,450	1.1%	520	14,877	82.3%	12,250
SJM	Smucker (J.M.)	4,711*	72.1%	3,396	7,508	33.8%	2,540
SLB	Schlumberger Ltd.	14,380*	38.1%	5,474	55,577	86.5%	48,080
SLG	SL Green Realty	13,436*	0.7%	99	9,169	87.6%	8,031
SNA	Snap-On Inc.	34,280	4.0%	1,361	5,046	79.8%	4,027
SNI	Scripps Networks Interactive Inc.	6,435	16.2%	1,041	74	100.0%	74
SO	Southern Co.	173,471*	14.9%	25,899	36,054	86.0%	30,992
SPG	Simon Property Group Inc	260,250	0.2%	468	114,538	77.8%	89,053
SPGI	S&P Global Inc.	2,054	82.7%	1,698	9,062	79.8%	7,231
SRCL	Stericycle Inc	2,950*	72.1%	2,127	217,538	91.5%	199,134
SRE	Sempra Energy	18,755	13.2%	2,472	10,169	81.3%	8,267
STI	SunTrust Banks	85,700	1.1%	926	560	94.4%	529
STT	State Street Corp.	12,384*	42.8%	5,302	368,385	93.6%	344,735
STX	Seagate Technology	17,750*	30.9%	5,483	40	87.7%	35
STZ	Constellation Brands	9,236*	69.5%	6,418	17,569	89.5%	15,728
SWK	Stanley Black & Decker	5,550*	80.8%	4,484	6,138	61.6%	3,782
SWKS	Skyworks Solutions	20,240*	38.8%	7,859	37,108	86.9%	32,243
SWN	Southwestern Energy	12,725*	72.3%	9,200	34,854	91.2%	31,776
SYF	Synchrony Financial	5,947*	93.7%	5,574	9,992	82.6%	8,253
SYK	Stryker Corp.	5,357*	68.0%	3,640	7,962	65.0%	5,178
SYMC	Symantec Corp.	60,875*	74.0%	45,041	216	82.0%	177
SYY	Sysco Corp.	7,368*	53.8%	3,963	16,077	89.6%	14,408
T	AT&T Inc	1,077,647	25.1%	270,489	444,077	50.9%	226,168
TAP	Molson Coors Brewing Company	140,500	0.2%	225	26,477	85.6%	22,670
TAPA	Molson Coors Brewing Company	123,300	0.0%	0	30	85.6%	26
TDC	Teradata Corp.	16,160*	21.8%	3,528	11,500	69.3%	7,973
TDG	TransDigm Group	4,559*	55.6%	2,536	6,400	88.6%	5,668
TEL	TE Connectivity Ltd.	22,115*	0.6%	135	3,938	75.5%	2,971
TGNA	Tegna	989*	60.3%	597	1,435	95.2%	1,367
TGT	Target Corp.	20,840*	48.1%	10,030	104,808	86.4%	90,596
TIF	Tiffany & Co.	20,890	12.7%	2,655	3,909	70.9%	2,771
TJX	TJX Companies Inc.	38,730	4.1%	1,588	31,677	79.4%	25,142
TMK	Torchmark Corp.	2,870*	17.1%	491	124	64.3%	80
TMO	Thermo Fisher Scientific	24,950*	5.5%	1,375	33,477	65.6%	21,958
TRIP	TripAdvisor	71,500	1.6%	1,173	19,285	69.3%	13,355
TROW	T. Rowe Price Group	7,455	17.4%	1,299	6,108	0.0%	0
TRV	The Travelers Companies Inc.	4,635*	35.3%	1,634	7,015	0.0%	0
TSCO	Tractor Supply Company	5,540	68.0%	3,767	13,892	85.3%	11,855
TSN	Tyson Foods	73,125	1.8%	1,331	24,915	74.9%	18,654
TSS	Total System Services	53,780	5.2%	2,813	257	100.0%	257
TWX	Time Warner Inc.	14,120	75.6%	10,676	1,729	89.0%	1,539
TXN	Texas Instruments	23,585*	84.1%	19,844	27,000	85.6%	23,101
TXT	Textron Inc.	15,790*	34.4%	5,430	12,054	73.0%	8,795
UA	Under Armour	102,618	19.8%	20,288	26,346	86.8%	22,868
UAL	United Continental Holdings	79,675	23.5%	18,692	388,923	0.0%	0

		Ticker Search			Ticker Stock Search		
		(i)	*(ii)*	*(iii)*	*(iv)*	*(v)*	*(vi)*
Ticker	**Name**	***Keyword Search***	***Investor Search***	***Estimated Search (i)×(ii)***	***TS-keyword Search***	***TS-Investor Search***	***Estimated Search (iv)×(v)***
UDR	UDR Inc	7,545	1.3%	97	2,254	86.3%	1,945
UHS	Universal Health Services Inc.	35,260	0.4%	130	5,315	82.0%	4,356
ULTA	Ulta Salon Cosmetics & Fragrance Inc	2,818,500	0.5%	12,683	46,323	87.1%	40,338
UNH	United Health Group Inc.	41,720	6.8%	2,845	74,923	78.8%	59,054
UNM	Unum Group	35,020	0.0%	0	8,762	87.0%	7,622
UNP	Union Pacific	13,235*	64.4%	8,526	26,100	97.0%	25,314
UPS	United Parcel Service	3,645,000	0.3%	10,206	347,385	79.7%	276,796
URBN	Urban Outfitters	10,825	16.7%	1,802	4,115	93.5%	3,848
URI	United Rentals Inc.	59,775	4.0%	2,367	10,254	51.2%	5,255
USB	U.S. Bancorp	74,000	2.2%	1,643	29,662	42.0%	12,467
UTX	United Technologies	26,585*	60.7%	16,132	5,869	88.9%	5,217
V	Visa Inc.	854,235*	3.3%	28,275	107,231	88.9%	95,275
VAR	Varian Medical Systems	16,450	1.1%	173	1,464	92.0%	1,346
VFC	V.F. Corp.	8,100*	21.3%	1,722	9,808	74.4%	7,302
VIAB	Viacom Inc.	4,200*	83.3%	3,500	43,800	76.3%	33,419
VLO	Valero Energy	14,729*	50.9%	7,490	56,808	95.5%	54,235
VMC	Vulcan Materials	8,085*	8.9%	716	6,885	90.2%	6,212
VNO	Vornado Realty Trust	1,525*	42.0%	641	6,777	78.1%	5,292
VRSK	Verisk Analytics	3,050*	82.7%	2,522	2,854	70.2%	2,004
VRSN	Verisign Inc.	3,188*	78.4%	2,499	2,777	85.3%	2,368
VRTX	Vertex Pharmaceuticals Inc	9,070*	59.8%	5,426	55,323	90.2%	49,929
VTR	Ventas Inc	6,330*	28.8%	1,825	39,577	75.0%	29,687
VZ	Verizon Communications	75,676*	56.7%	42,939	178,462	88.1%	157,171
WAT	Waters Corporation	72,275*	0.2%	116	1,815	91.9%	1,669
WBA	Walgreens Boots Alliance	18,347*	34.0%	6,234	84,731	87.7%	74,292
WDC	Western Digital	20,635*	45.6%	9,412	49,285	84.1%	41,439
WEC	Wisconsin Energy Corporation	9,680	3.6%	345	14,523	58.1%	8,431
WFC	Wells Fargo	82,825*	63.7%	52,726	284,000	88.2%	250,545
WHR	Whirlpool Corp.	9,422*	66.7%	6,286	12,162	89.3%	10,864
WLTW	Willis Towers Watson	1,056*	37.7%	398	1,623	74.4%	1,208
WM	Waste Management Inc.	33,971*	2.0%	693	33,046	88.8%	29,348
WMB	Williams Cos.	11,685*	63.8%	7,455	16,331	81.4%	13,295
WMT	Wal-Mart Stores	66,975*	69.1%	46,266	239,538	86.7%	207,703
WRK	Westrock Co	2,720*	13.1%	355	10,677	93.1%	9,945
WU	Western Union Co	33,100*	1.8%	596	3,177	96.8%	3,077
WY	Weyerhaeuser Corp.	18,147*	21.9%	3,980	15,862	81.2%	12,886
WYN	Wyndham Worldwide	4,129	52.4%	2,162	306	96.5%	295
WYNN	Wynn Resorts Ltd	40,253*	41.9%	16,870	112,269	73.0%	81,945
XEC	Cimarex Energy	1,750*	84.0%	1,470	3,423	83.6%	2,862
XEL	Xcel Energy Inc	4,333*	35.3%	1,528	6,538	63.5%	4,153
XL	XL Capital	18,965	4.7%	889	47,549	65.4%	31,111
XLNX	Xilinx Inc	6,495*	67.1%	4,357	17,215	88.3%	15,206
XOM	Exxon Mobil Corp.	122,300*	84.0%	102,683	381,231	83.9%	319,738
XRAY	Dentsply Sirona	98,300	2.4%	2,340	3,269	89.5%	2,925
XRX	Xerox Corp.	5,774*	78.8%	4,549	17,692	82.4%	14,585
XYL	Xylem Inc.	1,185*	25.4%	301	2,062	89.1%	1,837
YUM	Yum! Brands Inc	31,845*	42.5%	13,518	18,331	76.3%	13,994
ZBH	Zimmer Biomet Holdings	2,900*	59.5%	1,725	4,954	91.1%	4,514
ZION	Zions Bancorp	74,450	0.3%	194	4,085	67.6%	2,761
ZTS	Zoetis	2,917*	95.6%	2,787	8,646	94.2%	8,142

SM2 – Complete tabulation of Table 4: SVI around EAs, by decile of *Noise_Search*, with controls and week fixed effects

This table presents the full results from the analyses Panel B of Table 4. Panel A of this table is for SVI, Panel B of this table is for ASVI, and Panel C of this table is for ASVI2. See Table 4 for further details. Variable definitions are provided in Appendix A. T-statistics are in parentheses. Standard errors are clustered by firm. *, **, *** indicates statistical significance at the p < 0.10, 0.05, 0.01 level, respectively.

Panel A: SVI

	Pooled	By Decile of *Noise_Search*									
		1 [Low]	2	3	4	5	6	7	8	9	10 [High]
SVI	7.879***	12.340***	19.330***	14.592***	11.955***	4.801	4.834**	-3.350	-0.221	5.029	4.470**
	(5.17)	(6.60)	(7.73)	(3.98)	(5.31)	(1.60)	(2.09)	(-0.99)	(-0.06)	(1.27)	(2.07)
News Articles$_{i,t}$	0.345*	0.586***	0.303	0.794**	0.378*	0.771*	0.524*	0.996**	0.302	-0.308	-0.469**
	(1.92)	(4.15)	(1.36)	(2.34)	(1.71)	(1.85)	(1.98)	(2.35)	(0.71)	(-0.61)	(-2.36)
Abs Return$_{i,t}$	92.780***	89.380***	129.000***	171.300***	118.000***	72.510***	74.890***	85.010***	1.013	43.250	28.000
	(7.53)	(5.08)	(5.29)	(6.31)	(3.32)	(3.11)	(2.95)	(3.21)	(0.04)	(1.38)	(0.57)
MVE$_{i,q}$	0.773**	1.287***	0.591	0.701	0.227	2.045**	1.887	2.570*	3.765***	1.508	1.421
	(2.04)	(2.81)	(0.91)	(0.80)	(0.18)	(2.04)	(1.51)	(1.92)	(3.39)	(1.07)	(1.51)
Trading Volume$_{i,t}$	0.417	0.881	0.116	-0.230	3.296*	8.439***	2.713	4.501	-1.286	6.290	-1.370
	(0.44)	(0.72)	(0.11)	(-0.19)	(1.74)	(3.09)	(0.82)	(1.11)	(-0.42)	(1.61)	(-0.32)
Spread$_{i,t}$	-52.370	116.800**	120.30**	4.168	-70.130	-290.200***	-130.900	-16.960	101.600	-105.200	-71.730
	(-1.255)	(2.532)	(2.212)	(0.05)	(-0.91)	(-2.73)	(-1.42)	(-0.16)	(1.05)	(-1.08)	(-0.53)
Fourth Qtr$_{i,t}$	-0.593	-0.790	-0.301	-0.682	-0.377	2.088	-1.493	2.067	-0.294	-4.973**	-0.517
	(-1.17)	(-0.93)	(-0.43)	(-0.56)	(-0.38)	(0.97)	(-1.06)	(1.44)	(-0.21)	(-2.55)	(-0.29)
Total EAs$_t$	0.134***	0.085*	0.091	0.027	0.064	0.189***	0.266***	0.100	0.172**	0.099*	0.142**
	(6.52)	(1.99)	(1.47)	(0.45)	(0.98)	(2.81)	(4.13)	(1.51)	(2.57)	(1.71)	(2.04)
Analyst Following$_{i,t}$	-5.042**	-4.889*	-7.719**	-3.975	-5.912	-8.297*	4.477	0.105	-1.882	-11.920*	-2.955
	(-2.31)	(-1.90)	(-2.39)	(-0.71)	(-1.32)	(-1.90)	(0.67)	(0.015)	(-0.28)	(-1.78)	(-0.74)
Institutional Ownership$_{i,q}$	-6.195	-6.135	-11.680	-8.618	-12.080	-42.510*	-33.350	-3.362	0.865	-47.890**	34.070**
	(-1.05)	(-0.91)	(-1.14)	(-0.56)	(-0.56)	(-1.78)	(-1.59)	(-0.13)	(0.05)	(-2.51)	(2.44)
BTM$_{i,q}$	0.538*	0.132	-0.294	0.777	-0.314	-1.561*	-0.014	0.521	1.155	-0.491	0.973
	(1.73)	(0.31)	(-0.53)	(1.44)	(-0.42)	(-1.89)	(-0.02)	(0.58)	(1.47)	(-0.49)	(1.23)
Constant	43.740***	19.530**	45.240***	30.090*	49.400**	77.260***	37.310	16.430	18.140	101.300***	22.990*
	(5.44)	(2.21)	(2.70)	(1.69)	(2.09)	(2.79)	(1.42)	(0.66)	(0.87)	(3.68)	(1.72)
Year-Week FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
N	245,015	24,970	24,048	24,549	24,548	25,050	24,283	24,549	24,048	24,922	24,048
Adjusted R-squared	0.030	0.132	0.111	0.128	0.064	0.135	0.126	0.105	0.240	0.142	0.147

Panel B: ASVI

	Pooled	By Decile of *Noise Search*									
		1 [Low]	2	3	4	5	6	7	8	9	10 [High]
ASVI	0.470***	1.858***	1.901***	1.539***	0.723***	0.186	-0.012	0.168*	0.106	0.046**	0.001
	(13.08)	(6.19)	(5.98)	(5.28)	(4.76)	(1.36)	(-0.06)	(1.86)	(1.58)	(2.03)	(0.04)
News Articles$_{i,t}$	0.010***	0.054***	0.031***	0.027***	0.023***	0.019*	0.032	0.005**	-0.002	0.002	-0.001
	(8.32)	(5.38)	(4.78)	(2.84)	(4.91)	(1.73)	(1.27)	(2.12)	(-0.39)	(0.81)	(-1.01)
Abs Return$_{i,t}$	3.098***	14.110***	13.890***	8.694***	5.913***	0.573	3.651*	0.066	-2.818	-0.647	-0.070
	(9.82)	(5.81)	(5.72)	(4.48)	(3.53)	(0.41)	(1.76)	(0.10)	(-0.83)	(-1.54)	(-0.20)
MVE$_{i,q}$	0.000	-0.029*	-0.028	-0.021*	-0.006	-0.003	-0.050	-0.004	-0.025	-0.006	0.000
	(0.45)	(-1.90)	(-1.60)	(-1.69)	(-0.61)	(-0.26)	(-1.39)	(-1.02)	(-1.23)	(-1.19)	(0.30)
Trading Volume$_{i,t}$	-0.028***	-0.124***	-0.141***	-0.104***	-0.073**	-0.047	-0.122	-0.015	0.031	-0.027*	-0.006
	(-6.65)	(-2.96)	(-3.30)	(-2.88)	(-2.56)	(-1.65)	(-1.43)	(-1.19)	(0.62)	(-1.70)	(-0.90)
Spread$_{i,t}$	4.269***	16.580***	11.330***	13.760***	8.707***	4.841**	0.438	2.641**	-0.004	1.627	0.602
	(9.47)	(4.17)	(3.78)	(3.84)	(3.26)	(2.39)	(0.14)	(2.29)	(-0.01)	(1.40)	(1.32)
Fourth Qtr$_{i,t}$	-0.032**	-0.252**	-0.041	0.009	-0.054	-0.018	0.011	0.016	0.076	-0.133*	-0.023
	(-2.20)	(-2.40)	(-0.69)	(0.19)	(-0.90)	(-0.54)	(0.17)	(0.82)	(0.87)	(-1.94)	(-0.65)
Total EAs$_t$	-0.005***	-0.008	-0.018**	-0.027***	-0.018**	-0.013***	0.008	-0.004	0.010	-0.002	-0.001
	(-5.24)	(-1.17)	(-2.53)	(-3.18)	(-2.56)	(-2.73)	(1.44)	(-1.10)	(0.95)	(-1.15)	(-0.38)
Analyst Following$_{i,t}$	-0.002	-0.060	-0.016	-0.031	0.031	0.013	-0.130	-0.008	0.193	0.011	0.002
	(-0.19)	(-0.72)	(-0.28)	(-0.27)	(1.06)	(0.35)	(-0.58)	(-0.31)	(1.00)	(0.46)	(0.28)
Institutional Ownership$_{i,q}$	0.069***	0.315	0.232	-0.038	0.078	0.458**	0.503	-0.022	-0.133	0.102*	-0.003
	(2.81)	(1.48)	(1.45)	(-0.25)	(0.41)	(2.37)	(1.53)	(-0.18)	(-0.82)	(1.70)	(-0.12)
BTM$_{i,q}$	-0.003**	-0.021**	0.005	-0.014*	0.001	0.002	-0.010	-0.002	0.010	0.006	-0.000
	(-2.36)	(-2.33)	(0.57)	(-2.00)	(0.074)	(0.43)	(-0.47)	(-0.75)	(0.67)	(1.52)	(-0.15)
Constant	-0.033	0.195	0.099	0.369	-0.034	-0.293	0.498	0.088	-0.367	-0.028	0.020
	(-0.99)	(0.71)	(0.309)	(1.22)	(-0.15)	(-1.28)	(0.69)	(0.91)	(-0.75)	(-0.25)	(0.80)
Year-Week FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
N	245,015	24,970	24,048	24,549	24,548	25,050	24,283	24,549	24,048	24,922	24,048
Adjusted R-squared	0.037	0.077	0.084	0.065	0.043	0.015	0.018	0.029	0.008	0.027	0.009

Panel C: ASVI2

	Pooled	**By Decile of *Noise Search***									
		1 [Low]	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
ASVI2	0.297***	0.702***	0.759***	0.672***	0.379***	0.199***	0.147***	0.073*	0.086***	0.0367*	0.002
	(13.50)	(9.32)	(9.31)	(8.02)	(6.41)	(3.77)	(3.74)	(1.68)	(2.69)	(1.87)	(0.12)
News Articles$_{i,t}$	0.008***	0.020***	0.015***	0.011***	0.010***	0.006***	0.006**	0.005***	0.001	0.010	-0.002
	(8.52)	(6.46)	(6.62)	(3.46)	(4.00)	(2.84)	(2.14)	(2.72)	(1.08)	(0.75)	(-1.26)
Abs Return$_{i,t}$	2.054***	4.106***	4.732***	3.633***	2.866***	0.965*	1.484***	0.212	0.714**	-0.329	-0.067
	(9.11)	(5.12)	(5.41)	(5.15)	(3.68)	(1.75)	(2.88)	(0.50)	(2.01)	(-1.12)	(-0.20)
MVE$_{i,q}$	0.001	0.003	-0.002	-0.003	-0.004	-0.001	-0.002	-0.001	0.003	-0.002	0.000
	(1.01)	(0.73)	(-0.30)	(-0.69)	(-0.91)	(-0.48)	(-0.42)	(-0.62)	(0.84)	(-0.64)	(0.32)
Trading Volume$_{i,t}$	-0.022***	-0.036**	-0.047***	-0.047***	-0.039***	-0.021***	-0.020	-0.006	-0.004	-0.011	-0.011*
	(-7.24)	(-2.61)	(-3.51)	(-5.32)	(-4.62)	(-2.82)	(-1.63)	(-0.85)	(-0.43)	(-1.20)	(-1.87)
Spread$_{i,t}$	3.441***	8.782***	6.615***	6.546***	4.940***	1.911***	1.222	1.814**	-0.228	0.864	0.411
	(9.69)	(5.53)	(6.48)	(5.25)	(4.99)	(2.75)	(1.40)	(2.44)	(-0.46)	(1.30)	(1.19)
Fourth Qtr$_{i,t}$	-0.027**	-0.095**	-0.016	-0.011	-0.032	-0.011	-0.008	0.029	0.000	-0.116**	-0.020
	(-2.20)	(-2.42)	(-0.42)	(-0.45)	(-0.64)	(-0.45)	(-0.25)	(1.67)	(0.004)	(-2.18)	(-0.63)
Total EAs$_{t}$	-0.004***	-0.007*	-0.012***	-0.013***	-0.008**	-0.003	-0.001	-0.001	0.001	-0.002	-0.001*
	(-4.68)	(-1.85)	(-3.51)	(-3.57)	(-2.20)	(-0.99)	(-0.32)	(-0.44)	(0.43)	(-1.06)	(-1.81)
Analyst Following$_{i,t}$	-0.006	-0.042	-0.017	-0.008	0.013	0.011	0.011	-0.007	-0.017	-0.022	0.000
	(-1.15)	(-1.39)	(-0.72)	(-0.26)	(1.06)	(1.02)	(0.66)	(-0.54)	(-1.38)	(-1.67)	(0.02)
Institutional Ownership$_{i,q}$	0.022	0.059	0.091	-0.073	-0.039	0.127**	0.042	-0.017	-0.024	-0.020	0.015
	(1.49)	(0.80)	(1.54)	(-1.27)	(-0.67)	(2.11)	(0.98)	(-0.28)	(-0.91)	(-0.69)	(0.75)
BTM$_{i,q}$	-0.002**	-0.006	0.001	-0.007***	-0.001	0.001	0.003	-0.001	-0.004**	-0.000	0.001
	(-2.42)	(-1.54)	(0.39)	(-2.88)	(-0.29)	(0.48)	(1.36)	(-0.63)	(-2.17)	(-0.12)	(1.20)
Constant	-0.006	0.023	-0.031	0.139	0.033	-0.118	-0.057	0.021	0.081*	0.133***	0.005
	(-0.27)	(0.24)	(-0.31)	(1.59)	(0.51)	(-1.39)	(-1.03)	(0.43)	(1.86)	(2.99)	(0.27)
Year-Week FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
N	245,015	24,970	24,048	24,549	24,548	25,050	24,283	24,549	24,048	24,922	24,048
Adjusted R-squared	0.025	0.063	0.066	0.063	0.044	0.017	0.024	0.021	0.021	0.032	0.016

SM3 – Additional Specifications of Table 4

This table presents the γ_1 coefficient from estimating alternative versions of Equation (9) Untabulated controls include: *News Articles, Abs Return, MVE, Analyst Following, Trading Volume, Spread, Fourth Qtr, Total EAs, Inst Own*, *BTM,* and *Year-Week* fixed effects. The dependent variable is *SVI, ASVI,* or *ASVI2*. Variable definitions are provided in Appendix A and t-statistics are in parentheses. Standard errors are clustered by firm. *, **, *** indicates statistical significance at the p < 0.10, 0.05, 0.01 level, respectively.

Panel A excludes one- and two-letter tickers and the "ambiguous" tickers listed in the header of Table 3. Panel B repeats Panel A but excludes 10 additional ambiguous tickers that were added to the S&P 500 after DRT's sample period: AMG, CERN, DAL, FOX, LEG, LUV, MAC, O, SIG, V. Panel C includes only tickers for which a Google search produces a market summary box, as indicated in Table SM1 of our Supplementary Materials. Panel D tabulates results that include untabulated firm fixed effects.

Panel A: With controls and week fixed effects, and dropping "ambiguous" tickers listed in Table 3 and one-letter and two-letter tickers

	Pooled	**By Decile of *Noise_Search***									
		1 [Low]	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
Observations	205,702	24,469	23,547	23,547	22,544	19,539	19,539	19,539	18,036	17,908	17,034
Average *Noise_Search*	0.655	0.176	0.311	0.431	0.572	0.730	0.830	0.908	0.959	0.985	0.997
γ_1 for *SVI*	9.958***	12.400***	19.060***	17.500***	11.850***	4.863***	5.933**	0.150	7.331***	0.997	3.122
	(8.91)	(6.49)	(7.59)	(5.33)	(5.21)	(3.22)	(2.29)	(0.05)	(2.87)	(0.47)	(1.54)
Adjusted R-squared	0.026	0.142	0.123	0.101	0.101	0.063	0.132	0.071	0.188	0.085	0.193
γ_1 for *ASVI*	0.547***	1.855***	1.946***	1.547***	0.785***	0.251	-0.038	0.198*	0.108	0.057*	-0.002
	(13.20)	(6.05)	(6.04)	(4.95)	(4.85)	(1.45)	(-0.15)	(1.78)	(1.06)	(1.76)	(-0.11)
Adjusted R-squared	0.044	0.080	0.086	0.067	0.046	0.018	0.022	0.032	0.010	0.034	0.011
γ_1 for *ASVI2*	0.345***	0.706***	0.775***	0.673***	0.408***	0.257***	0.177***	0.081	0.118***	0.045	0.001
	(13.69)	(9.18)	(9.44)	(7.45)	(6.57)	(3.87)	(3.66)	(1.58)	(2.75)	(1.63)	(0.03)
Adjusted R-squared	0.030	0.065	0.067	0.065	0.047	0.021	0.029	0.025	0.025	0.040	0.020

Panel B: With controls and week fixed effects, and dropping an updated list of "ambiguous" tickers and one-letter and two-letter tickers

	Pooled	**By Decile of *Noise_Search***									
		1 [Low]	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
Observations	201,694	24,469	23,547	23,046	22,544	19,038	19,539	19,038	18,036	17,407	15,030
Average *Noise_Search*	0.689	0.177	0.311	0.432	0.574	0.729	0.827	0.912	0.960	0.985	0.997
γ_1 for *SVI*	10.16***	12.40***	19.060***	17.930***	11.850***	5.129***	5.933**	0.841	7.331***	1.031	1.915
	(8.93)	(6.48)	(7.59)	(5.39)	(5.20)	(3.45)	(2.29)	(0.30)	(2.87)	(0.47)	(0.79)
Adjusted R-squared	0.026	0.142	0.123	0.104	0.101	0.043	0.132	0.082	0.188	0.091	0.199
γ_1 for *ASVI*	0.557***	1.855***	1.946***	1.587***	0.785***	0.252	-0.038	0.201*	0.108	0.062*	-0.002
	(13.19)	(6.07)	(6.03)	(5.01)	(4.84)	(1.43)	(-0.15)	(1.77)	(1.05)	(1.88)	(-0.11)
Adjusted R-squared	0.030	0.065	0.067	0.066	0.047	0.021	0.029	0.025	0.025	0.043	0.027
γ_1 for *ASVI2*	0.349***	0.706***	0.775***	0.690***	0.408***	0.257***	0.177***	0.082	0.118***	0.046	-0.003
	(13.64)	(9.13)	(9.43)	(7.57)	(6.571)	(3.76)	(3.66)	(1.56)	(2.74)	(1.62)	(-0.14)
Adjusted R-squared	0.027	0.065	0.066	0.065	0.045	0.018	0.024	0.022	0.022	0.035	0.022

Panel C: With controls and week fixed effects, and keeping only tickers for which Google brings up a stock price information box

	Pooled	**By Decile of *Noise_Search***									
		1 [Low]	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
Observations	152,303	22,044	22,545	23,046	23,546	17,535	15,531	11,022	7,515	6,513	3,006
Average *Noise_Search*	0.568	0.176	0.310	0.432	0.573	0.730	0.826	0.902	0.960	0.985	0.997
γ_1 for *SVI*	12.41***	12.74***	20.08***	16.05***	12.58***	7.249***	6.473**	1.740	6.212**	-0.760	3.154
	(8.87)	(6.477)	(7.944)	(4.272)	(5.575)	(4.229)	(2.159)	(0.531)	(2.173)	(-0.296)	(1.642)
Adjusted R-squared	0.052	0.155	0.106	0.157	0.081	0.137	0.213	0.106	0.397	0.612	0.624
γ_1 for *ASVI*	0.706***	1.151***	1.358***	1.164***	0.621***	0.303***	0.255***	0.138	0.140	-0.004	-0.033
	(13.36)	(8.69)	(8.77)	(8.02)	(6.26)	(2.93)	(3.59)	(1.23)	(1.71)	(-0.09)	(-0.89)
Adjusted R-squared	0.055	0.093	0.118	0.108	0.072	0.023	0.036	0.039	0.030	0.102	0.078
γ_1 for *ASVI2*	0.441***	0.744***	0.791***	0.716***	0.393***	0.249***	0.179***	0.048	0.112	-0.0059	-0.029
	(13.85)	(9.36)	(9.35)	(8.44)	(6.44)	(3.34)	(3.66)	(0.58)	(1.54)	(-0.13)	(-0.86)
Adjusted R-squared	0.034	0.066	0.068	0.067	0.046	0.017	0.027	0.025	0.024	0.105	0.064

Panel D: With controls and week fixed effects, and adding firm fixed effects

	Pooled	**By Decile of *Noise_Search***									
		1 [Low]	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
Observations	245,015	24,970	24,048	24,549	24,548	25,050	24,283	24,549	24,048	24,922	24,048
Average *Noise_Search*	0.689	0.177	0.311	0.432	0.574	0.729	0.827	0.912	0.960	0.985	0.997
γ_1 for *SVI*	6.925***	12.850***	17.790***	15.570***	9.994***	4.375***	4.393***	2.550*	3.188***	0.820	0.071
	(13.04)	(7.73)	(9.71)	(7.24)	(6.17)	(4.05)	(3.17)	(1.94)	(3.27)	(1.33)	(0.094)
Adjusted R-squared	0.700	0.396	0.476	0.550	0.622	0.643	0.643	0.670	0.731	0.738	0.680
γ_1 for *ASVI*	0.438***	1.123***	1.247***	1.011***	0.573***	0.203***	0.185***	0.117**	0.059	0.028	-0.007
	(12.74)	(8.77)	(8.29)	(7.46)	(6.28)	(2.88)	(3.33)	(2.09)	(1.42)	(1.40)	(-0.54)
Adjusted R-squared	0.040	0.077	0.104	0.097	0.052	0.026	0.025	0.019	0.016	0.023	0.011
γ_1 for *ASVI2*	0.270***	0.719***	0.721***	0.623***	0.353***	0.154***	0.114***	0.063	0.052	0.030	-0.005
	(12.78)	(9.41)	(8.44)	(7.89)	(6.31)	(3.09)	(3.02)	(1.54)	(1.62)	(1.38)	(-0.34)
Adjusted R-squared	0.022	0.049	0.054	0.054	0.028	0.012	0.013	0.011	0.011	0.016	0.006

SM4 – Simulation Results of Induced Increase in Ticker Search on Random Days

A weakness with the analyses in Table 4 is that it is possible that true *Investor_Search* around earnings announcements is lower for firms that have higher *Noise_Search*, in which case it is impossible to isolate the effects of measurement error. We address this concern using simulations in which we induce specified increases in *Investor_Search* around random dates. Our procedures are as follows:

1) Drop all EA days and replace each with a randomly selected non-EA day (*Random_Day*).
2) Induce a specific amount of *Investor_Search* on each *Random_Day*. For example, the ticker UNM has *Noise_Search* of 99.2%, so inducing a 100% increase in *Investor_Search* increases SVI by 0.8. For a ticker with 0% *Noise_Search*, inducing a 100% increase in *Investor_Search* increases SVI by 100.[28] Calculate ASVI and ASVI2 using the updated data.
3) Estimate model (8) where *Random_Day* replaces EA to see whether the model rejects the null that the *Random_Day* coefficient is equal to zero at a 5 percent level of confidence (two-tailed).
4) Repeat this process 1,000 times, selecting *Random_Day* with replacement.

Panels A through C below summarize the simulation results for SVI, ASVI, and ASVI2. For each simulation of 1,000 trials, we report the average γ_1 estimate and percent of trials that reject the null that there is no difference in search. The rows have induced increases in *Investor_Search* ranging from 5% to 500%. The shaded cells reject the null in at least 50 percent of trials. Controls and fixed effects are untabulated. Standard errors are clustered by firm.

Starting with 5% inducement for SVI in Panel A, column (i) finds an average pooled coefficient of 0.410. In total 41.9% of trials reject the null hypothesis, indicating that a pooled sample of roughly 245,000 observations is unlikely to identify a 5% increase in *Investor_Search*. Looking at columns (ii) through (xi) in Panel A, the γ_1 estimates and t-statistics tend to decline as *Noise_Search* increases. However, coefficient estimates are not reliably significant even in the lowest deciles of *Noise_Search*, primarily due to the reduction in sample size relative to column (i). These results indicate that samples of roughly 24,500 are unlikely to identify 5% increases in *Investor_Search* even among firms with the least *Noise_Search*.

The lower rows in Panel A show that rejection rates improve as the induced increase in *Investor_Search* grows. At 10%, the pooled model identifies an increase in SVI in 94.0% of trials. However, the deciles continue to perform poorly, especially those higher in *Noise_Search*. Even with a 500% inducement in *Investor_Search* in the bottom row of Panel A, only 18.9% of trials reject the null in the highest decile of *Noise_Search*. Panels B and C show that ASVI and ASVI2 generally perform even worse than SVI in rejecting the null hypothesis.

The important takeaway from this section is to confirm that *Noise_Search* causes attenuated coefficient estimates, even when we are sure that increases in true *Investor_Search* are the same for all firms.

[28] As discussed, Google scales SVI from 0 to 100 within each ticker. To maintain consistency between our induced search and true SVI, we also rescale SVI from 0 to 100 after inducing *Investor_Search*. That said, untabulated results produce larger coefficients but highly similar rejection rates if we do not rescale SVI.

Panel A: SVI

		(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)
		Pooled	**Decile Partitions on *Noise Search***									
Induced Increase			**1 [Low]**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
5%	Avg. coefficient	0.410	0.627	0.682	0.684	0.682	0.489	0.399	0.236	0.043	0.001	0.020
	rejected at 5%	41.9%	14.6%	14.4%	15.6%	13.8%	9.0%	8.8%	6.0%	3.7%	2.4%	2.6%
10%	Avg. coefficient	0.801	1.262	1.413	1.352	1.360	1.005	0.759	0.421	0.129	0.034	0.028
	rejected at 5%	94.0%	42.4%	48.4%	45.8%	40.6%	21.3%	17.6%	9.3%	5.0%	2.6%	2.7%
15%	Avg. coefficient	1.191	1.894	2.141	2.019	2.036	1.519	1.119	0.606	0.215	0.069	0.036
	rejected at 5.0%	99.9%	76.9%	80.7%	79.2%	73.3%	44.4%	30.1%	13.8%	6.2%	3.1%	2.7%
20%	Avg. coefficient	1.579	2.524	2.865	2.683	2.709	2.032	1.478	0.791	0.301	0.104	0.044
	rejected at 5.0%	100.0%	92.5%	95.7%	94.4%	91.1%	68.7%	45.8%	20.4%	7.0%	3.2%	2.9%
25%	Avg. coefficient	1.966	3.150	3.587	3.345	3.379	2.543	1.837	0.975	0.387	0.139	0.052
	rejected at 5.0%	100.0%	99.1%	99.8%	99.3%	98.7%	86.3%	64.1%	27.6%	8.9%	3.8%	2.9%
50%	Avg. coefficient	3.868	6.22	7.122	6.573	6.66	5.061	3.623	1.898	0.816	0.313	0.092
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.6%	73.0%	20.9%	7.0%	2.9%
100%	Avg. coefficient	7.399	11.840	13.547	12.454	12.618	9.819	7.103	3.732	1.673	0.662	0.172
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.9%	61.1%	17.4%	4.1%
200%	Avg. coefficient	13.088	20.304	23.067	21.632	21.777	17.840	13.389	7.329	3.380	1.359	0.333
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.3%	46.3%	5.8%
300%	Avg. coefficient	17.262	25.756	29.312	27.913	28.17	23.983	18.568	10.763	5.07	2.053	0.493
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	79.4%	9.0%
500%	Avg. coefficient	22.843	31.858	36.334	35.330	36.194	32.336	26.294	16.879	8.352	3.428	0.812
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.5%	18.9%

Panel B: ASVI

		(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)
		Pooled	**Decile Partitions on *Noise Search***									
Induced Increase			**1 [Low]**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
5%	Avg. coefficient	0.018	0.058	0.038	0.027	0.030	0.017	-0.005	0.008	-0.001	0.002	0.001
	rejected at 5%	3.9%	6.0%	3.9%	2.4%	3.4%	0.8%	0.3%	1.8%	0.3%	1.3%	0.5%
10%	Avg. coefficient	0.039	0.119	0.083	0.067	0.055	0.035	0.021	0.013	-0.002	0.002	0.001
	rejected at 5%	20.7%	12.8%	14.2%	7.5%	7.8%	3.9%	0.1%	2.8%	0.1%	0.8%	0.8%
15%	Avg. coefficient	0.059	0.177	0.127	0.101	0.082	0.052	0.031	0.018	0.001	0.003	0.001
	rejected at 5.0%	55.0%	27.1%	35.2%	19.6%	16.7%	7.6%	0.2%	4.1%	0.1%	0.8%	0.8%
20%	Avg. coefficient	0.079	0.234	0.17	0.134	0.108	0.069	0.041	0.023	0.003	0.004	0.001
	rejected at 5.0%	85.7%	43.0%	58.5%	38.3%	32.4%	13.1%	0.2%	5.4%	0.1%	0.8%	0.9%
25%	Avg. coefficient	0.098	0.291	0.213	0.167	0.135	0.085	0.051	0.028	0.005	0.005	0.001
	rejected at 5.0%	96.3%	62.1%	77.7%	55.9%	49.8%	22.6%	0.5%	7.2%	0.1%	0.9%	1.0%
50%	Avg. coefficient	0.193	0.566	0.427	0.324	0.268	0.167	0.085	0.053	0.017	0.011	0.002
	rejected at 5.0%	99.7%	98.1%	99.7%	98.1%	97.3%	75.5%	4.9%	22.8%	0.3%	1.9%	1.1%
100%	Avg. coefficient	0.377	1.092	0.822	0.642	0.513	0.329	0.196	0.104	0.041	0.02	0.004
	rejected at 5.0%	100.0%	99.3%	100.0%	100.0%	100.0%	98.9%	47.0%	70.5%	2.1%	3.9%	1.6%
200%	Avg. coefficient	0.684	1.928	1.463	1.169	0.932	0.613	0.374	0.203	0.089	0.039	0.007
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	92.4%	98.8%	11.9%	15.0%	2.7%
300%	Avg. coefficient	0.916	2.519	1.92	1.57	1.255	0.844	0.528	0.300	0.136	0.059	0.01
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	95.2%	99.8%	30.8%	34.2%	3.7%
500%	Avg. coefficient	1.228	3.234	2.469	2.084	1.693	1.179	0.773	0.478	0.228	0.097	0.016
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	96.4%	100.0%	81.3%	75.2%	8.0%

Panel C: ASVI2

Induced Increase		(i) Pooled	(ii) 1 [Low]	(iii) 2	(iv) 3	(v) 4	(vi) 5	(vii) 6	(viii) 7	(ix) 8	(x) 9	(xi) 10 [High]
			Decile Partitions on *Noise Search*									
5%	Avg. coefficient	0.013	0.034	0.027	0.024	0.018	0.012	0.007	0.006	0.002	0.002	0.000
	rejected at 5%	22.2%	11.9%	10.4%	9.1%	7.8%	6.9%	4.3%	4.8%	2.9%	3.1%	2.6%
10%	Avg. coefficient	0.026	0.064	0.055	0.047	0.037	0.025	0.015	0.01	0.004	0.002	0.000
	rejected at 5%	65.4%	24.6%	25.7%	22.6%	17.4%	12.3%	9.3%	6.9%	3.8%	3.1%	2.4%
15%	Avg. coefficient	0.038	0.092	0.082	0.071	0.055	0.036	0.023	0.014	0.005	0.003	0.001
	rejected at 5.0%	92.5%	41.9%	46.8%	44.5%	29.9%	19.7%	14.5%	9.5%	5.2%	3.8%	2.8%
20%	Avg. coefficient	0.050	0.119	0.108	0.093	0.072	0.048	0.031	0.018	0.007	0.004	0.001
	rejected at 5.0%	99.3%	60.9%	66.5%	64.1%	45.0%	29.4%	20.5%	13.2%	6.1%	3.9%	2.9%
25%	Avg. coefficient	0.062	0.146	0.134	0.113	0.09	0.059	0.037	0.023	0.01	0.004	0.001
	rejected at 5.0%	100.0%	76.6%	79.1%	78.2%	60.3%	40.6%	28.2%	17.6%	6.0%	4.0%	2.3%
50%	Avg. coefficient	0.117	0.268	0.252	0.215	0.172	0.115	0.073	0.042	0.019	0.007	0.002
	rejected at 5.0%	100.0%	99.4%	100.0%	99.2%	98.5%	82.2%	64.8%	40.8%	14.9%	5.1%	3.1%
100%	Avg. coefficient	0.213	0.465	0.449	0.393	0.316	0.218	0.146	0.081	0.036	0.015	0.003
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.8%	99.0%	85.0%	39.5%	14.7%	3.9%
200%	Avg. coefficient	0.365	0.753	0.744	0.665	0.549	0.394	0.273	0.154	0.071	0.029	0.006
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	83.9%	34.7%	5.6%
300%	Avg. coefficient	0.484	0.962	0.962	0.868	0.735	0.541	0.384	0.221	0.104	0.043	0.008
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	97.2%	57.2%	7.8%
500%	Avg. coefficient	0.666	1.248	1.271	1.171	1.012	0.778	0.573	0.344	0.167	0.07	0.013
	rejected at 5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	91.1%	16.3%

SM5 – Complete tabulation of Table 7: TS-SVI around EAs, by decile of *TS-Noise_Search*, with controls and week fixed effects

This table presents the full results from the analyses in Table 7. Panel A of this table is for TS-SVI, Panel B of this table is for TS-ASVI, and Panel C of this table is for TS-ASVI2. See Table 7 for further details. Variable definitions are provided in Appendix A. T-statistics are in parentheses. Standard errors are clustered by firm. *, **, *** indicates statistical significance at the p < 0.10, 0.05, 0.01 level, respectively.

Panel A: TS-SVI

	Pooled	**By Decile of *TS-Noise_Search***									
		1 [Low]	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
γ_1 for *TS-SVI*	3.487***	3.887***	2.704*	2.700*	1.838	6.553***	4.192**	1.977	5.323***	1.914*	5.221**
	(5.52)	(3.34)	(1.67)	(1.37)	(1.12)	(3.53)	(2.12)	(1.14)	(3.24)	(1.36)	(2.17)
News Articles$_{i,t}$	0.283***	0.051	0.168	0.504**	0.427**	0.189	0.303*	0.640***	0.017	0.298**	-0.031
	(4.32)	(0.74)	(1.05)	(2.44)	(2.04)	(1.15)	(1.94)	(3.51)	(0.12)	(2.32)	(-0.12)
Abs Return$_{i,t}$	42.600***	31.800*	30.650	44.400*	28.960	35.560	9.205	32.920**	80.430***	45.100***	65.200***
	(5.74)	(1.74)	(1.50)	(1.99)	(1.44)	(1.31)	(0.38)	(2.08)	(3.76)	(2.99)	(3.24)
MVE$_{i,q}$	1.407***	1.265***	0.301	1.879***	1.206**	1.936***	1.386***	1.096**	1.623***	1.766***	1.442**
	(8.56)	(3.23)	(0.47)	(4.44)	(2.48)	(5.82)	(3.53)	(2.55)	(3.56)	(5.19)	(2.28)
Trading Volume$_{i,t}$	2.219***	2.268*	-0.263	0.936	0.637	3.473***	3.199**	3.710***	2.114**	3.374***	1.052
	(5.60)	(1.87)	(-0.26)	(0.89)	(0.45)	(5.18)	(2.41)	(3.09)	(2.32)	(4.11)	(0.84)
Spread$_{i,t}$	3.128	6.507	36.630	15.690	37.590	13.990	56.890	-19.530	9.615	-16.260	-59.080
	(0.15)	(0.17)	(0.63)	(0.29)	(0.70)	(0.33)	(0.75)	(-0.38)	(0.22)	(-0.47)	(-1.09)
Fourth Qtr$_{i,t}$	0.185	-0.683	-0.272	0.838	0.943*	0.901	-0.288	-0.125	-0.180	0.968**	-0.734
	(0.82)	(-1.41)	(-0.58)	(1.61)	(1.71)	(1.12)	(-0.36)	(-0.14)	(-0.33)	(2.18)	(-0.96)
Total EAs$_t$	0.0561**	0.122	0.0094	0.059	0.094	0.067	0.096	-0.101	0.095	0.072	0.044
	(2.17)	(1.45)	(0.13)	(0.67)	(1.21)	(0.97)	(1.21)	(-1.18)	(1.12)	(0.87)	(0.51)
Analyst Following$_{i,t}$	0.773	1.132	2.369	-1.458	2.416	-3.388**	2.742	1.021	-0.230	0.144	2.920
	(0.84)	(0.87)	(1.23)	(-0.51)	(0.91)	(-2.30)	(1.00)	(0.58)	(-0.09)	(0.07)	(0.96)
Institutional Ownership$_{i,q}$	-15.980***	-15.560*	-24.490***	-2.259	-10.350	-26.250***	-2.676	-29.210***	-27.960***	-16.420***	-15.000*
	(-5.36)	(-1.79)	(-3.13)	(-0.32)	(-1.51)	(-5.21)	(-0.16)	(-3.18)	(-3.87)	(-3.27)	(-1.94)
BTM$_{i,q}$	0.011	-0.137	-0.336	0.448	0.006	-0.270	-0.438	-0.604*	0.395	0.510**	0.483
	(0.09)	(-0.40)	(-0.86)	(1.13)	(0.02)	(-0.85)	(-0.89)	(-1.94)	(1.14)	(2.17)	(0.95)
Constant	9.054**	8.735	23.370**	0.647	1.459	26.220***	-7.024	22.500**	21.110**	3.740	2.319
	(2.22)	(0.93)	(2.21)	(0.06)	(0.12)	(3.54)	(-0.40)	(2.56)	(2.08)	(0.49)	(0.28)
Year-Week FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	245,015	24,549	24,549	24,548	24,784	24,549	24,048	24,970	24,047	24,549	24,422
Adjusted R-squared	0.078	0.049	0.052	0.087	0.094	0.138	0.063	0.144	0.077	0.110	0.074

<u>*Panel B: TS-ASVI*</u>

	Pooled	**By Decile of *TS-Noise Search***									
		1 [Low]	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 [High]**
γ_1 for *TS-ASVI*	0.928***	1.080***	0.745***	0.666***	0.690***	0.940***	1.218***	1.045***	1.015***	0.812**	0.925***
	(10.24)	(2.89)	(2.80)	(2.88)	(3.47)	(3.31)	(4.49)	(3.55)	(3.49)	(2.36)	(3.05)
News Articles$_{i,t}$	0.005	0.014	0.011	0.017	-0.001	0.005	-0.005	-0.004	0.001	0.011	0.009
	(1.57)	(0.90)	(1.25)	(1.58)	(-0.13)	(0.68)	(-0.68)	(-0.38)	(0.14)	(0.88)	(0.99)
Abs Return$_{i,t}$	5.324***	6.618	4.993	11.39***	5.342*	6.970**	2.303	3.111	0.723	5.855	6.165
	(4.99)	(1.66)	(1.52)	(2.71)	(1.84)	(2.17)	(0.93)	(0.88)	(0.25)	(1.63)	(1.52)
MVE$_{i,q}$	-0.062***	-0.046***	-0.055***	-0.105***	-0.072***	-0.063***	-0.071***	-0.065***	-0.058***	-0.044**	-0.055***
	(-11.79)	(-3.01)	(-3.22)	(-8.12)	(-3.81)	(-5.55)	(-5.21)	(-4.49)	(-3.91)	(-2.59)	(-3.02)
Trading Volume$_{i,t}$	-0.156***	-0.134***	-0.149***	-0.157***	-0.167***	-0.118***	-0.163***	-0.230***	-0.170***	-0.177***	-0.152***
	(-13.00)	(-2.96)	(-3.26)	(-4.57)	(-3.28)	(-4.15)	(-3.92)	(-6.52)	(-6.43)	(-4.21)	(-3.93)
Spread$_{i,t}$	5.036***	2.168	4.926	0.914	1.971	3.870	4.545	8.967*	16.430***	5.939	3.430
	(4.02)	(0.57)	(1.07)	(0.28)	(0.66)	(1.03)	(1.48)	(1.79)	(3.80)	(1.37)	(0.82)
Fourth Qtr$_{i,t}$	-0.060**	-0.154**	-0.138	-0.006	-0.009	0.067	-0.122*	-0.079	-0.120**	0.020	-0.106
	(-2.55)	(-2.02)	(-1.29)	(-0.06)	(-0.22)	(1.35)	(-1.88)	(-1.51)	(-2.35)	(0.14)	(-1.20)
Total EAs$_t$	-0.010*	0.012	-0.018	0.004	0.010	-0.030*	-0.005	-0.033*	-0.042**	0.023	-0.023
	(-1.69)	(0.59)	(-0.89)	(0.17)	(0.56)	(-1.97)	(-0.29)	(-1.90)	(-2.41)	(1.08)	(-1.40)
Analyst Following$_{i,t}$	-0.034	-0.087	-0.139*	0.063	-0.062	0.018	0.037	-0.001	0.058	0.074	-0.201*
	(-1.16)	(-1.33)	(-1.90)	(0.85)	(-0.63)	(0.23)	(0.57)	(-0.03)	(0.86)	(0.97)	(-2.00)
Institutional Ownership$_{i,q}$	0.636***	0.869***	0.795**	-0.139	0.353	0.627***	0.075	0.770***	1.139***	0.748***	0.942***
	(6.59)	(3.05)	(2.68)	(-0.70)	(1.28)	(3.54)	(0.21)	(2.96)	(4.64)	(4.11)	(3.94)
BTM$_{i,q}$	-0.007*	-0.013	0.006	-0.022**	-0.008	0.017	-0.005	0.021	-0.026**	-0.010	-0.020
	(-1.77)	(-1.03)	(0.35)	(-2.02)	(-0.64)	(1.18)	(-0.43)	(1.59)	(-2.65)	(-0.83)	(-1.49)
Constant	0.622***	0.493	0.746*	1.284***	0.938**	0.313	0.946**	0.537*	0.031	-0.037	0.992***
	(5.23)	(1.58)	(1.72)	(4.74)	(2.21)	(1.27)	(2.47)	(1.68)	(0.08)	(-0.14)	(3.52)
Year-Week FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	245,015	24,549	24,549	24,548	24,784	24,549	24,048	24,970	24,047	24,549	24,422
Adjusted R-squared	0.008	0.006	0.007	0.007	0.006	0.004	0.007	0.009	0.011	0.007	0.006

Panel C: TS-ASVI2

	Pooled	By Decile of *TS-Noise Search*									
		1 [Low]	2	3	4	5	6	7	8	9	10 [High]
γ_1 for *TS-ASVI2*	0.316***	0.307***	0.263***	0.462***	0.254***	0.425***	0.499***	0.264***	0.398***	0.266**	0.216**
	(10.27)	(3.16)	(2.76)	(4.96)	(3.12)	(5.04)	(5.24)	(3.24)	(3.82)	(2.41)	(2.29)
News Articles$_{i,t}$	0.020***	0.009*	0.017**	0.015**	0.032***	0.016***	0.010	0.022***	0.013*	0.021***	0.021***
	(10.08)	(1.90)	(2.51)	(2.43)	(6.56)	(3.44)	(1.60)	(4.01)	(1.81)	(3.07)	(4.45)
Abs Return$_{i,t}$	3.335***	1.802	4.292***	7.833***	2.810**	3.172*	2.866**	3.524***	3.962***	1.795	1.743
	(6.60)	(1.11)	(3.48)	(5.04)	(2.49)	(1.77)	(2.38)	(3.21)	(3.26)	(1.25)	(1.04)
MVE$_{i,q}$	0.027***	-0.000	0.010	0.055***	0.035***	0.051***	0.048***	0.017	0.024	0.008	0.015
	(5.63)	(-0.02)	(0.69)	(3.31)	(3.01)	(4.91)	(3.30)	(0.90)	(1.43)	(0.52)	(0.98)
Trading Volume$_{i,t}$	0.059***	0.058	0.046*	0.048	0.052*	0.081***	0.072	0.051	0.050*	0.087**	0.042
	(5.52)	(0.86)	(1.85)	(1.12)	(1.83)	(4.34)	(1.60)	(1.19)	(1.80)	(2.28)	(1.57)
Spread$_{i,t}$	3.832***	3.691*	3.453*	1.393	2.720*	5.646***	4.173**	3.563*	4.806**	2.055	5.475**
	(5.62)	(1.94)	(1.98)	(0.73)	(1.96)	(2.78)	(2.03)	(1.80)	(2.30)	(1.00)	(2.60)
Fourth Qtr$_{i,t}$	-0.005	0.020	-0.087	0.012	-0.047	0.019	0.026	-0.022	-0.002	0.014	-0.052
	(-0.42)	(0.69)	(-1.31)	(0.304)	(-1.38)	(0.39)	(0.71)	(-0.49)	(-0.07)	(0.35)	(-1.39)
Total EAs$_t$	-0.004*	-0.003	-0.002	-0.013	0.000	-0.007	0.006	-0.013*	-0.009	0.006	-0.002
	(-1.73)	(-0.45)	(-0.32)	(-1.65)	(0.00)	(-1.37)	(0.91)	(-1.83)	(-1.33)	(0.78)	(-0.29)
Analyst Following$_{i,t}$	-0.014	-0.047	-0.019	-0.207**	0.022	-0.127*	0.046	0.094	0.020	-0.102	0.139*
	(-0.57)	(-1.10)	(-0.33)	(-2.20)	(0.44)	(-1.90)	(0.61)	(0.95)	(0.27)	(-1.58)	(2.00)
Institutional Ownership$_{i,q}$	-0.432***	-0.717***	-0.295	-0.194	-0.204	-0.231	-0.325	-0.719**	-0.885**	-0.248	-0.595***
	(-5.11)	(-2.71)	(-1.51)	(-0.79)	(-1.33)	(-1.08)	(-0.79)	(-2.26)	(-2.54)	(-1.17)	(-2.97)
BTM$_{i,q}$	-0.006	-0.016	-0.005	0.015	0.001	-0.028**	0.010	-0.018	0.002	-0.001	-0.002
	(-1.48)	(-1.52)	(-0.48)	(1.19)	(0.14)	(-2.43)	(0.71)	(-1.27)	(0.16)	(-0.14)	(-0.19)
Constant	-0.647***	-0.156	-0.619**	-0.538	-1.008***	-0.531*	-1.189***	-0.492	-0.380	-0.553**	-0.911***
	(-5.71)	(-0.59)	(-2.59)	(-1.47)	(-3.79)	(-1.91)	(-2.91)	(-1.35)	(-1.06)	(-2.19)	(-3.71)
Year-Week FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	245,015	24,549	24,549	24,548	24,784	24,549	24,048	24,970	24,047	24,549	24,422
Adjusted R-squared	0.019	0.012	0.016	0.024	0.024	0.030	0.025	0.028	0.024	0.017	0.021

SM6 - Published Papers Using Google SVI as a Measure of Attention (through mid-2022)

Year	Author(s)	Title	Journal
2011	Da, Engelberg, and Gao	In search of attention	*Journal of Finance*
2011	Bank, Larch, and Peter	Google search volume and its influence on liquidity and returns of German stocks	*Financial Markets and Portfolio Management*
2011	Joseph, Wintoki, and Zhang	Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search	*International Journal of Forecasting*
2012	Drake, Roulstone, and Thornock	Investor information demand: Evidence from Google searches around earnings announcements	*Journal of Accounting Research*
2012	Bordino, Battiston, Caldarelli, Cristelli, Ukkonen and Weber	Web Search Queries can predict stock market volumes	*PLoS ONE*
2012	Choi and Varian	Predicting the present with Google Trends.	*Economic Record 88*
2012	Vlastakis and Markellos	Information demand and stock market volatility	*Journal of Banking & Finance*
2013	Aouadi, Arouri, and Teulon	Investor attention and stock market activity: Evidence from France	*Economic Modelling*
2013	Carrière-Swallow and Labbé	Nowcasting with Google Trends in an emerging market	*Journal of Forecasting*
2013	Jiang and Li	Investor sentiment and IPO pricing during pre-market and aftermarket periods: Evidence from Hong Kong	*Pacific-Basin Finance Journal*
2013	Korkeamaki and Takalo	Valuation of innovation and intellectual property: The case of the iPhone	*European Management Review*
2013	Kristoufek	Can Google Trends search queries contribute to Risk Diversification	*Nature*
2013	Preis, Moat, and Stanley	Quantifying Trading Behavior in Financial Markets Using Google Trends	*Nature*
2013	Luo, Zhang, and Duan	Social media and firm equity value	*Information Systems Research*
2013	Siganos	Google attention and target price run ups	*International Review of Financial Analysis*
2013	Xiong and Bharadwaj	Asymmetric roles of advertising and marketing capability in financial returns to news: Turning bad into good and good into great	*Journal of Marketing Research*
2013	Xu and Zhang	Impact of Wikipedia on market information: Evidence on management disclosure and investor reaction	*MIS Quarterly*
2013	Zhang, Shen, Zhang, and Xiong	Open-source information, investor attention, and asset pricing	*Economic Modelling*
2014	Gwilym, Kita, Wang	Speculate against speculative demand	*International Review of Financial Analysis*
2014	Knittel and Stango	Celebrity endorsements, firm value, and reputation risk: Evidence from the Tiger Woods scandal	*Management Science*
2014	Liu, Ye and Li	Impacts of interactions between news attention and investor attention on stock returns: Empirical investigation on financial shares in China.	*Journal of Management Sciences in China*
2014	Takeda and Wakao	Google search intensity and its relationship with returns and trading volume of Japanese stocks	*Pacific-Basin Finance Journal*
2014	Vaughan	Discovering business information from search engine query data	*Online Information Review*
2014	Vozlyublennaia	Investor attention, index performance, and return predictability	*Journal of Banking & Finance*
2014	Zhang, An, Feng	Can online searches be used to forecast stock market performance?	*Journal of Financial Research*
2015	Brown, Stice, and White	Mobile Communication and Local Information Flow: Evidence from Distracted Driving Laws	*Journal of Accounting Research*
2015	Cergol and Omladic	What can Wikipedia and Google tell us about stock prices under different market regimes?	*Ars Mathematica Contemporanea*
2015	deHaan, Shevlin, Thornock	Market (In)Attention and the Strategic Scheduling and Timing of Earnings Announcements	*Journal of Accounting and Economics*

2015	Ding and Hou	Retail investor attention and stock liquidity	*Journal of International Financial Markets, Institutions & Money*
2015	Drake, Roulstone, and Thornock	The Determinants and Consequences of Information Acquisition via EDGAR	*Contemporary Accounting Research*
2015	Goddard, Kita and Wang	Investor attention and FX market volatility	*Journal of International Financial Markets, Institutions & Money*
2015	Hoopes, Reck, Slemrod	Taxpayer Search for Information: Implications for Rational Attention	*American Economic Journal: Economic Policy*
2015	Kristoufek	Power-law correlations in finance-related Google searches, and their cross-correlations with volatility and traded volume	*Physica A: Statistical Mechanics and its Applications*
2015	Li, Ma, Wang, Zhang	How does Google search affect trader positions and crude oil prices?	*Economic Modelling*
2016	Bijl, Kringhaug, Molnar, Sandvik	Google Searches and Stock Returns	*International Review of Financial Analysis*
2016	Curtis, Richardson, and Schmardebeck	Investor attention and the pricing of earnings news	*Handbook of Sentiment Analysis in Finance*
2017	Drake, Jennings, Roulstone and Thornock	The co-movement of Investor Attention	*Management Science*
2016	Fang, Huang, Karpoff	Short Selling and Earnings Management: A Controlled Experiment	*Journal of Finance*
2017	Ben-Rephael, Da, Israelsen	It Depends on Where You Search: Institutional Investor Attention and Underreaction to News	*Review of Financial Studies*
2017	Boulland and Dessaint	Announcing the Announcement	*Journal of Banking & Finance*
2017	Chi and Shantikumar	Local Bias in Google Search and the Market Response around Earnings Announcements	*The Accounting Review*
2017	Colaco, De Cesari, and Hegde	Retail Investor Attention and IPO Valuation	*European Financial Management*
2017	Kong, Lin, Liu	Does Information Acquisition Alleviate Market Anomalies? Categorization Bias in Stock Splits	*Review of Finance*
2017	Madsen	Anticipated Earnings Announcements and the Customer–Supplier Anomaly	*Journal of Accounting Research*
2017	Welagedara, Deb, and Singh	Investor attention, analyst recommendation revisions, and stock prices	*Pacific-Basin Finance Journal*
2018	Chang and Kwon	Ambiguities in valuing information technology firms: Do internet searches T help?	*Journal of Business Research*
2018	Chronopoulos, Papadimitriou, and Vlastakis	Information demand and stock return predictability	*Journal of International Money and Finance*
2018	Frank and Sanati	How does the stock market absorb shocks?	*Journal of Financial Economics*
2018	Hasan, Kumas, Smith	Market ambiguity and individual investor information demand	*Journal of Contemporary Accounting & Economics*
2018	Kupfer and Zorn	Valuable information in early sales proxies: The use of Google search ranks in portfolio optimization	*Journal of Forecasting*
2018	Mbanga, Darrat, and Park	Investor sentiment and aggregate stock returns: the role of investor attention	*Review of Quantitative Finance and Accounting*
2018	Pantzalis and Ucar	Allergy onset and local investor distraction	*Journal of Banking & Finance*
2018	Reyes	Limited attention and M&A announcements	*Journal of Empirical Finance*
2018	Reyes	Negativity Bias in Attention Allocation: Retail Investors' Reaction to Stock Returns	*International Review of Finance*
2018	Reyes and Waissbluth	Saddled with Attention: Overreaction to Bankruptcy filings	*International Review of Finance*
2018	Wang, Choi, Siraj	Local investor attention and post-earnings announcement drift	*Review of Quantitative Finance and Accounting*
2018	Gargano and Rossi	Does It Pay to Pay Attention?	*Review of Financial Studies*

2018	Pantzalis and Ucar	Allergy onset and local investor distraction	*Journal of Banking & Finance*
2019	Chen and Lo	Online search activities and investor attention on financial markets	*Asia Pacific Management Review*
2019	Swamy, Dharani and Takeda	Investor Attention and Google Search Volume Index: Evidence from an Emerging Market using Quantile Regression Analysis.	*Research in International Business and Finance*
2019	Heyman, Lescrauwaet, and Stieperaere	Investor Attention and Short-term Return Reversals.	*Finance Research Letters*
2019	Lučivjanská,, Molnár, and Villa	Google searches and stock market activity: Evidence from Norway	*Finance Research Letters*
2019	Huang, Huang, Lin	Attention allocation and return co-movement: Evidence from repeated natural experiments	*Journal of Financial Economics*
2019	Madsen and Niessner	Is Investor Attention for Sale? The Role of Advertising in Financial Markets	*Journal of Accounting Research*
2020	Blankespoor, deHaan, and Marinovic	Disclosure Processing Costs, Investors' Information Choice, and Equity Market Outcomes: A Review	*Journal of Accounting and Economics*
2020	Cheng, Huang, Hu	Investor attention and stock price movement.	*Journal of Behavioral Finance*
2020	Subramaniam and Chakraborty	Investor Attention and Cryptocurrency Returns: Evidence from Quantile Causality Approach.	*Journal of Behavioral Finance*
2020	Hu and Xiangfei	Does individual investors' online search activities reduce information asymmetry? Evidence from stock exchanges' comment letters in China	*Asia-Pacific Journal of Accounting & Economics*
2020	Choi, Gao and Jiang	Attention to Global Warming	*The Review of Financial Studies*
2020	Cziraki, Mondria, and Wu	Asymmetric attention and stock returns.	*Management Science*
2020	Chen, Wang, and Wang	Corporate social responsibility and information flow	*Accounting & Finance*
2020	Dang and Nguyen	Valuation Effect of Emotionality in Corporate Philanthropy	*Journal of Business Ethics*
2020	Gavish, Qadan, and Yangil	Net Buyers of Attention-Grabbing Stocks? Who Exactly Are They?	*Journal of Behavioral Finance*
2020	Zambrana	Asset Management and Financial Conglomerates: Attention Through Stellar Funds	*Management Science*
2020	Tao, Brooks, and Bell	Tomorrow's fish and chip paper? Slowly incorporated news and the cross-section of stock returns	*The European Journal of Finance*
2020	Cookson and Niessner	Why Don't We Agree? Evidence from a Social Network of Investors	*Journal of Finance*
2020	Chiu, Lourie, Nekrasov, and Teoh	Cater to Thy Client: Analyst Responsiveness to Institutional Investor Attention	*Management Science*
2020	Focke, Ruenzi, and Ungeheuer	Advertising, Attention, and Financial Markets	*Review of Financial Studies*
2020	Clifford, Fulkerson, Jame, and Jordan	Salience and Mutual Fund Investor Demand for Idiosyncratic Volatility	*Management Science*
2020	Cookson and Niessner,	Why don't we agree? Evidence from a social network of investors	*The Journal of Finance*
2021	Desagre and D'Hondt	Googlization and retail trading activity	*Journal of Behavioral and Experimental Finance*
2021	Chen. Wang and Wang	Corporate social responsibility and information flow	*Accounting and Finance*
2021	Liaukonytė and Žaldokas	Background noise? TV advertising affects real-time investor behavior.	*Management Science*
2021	Chen, Schmidt and Wang	Retail investor risk-seeking, attention and the January effect.	*Journal of Behavioral and Experimental Finance*
2021	Kupfer and Schmidt	In search of retail investors: the effect of retail investor attention on odd lot trades	*Journal of Empirical Finance*
2021	Liu and Krystiniak	Investor Attention and Merger Announcements	*Journal of Behavioral Finance*
2021	Behrendt and Prange	What are you searching for? On the equivalence of proxies for online investor attention.	*Financial Research Letters*
2021	Chen, Chen, Lai	Internet search, fund flows and fund performance	*Journal of Banking and Finance*
2021	Chai, Dai, Gharghori, Hong	Internet search intensity and its relation with trading activity and stock returns	*International Review of Finance*
2021	Ozik, Sadka, Shen	Flattening the illiquidity curve: retail trading during the COVID-19 lockdown	*Journal of Financial and Quantitative Analysis*
2021	Chen, Schmidt, Wang	Retail investor risk-seeking, attention, and the January effect	*Journal of Behavioral and Experimental Finance*
2021	Nekrasov, Teoh, Wu	Visuals and attention to earnings news on twitter	*Review of Accounting Studies*

2022	Foederer and Schuetz	Data breach announcements and stock market reactions a matter of timing?	*Management Science*
2022	Israeli, Kasznik, and Sridharan	Unexpected distractions and investor attention to corporate announcements	*Review of Accounting Studies*
2022	Ballinari, Audrino, and Sigrist	When does attention matter? The effect of investor attention on stock market volatility around news releases.	*International Review of Financial Analysis*
2022	Chen, Tang, Yao, Zhou	Investor Attention and Stock Returns	*Journal of Financial and Quantitative Analysis*
2022	Wu, Tsai, Lu, Zhang	Google searches around analyst recommendation revision announcements: evidence from the Taiwan stock markets	*International Review of Economics and Finance*
2022	Ma, Marshall, Nguyen, Nguyen, Vasltonachoti	Climate events and return co-movement	*Journal of Financial Markets*
2022	Ben-Rephael, Da, Eason, Israelsen	Who Pays Attention to SEC Form 8-K?	*The Accounting Review*
2022	Coles, Heath, Ringgenberg	On index investing	*Journal of Financial Economics*
2022	Hirshleifer, Sheng	Macro news and micro news: Complements or substitutes?	*Journal of Financial Economics*
2022	Saxena, Chakraborty	Does it pay to pay attention to attention? Evidence from an emerging market	*Managerial Finance*
2022	Hafeez, Kabir, Wongchoti	Are retail investors really passive? Shareholder activism in the digital age	*Journal of Business, Finance, and Accounting*
2022	Barber, Huang, Odean, Schwarz	Attention-Induced Trading and Returns: Evidence from Robinhood Users	*Journal of Finance*