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Market Ambiguity and Individual Investor Information Demand

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Abstract

Investigating the flow of information to uninformed market participants, we examine whether ambiguity in the market leads to an increase in information demand by individual investors. Basing our hypotheses on the asset-pricing model proposed by Mele and Sangiorgi (2015), which incorporates market ambiguity, we measure individual information demand using daily Google searches and measure market ambiguity using a metric based on the market trades of institutional investors. We find that individual investors increase their information demand during periods of greater market ambiguity. We also provide evidence that information demand from individual investors spikes around earnings announcement days primarily when market uncertainty is driven by net-selling activity. Overall, these results suggest that the disagreement among institutional investors either represents uncertainty or contributes to the uncertainty related to a stock, leading to increased demand for information from individual investors.

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1. Introduction

Underlying the efficiency of capital markets is the flow of information. Given the importance of the information channel, it is not surprising that it has been a focus in prior research. Much of this research examines the role of information intermediaries, such as financial analysts (Healey and Palepu 2001) and the media (Peress 2014). More recent research has explored how the flow of information through the Internet and social media outlets, e.g., Twitter, affects capital markets (Drake, Roulstone and Thornock 2012; Blankespoor, Miller and White 2014). Building on this research we examine how ambiguity in the market leads to an increase in information demand by uninformed market participants, i.e., individuals, measuring individual information demand using daily Google searches (Drake et al. 2012; Brown, Stice and White 2015), and extend the research on this information channel. We base our hypotheses on the asset-pricing model proposed by Mele and Sangiorgi (2015) which shows that investors mitigate market ambiguity, Knightian uncertainty, through information acquisition. We also introduce a unique measure of market ambiguity, uncertainty among institutional investors.

The primary drivers of firm-level uncertainty are the unknown and/or random factors affecting the information environment of the firm (Diamond and Verrecchia 1991). Such uncertainty creates disagreement among not only uninformed market participants but also among informed participants, and this uncertainty is reflected in their trading practices (i.e., some will buy and some will sell). In the U.S. market, institutional investors own more than 60 percent of all publicly traded stocks and account for an even larger share of trading volume, making them one of the most important participants in the equity market.[1] Prior research provides evidence that these institutional investors have the resources to analyze publicly available information and the ability to

[1] Source: Securities Industry and Financial Markets Association (2015).

access proprietary information. For example, they are invited to investor conferences with corporate executives that are not available to other market participants (Ke and Ramalingegowda 2005; Green, Jame, Markov, Subasi 2014; Ng and Troianovski 2015; Solomon and Soltes 2015). Therefore, the disagreement reflected in the trades of the most sophisticated investors suggests the existence of ambiguity about the fundamental value of the underlying stock, which leads uninformed individual investors to be uncertain about the information held by the informed institutional investors (Mele and Sangiorgi 2015).

Differential trading activity among informed institutional investors, who have the resources to assess risk, reflects the uncertainty associated with a particular security. We may also view this type of trading activity as a lack of consensus among institutional investors' interpretation of market information, i.e., some institutional investors interpret the information as good news while others interpret it as bad news. As a result, some institutional investors sell in large orders, pushing down the price, whereas other institutions buy, pushing up the price. We argue that this type of institutional investor trading behavior not only suggests a disagreement among informed investors but also proxies for market-wide uncertainty existing about the true state of the underlying security. Therefore, we assess overall market uncertainty on a particular security by measuring the level of disagreement in the trades of these informed institutional investors, i.e., *informed uncertainty*. We develop our measure of investor disagreement based on literature examining the impact of institutional investor order imbalances on market activity (Chordia, Roll and Subrahmanyam 2001; Chordia and Subrahmanyam 2004).[2]

Mele and Sangiorgi (2015) hypothesize that uninformed, risk averse investors in an uncertain market will be motivated to seek information from informed investors. Based on this theory, we hypothesize that individual investors not only demand information during the earnings

[2] Chordia and Subrahmanyam (2004) suggest a large order imbalance could denote informed trading (page 510).

announcement periods, as suggested by Drake et al. (2012), but also undertake similar information search behavior during days when the trades of informed investors indicate higher levels of differential interpretation of the market information. In other words, individual investors increase their information demand around the days when large investors' trading behavior reflects market uncertainty in an attempt to decrease ambiguity and more accurately interpret the information revealed by stock prices.

We create a metric measuring institutional investor disagreement as a proxy for market uncertainty and then investigate the relation between market uncertainty and individual investors' demand for information. We employ the daily Google Search Volume Index (SVI) on a particular security as a measure of demand for information by individual investors. We follow the construction of the search metric from Drake et al. (2012) to capture the abnormal information demand from individual investors.

Overall, we find that individual investors increase their information demand during periods of high market uncertainty. Further, our results show that during earnings announcement periods, when there is higher disagreement among institutional investors, i.e., low consensus, individual investors demand more information. While this evidence corroborates Drake et al.'s (2012) finding that information demand from individual investors spikes around earnings announcements, further analysis shows that this heightened information demand from individual investors occurs primarily around earnings announcement days when market ambiguity is driven by net selling pressure. These results collectively indicate that market uncertainty, as measured by the trading patterns of informed investors, influences information demand by uninformed investors, suggesting that the disagreement among institutional investors either represents uncertainty or contributes to the uncertainty related to a stock. This ambiguity leads to increased demand for information from individual investors.

Our study contributes to the literature in several ways. First, we add to the limited research seeking to understand the relation between informed uncertainty and information demand from uninformed investors. Second, we develop and introduce a unique measure of market uncertainty based on institutional investor trading activity that reflects the composition of today's equity market. Further, we expand the recent research examining the flow of information through Internet searches adding to our understanding of the ways in which information flows from firms to individual investors. We also contribute to the growing literature suggesting that information searches revise investors' beliefs by reducing information asymmetry. Thus, we expand the evidence on market efficiency and provide support for research proposing explanations for market volatility based on information demand. Finally, our measurement of trading imbalance among institutional investors adds to the work examining order imbalance and trading activity.

We organize our paper as follows. The next section discusses the literature and develops our hypotheses. Section 3 presents our Google Search Volume index extraction method and the institutional investor daily trading data used in our sample. Section 4 and 5 present our research design and results, respectively. Finally, we discuss our conclusions and research limitations in Section 6.

2. Literature and Hypotheses Development

2.1 The flow of information

The efficient flow of information is fundamental to a capital market that relies on investors to select the firms in which they wish to invest. Healey and Palepu (2001) argue that within this capital market structure the "demand for financial reports and disclosure arises from information asymmetry" (p. 406). In their model, presented in Figure 1, information flows from firms directly to individual investors through financial reports and press releases and indirectly through information

intermediaries such as financial analysts. Capital flows from investors to firms through the financial markets and financial intermediaries, such as institutional investors. However, with the availability of internet technologies, the way in which firm information and financial disclosures flow to individuals is evolving. Research provides evidence that individual investors seek to resolve the long-standing information asymmetry issue by searching for firm information on Google and social media platforms such as Twitter, Facebook, and Wikipedia.

[Insert Figure 1 here]

Drake et al. (2012) use Google search volume index (SVI) as a proxy for individual information demand. They find that investor search activity in the pre-earnings announcement period is positively associated with trading volume and the market reaction to earnings surprises, implying that Google searches disseminate information, which the market incorporates prior to the earnings announcement. Supporting this implication is Xu and Zhang's (2013) finding that firm information provided on Wikipedia moderates investors' reaction to bad news and Brown et al.'s (2015) finding that constraints on individual investors' ability to conduct internet searches negatively impact trading volume. There is also evidence that internet information searches are positively related to trading activity (Drake et al. 2012; Xu and Zhang 2013; Brown et al. 2015) legitimizing it as an important and useful individual investor information channel.

The evidence also implies that investors are increasing their search activity in reaction to news events such as, earnings surprises and disclosures of bad news, that indicate times of uncertainty in the market. This evidence is supported by the asset pricing model developed by Mele and Sangiorgi (2015). They propose a model in which market ambiguity motivates the demand for information by uninformed investors as they seek to resolve their ambiguity. In their model, increases in the number of informed agents increase the incentives for uninformed agents to become informed. As asset prices become more informative the incentive to reduce risk decreases while the

incentive to reduce ambiguity does not. Therefore, uninformed investors will try to understand price changes by seeking more information from informed investors and the more information they acquire the more motivated the remaining uninformed investors will be to seek information.

This is consistent with literature examining trading volume, which finds that investor disagreement, as measured by disagreement in opinion among financial analysts, is positively associated with trading activity (Ziebart 1990; Chordia, Huh and Subrahmanyam 2007). Ziebart (1990) finds that change in the levels of consensus of belief among analysts around earning announcements is related to abnormal trading activity. Chordia et al. (2007), examining monthly trading activity over a 40-year period, also find that analyst forecast dispersion is related to trading volume, however, the number of analysts following a firm is not. They interpret these findings in a manner that supports the role of analysts as intermediaries, that is, analysts provide information through their forecasts to the public (Healy and Palepu 2001). Building on this work, we hypothesize that the availability of the Internet as an information channel provides individual investors access to a broader amount of firm information than just analysts' forecasts and direct firm communications.

2.2 Institutional investors and market ambiguity

In the U.S. equity market, institutional investors are one of the most important players, as measured by their ownership percentage of firms and market trading volume. We argue that differential trading activity among institutional investors reflects an informed disagreement about the true state of the underlying stock. These large investors have resources that can be used to obtain and/or generate superior information through either their own research or their connections with financial analysts, investment bankers, top management, and boards of directors. For example, some buy-side hedge and mutual funds are large enough to perform their own surveys and even independently able to gather private information in order to obtain valuable insights to inform their

investment decisions. Institutions also are more informed than the general public since they have the ability to hire skilled fund managers and star analysts to perform risk analyses, data collection and detailed analysis of publicly available firm information (Sias and Starks 1997; Boehmer and Kelley 2009).[3]

Institutional investors often have access to proprietary information channels, that are mostly unavailable to individual investors who therefore generally rely on publicly available information (Jegadeesh and Tang 2010; Bushee, Jung and Miller 2011; Green et al. 2014; Soltes 2014). This access provides institutions an informational advantage (Jegadeesh and Tang 2010; Puckett and Yan 2011). For example, a recent Wall Street Journal article reports that institutional investors are granted private access to companies which provides them with company facts and perhaps more importantly, the opportunity to observe executives' body language and voice tone for subtle, unspoken clues during private meetings with top executives.[4] Institutions also gain additional information by participating in singular corporate events, such as in the IPO process, which may provide non-public information to favored clients, such as, mutual funds. For example, Chemmanur, Hu and Huang (2010) show that large investors participating in an IPO equity allocation process outperform other investors in the post-IPO period when there is high information asymmetry about the IPO firm.

Finally, institutional investors have more interactions with financial analysts than individual investors (O'Brien and Bhushan 1990). In particular, they tend to have close communications with analysts who have ties to company management (Brown, Feigin and Ferguson 2014; Soltes 2014). This supplemental line of communication enables them to gain better insight regarding a company's potential performance. In line with this view, Badrinath, Kale and Noe (1995) and Boehmer and

[3] Jegadeesh and Tang (2010) note that the top performing mutual fund manager in 2008 attributed his success to focusing on companies with strong competitive positions, strong balance sheets and strong cash flows, suggesting that his ability to process public information gives him an advantage.

[4] Please see http://www.wsj.com/articles/how-some-investors-get-special-access-to-companies-1443407097?mod=djemCFO_h&mg=id-wsj (Last accessed April 8, 2017).

Kelley (2009) show that stocks with higher institutional ownership incorporate price-relevant information into share prices faster than other stocks.

Given institutional investors' informational advantage, many studies examine trading patterns around price-relevant corporate announcements in order to assess whether informed investors use their information advantage to strategically time their trades. For example, Irvine, Lipson and Puckett (2007) investigate institutional trading patterns around analyst recommendation revisions and find that institutional investors start buying five days before the "buy" recommendations are publicly released. Similarly, Geiger, Keskek, and Kumas (2018) document that institutions begin selling shares of firms receiving first-time going-concern modified audit reports ten days prior to release date of the audit report. Overall, the preponderance of evidence suggests that institutional investors are informed traders, thus a low consensus in their trading activities (i.e., some buy and some sell) suggests investor disagreement on the fundamentals of the underlying stock, indicating market ambiguity.

2.3 Hypotheses development

As suggested by the previous literature, we employ the level of internet information search activity on firms as a proxy for the individual investors' demand for information. Given that access and information on the internet is not limited to particular periods such as earnings seasons we expect increased search activity during periods when the market is experiencing high levels of ambiguity, as reflected in the trading activity of informed institutional investors. Thus, consistent with the Mele and Sangiorgi (2015) model, we hypothesize that individual investors, when faced with market uncertainty, will increase their internet search activity for firm information and the higher the uncertainty the higher the search activity.

H1: *Market ambiguity, as measured by institutional investor disagreement, is positively related to the internet search activity of individual investors.*

Drake et al. (2012) find that internet searches increase in the period prior to an earnings announcement, at the earnings announcement, and remain high for a period after the announcement. If market ambiguity is related to investor information demand, then we would expect to see increased internet search activity around earnings announcement periods when market ambiguity is high. Our second hypothesis follows.

H2: *Market ambiguity is positively related to the internet search activity of individual investors during earnings announcement periods.*

To test these hypotheses, we conduct regression analyses measuring individual information demand based on search volume on the internet and measuring market ambiguity based on the daily trading activity of institutional investors. We present a description of the sampling process, variables and our regression models in the following sections.

3. Sample

We extract SVI from *Google Trends* (previously *Google Insights for Search*) for over 500 of the largest U.S. firms (including all S&P 500 firms) for the period from 2006 to 2010. These companies represent approximately 80% of the U.S. equity market as measured by capitalization.[5] We use the SVI as a proxy for the demand for firm information from individual investors (Drake et al. 2012; Brown et al. 2015). Google constructs the daily SVI for each search term. Consistent with prior research (Drake et al. 2012; Da, Engelberg and Gao 2011) we use a firm's TICKER symbol search on Google as the proxy for information demand since it is "more likely to reflect searches for financial information than searches for nonfinancial information" (Drake et al. 2012, p. 1009). We include all TICKER symbol searches even those with common words such as CAT, the ticker

[5] https://us.spindices.com/indices/equity/sp-500 (Last accessed April 8, 2017).

symbol for Caterpillar Inc. While this is a limitation of our method, it is likely to weaken our results by possibly introducing non-financial search spikes to our data.[6]

Search data may be downloaded for different windows; weekly, monthly, quarterly, or for any custom date range. We scale our data for each quarter such that the number of searches for a specific TICKER symbol is scaled by the number of searches for that symbol within that calendar quarter. The date on which the specific search term had the highest search is given an index value of 100 and searches on other days are indexed against that highest search date. Thus, an SVI of 80 means that on that on that specific date, the search for that particular term was 0.8 times that of the highest search day within that quarter. We extracted daily Google SVI data by calendar quarter, i.e. we set the range for data extraction by calendar quarter and Google Trend provided us daily SVI data for all days in that calendar quarter. When extraction range is set to any window larger than a calendar quarter, Google Trend by default changes the SVI data format to weekly index instead of daily SVI index. Hence, with quarterly extraction range, we have at least one day for each calendar quarter when SVI is 100 and SVIs for the remaining days are pegged against the highest SVI date.

Our measure of market ambiguity is computed using the institutional investor daily trading data from Ancerno Ltd. which provides transaction cost analysis for its customers (formerly known as *Abel Noser*). The Ancerno database does not provide the name of the institutional investor, but, each institution can be identified with a unique investor code and Ancerno provides company identifiers (TICKER symbol) for trades, as well as execution date, execution share volume, execution share price, and the position of the trade, i.e., buy or sell.[7] We exclude firms that are not followed by at least two institutional investors from Ancerno. After merging *Google Trends*, *Ancerno,* and other firm-specific variables constructed using *CRSP*, *Compustat*, *Thomson Reuters*

[6] We have fourteen possibly confusing tickers out of our sample of 453 distinct ticker symbols. In sensitivity analysis, excluding these fourteen tickers does not qualitatively change our results or conclusions.
[7] For these reasons we do not use the Lee and Ready (1991) methodology to infer the direction of the trade.

and *IBES*, our final sample consists of 463,659 trading days, 453 distinct firms, and 20,947 quarterly earnings announcement days over our sample period, 2006 -2010.

4. Research Design

In order to capture the idiosyncratic nature of information demand from individual investors for each company, we construct an abnormal SVI measure, *ABN_SVI*. Following Drake et al. (2012), *ABN_SVI* is the average value of raw SVI for a TICKER on a given day t minus the average SVI for the same ticker on the same weekday over the past 10 weeks, scaled by the average SVI for the same ticker on the same weekday over the past 10 weeks. In other words, *ABN_SVI*, on average, represents the percentage change for information demand for each firm on any given day *t* compared to past 10 weeks of the same weekday.

Next, we measure investor disagreement among informed market participants based on their trading activities. Following the implications of the prior literature, we assume that buy and sell order imbalances represent disagreement among investors. We closely follow the order imbalance calculation described by Chordia and Subrahmanyam (2004). However, we do not need to estimate signed trades since we have actual buy and sell trade data from Ancerno. Specifically, we construct our investor disagreement measure (*DISAGREE*) as 1 minus the absolute value of order imbalance (OIB) for firm *i* on day *t* and OIB is computed as $(BUY_{i,t} - SELL_{i,t})/(BUY_{i,t} + SELL_{i,t})$ where BUY_{it} $(SELL_{it})$ represents total number of shares purchased (sold) by the *Ancerno* investors in firm *i* on day *t*. Therefore,

$$\text{DISAGREE} = 1 - Abs\left(\frac{\text{BUYi, t - SELLi, t}}{\text{BUYi, t + SELLi, t}}\right) \qquad (1)$$

For example, if total *BUY*=70 shares and *SELL*=30 shares, *DISAGREE*=0.60, suggesting that investors strongly disagree on the news circulating on day t.[8]

We construct the disagreement measure (*DISAGREE[t-n, t])* over multiple days by averaging the *DISAGREE* for the period between day *t-n* and day *t* to incorporate informed investors' pre-disclosure information into the computation of the disagreement metric. For example, a *DISAGREE[t-n, t]* of 1 means that informed investors are equally divided between buyer and seller groups over the days from *t-n* to *t*, suggesting a strong disagreement on the content of the news. On the other hand, a *DISAGREE[t-n, t]* of 0 means that all informed investors are either buying or selling the stocks and as a result, there is no disagreement among them. Consistent with the arguments above on informed investors, we suggest that investor disagreement represents the uncertainty in the existing information environment for a particular stock and hence it may take a few days for uninformed investors to realize and react to this market ambiguity. Therefore, we employ a 4-day average disagreement measure (*DISAGREE[-3, 0]*) throughout our empirical analysis.

To test the relation between market uncertainty and individual information demand, we adapt the empirical model from Drake et al. (2012). We include controls for firm size (*SIZE*), return (*RET*), analyst following (*NUM_ANALYSTS)*, institutional ownership (*INST_OWNERS*) and for our earnings announcement sample, earnings surprises (*ABS_UE)*. In addition to these control variables, we include factors that potentially explain individual investors demand for information in response to market ambiguity. For example, we include an earnings quality indicator measured by discretionary accruals (*DISC_ACCRUALS)* and an audit quality indicator measured based on whether the company uses a Big-4 audit firm (*KPMG, EY, PWC,* and *Deloitte*) for its annual audit (*TOP4_AUDITOR*). We also include liquidity measures, calculated based on trading volume

[8] Notice that *DISAGREE* mathematically can only take values between 0 and 1, with 0 suggesting no disagreement while 1 suggests perfect disagreement.

(*TURNOVER*) and the difference in the daily bid and ask price for a stock (*SPREAD*). We estimate variations of the following general model throughout our analyses:

$$ABN\_SVI = b0 + b1*DISAGREE[-3, 0] + b2*SIZE + b3*RET + b4*NUM\_ANALYSTS + b5*INST\_OWNERS + b6* DISC\_ACCRUALS + b7*TOP4\_AUDITOR + b8*TURNOVER + b9*SPREAD + b10*DUMMIES + e \quad (2)$$

where:

ABN_SVI is measured as SVI on day *t* minus the average SVI for the same weekday over the past 10 weeks, scaled by the average SVI for the same weekday over the past 10 weeks;

DISAGREE[-3, 0] is measured as the average DISAGREE over the 4-day period from day *t-3* to day *t*;

SIZE is annual decile rank of market value of equity *(MVE)* for each firm;

RET is the absolute value of the difference between return of a stock on day *t* and the value-weighted CRSP index return for the market on day *t*;

NUM_ANALYSTS is the number of analyst following each firm per quarter;

INST_OWNERS is the percentage of shares owned by institutional investors;

DISC_ACCRUALS is the absolute value of performance-matched discretionary accruals as suggested by Kothari, Leone, and Wasley (2005);

TOP4_AUDITOR is an indicator variable taking the value of 1 if the external auditor is one of the top 4 auditors;

TURNOVER is decile rank of annual turnover for each firm where turnover is computed as annual trading volume scaled by shares outstanding; and

SPREAD is daily spread calculated for each firm based on the high-low estimate as (Askhi – Bidlo)/((Askhi + Bidlo)/2).

[9] We use the White (1980) heteroscedasticity adjusted robust standard errors and also include fixed effects for weekday, month, year, and industry in the regression models to control for time period and industry effects.

The main variable of interest throughout our analyses is *DISAGREE[-3, 0]* and we hypothesize a significant positive coefficient, $b_{1,}$ indicating that individual investors demand more information in response to market ambiguity, as measured by the disagreement among sophisticated market participants.

5. Results

5.1 Univariate Results

In this study, we examine the relation between market ambiguity and individual investor information demand. Table 1 presents descriptive statistics showing that average abnormal demand for information, *ABN_SVI*, as measured by Internet searches on any given day is positive (.016) with a p-value of <.01. The average disagreement among institutional investors on any given day is .446, reflecting a high degree of disagreement among these investors. More interestingly, an average *DISAGREE* of .446 means that on average buy trades are 3.48 times more than sell trades or vice versa.[10] As a robustness check, we also employ disagreement metrics computed at different time intervals (ranging from [-1, 0] to [-4, 0]). Our sample from S&P 500 firms consists of large companies with an average market capitalization (*MVE*) of $21.29 billion; abnormal return, *RET*, on average for our sample firms is close to 0; and earnings surprise, *ABS_UE*, for our sample firms on average is 28.1% based on the consensus estimate. On average, per Thomson Reuters institutional investor own 76.9% of our sample firms shares outstanding; this is consistent with institutional ownership in the U.S. market. Furthermore, the largest four audit firms, Big-4, are the external auditors for the majority, 88.8%, of our sample firms. Firms in our sample are large, and on average, they are followed by 13.8 analysts.

[10] The way that we compute the multiples is as follows. First, solving for the equation (1) yields 1-Abs(OIB)=.446, and therefore Abs(OIB)=.554, which suggests that OIB is either .554 or -.554. Hence, solving for both possibilities yields that either Buy=3.482*Sell or Sell=3.482*Buy, respectively.

[Insert Table 1 here]

Table 2 presents the Pearson correlation coefficients for our variables. Univariate results show positive correlation (.004) albeit weak between our disagreement measure (*DISAGREE*) and information demand *(ABN_SVI*), which provides the initial support for *H1* that market ambiguity is positively related to individual investor information demand. We also find that size, *SIZE*, has a moderate positive (0.357) correlation with disagreement and weak positive correlation (.003) with individual investor information demand, *ABN_SVI*. There is negative correlation between the magnitude of surprise measured either as unexpected earnings, *ABS_UE*, or as absolute abnormal return, *RET*, and our disagreement measure, *DISAGREE*. These unconditional statistics for *ABS_UE* particularly suggest that the new information provided by earnings announcements narrows the information gap among investors and/or decreases information asymmetry, reducing the disagreement existing prior to the announcement.

[Insert Table 2 here]

Next, we graphically illustrate the general relationship between market ambiguity and information demand. In order to reduce the complexity of our graphical demonstration we partition our sample into ten groups (deciles) based on the disagreement measure (*DISAGREE [-3, 0]*) and plot average abnormal information demand (*ABN_SVI*) for each group. Figure 2 shows the average information demand for each disagreement decile. Our results indicate that average information demand for the highest disagreement decile (.0201 for decile 10) is more than 63 percent (.0201/.0123) greater than the average information demand for the lowest disagreement decile (.0123 for decile 1), clearly supporting our initial hypothesis, *H1*, the higher the market ambiguity the greater the information demand from individual investors.

[Insert Figure 2 here]

When we move from our full sample of all trading days (n=463,659) to only earnings announcement (EA) days (n=20,947), we find that average information demand has substantially increased. The average information demand (*ABN_SVI*) for our full sample is .016 (Table 1), while the average information demand for the earnings announcement sample is .101, which represents an increase of almost 631 percent (.101/.016). These results corroborate the evidence in Drake et al. (2012) showing that demand for information peaks on earnings announcement days. Figure 3 shows the average information demand for each disagreement decile, constructed by partitioning our earnings announcement sample (n=20,947) into decile groups based on the disagreement measure (*DISAGREE* [-3, 0]) and plotting the average abnormal information demand (*ABN_SVI*) for each group. We show that average information demand for the highest disagreement decile (.19 for decile 10) is around 404 percent (.19/.047) greater than the average information demand for the lowest disagreement decile (.047 for decile 1). In sum, Figure 3 suggests that uninformed investors on average demand more information when there is market uncertainty (decile 10) surrounding the content of the news released from the earnings announcements.

[Insert Figure 3 here]

Overall, both Figures 2 and 3 show that as we move from low disagreement deciles to high disagreement deciles we generally observe a drastic increase in information demand by uninformed investors, 63 percent and 404 percent, respectively. These univariate analyses indicate a positive relation between informed investor disagreement, as measured by differential trading activities, and the information demand from the retail investors.

5.2 Multivariate Results

In order to examine the relation between individual investor information demand and market uncertainty, we estimate equation (2) for the full sample (n=463,659) controlling for other factors associated with individual investor demand for information. We present the results in Table 3. First,

the significant, positive coefficient (.0117, p<.01) on *DISAGREE [-3, 0]* in Column 1 of Table 3 suggests that greater market ambiguity leads to higher information demand by individual investors when no other control variables are included. After introducing control variables in our model, one by one, to better observe their impact on information demand, Columns 2 through 8 of Table 3, we still find a very significant, positive coefficient on *DISAGREE [-3, 0]* (e.g., .00833, p-value<.01 in Column 8). This finding indicates that the disagreement among informed investors, as revealed by their trading activity, leads to higher demand for information by uninformed investors.[11] These results provide evidence supporting *H1*, i.e., market ambiguity is positively related to individual investor information demand. As a robustness check, we employ *DISAGREE[-1, 0]* reducing the period where disagreement is measured, and find that the inferences from *DISAGREE[-1, 0]*, untabulated, are substantially similar in sign, magnitude and significance to those reported in Tables 3. Thus, our results do not appear to be overly sensitive to the period, [-3, 0] over which we measure the investor disagreement metric.[12]

The majority of the control variables in our regression analyses behave in the expected direction. For example, from our full model, column 8, we see that more information is demanded by individual investors for larger firms as evidenced by the positive coefficient on *SIZE (.00345, p<.01)*. The magnitude of surprise, as proxied by *RET*, on any given trading day necessitates higher demand for information as well. *TURNOVER* (.00402, p<.01) is positive indicating the more volatility observed in the market, the higher the information demand. Our proxies for earnings and audit quality behave as expected. If a firm uses a Big-4 audit firm, less information is demanded (*TOP4_AUDITOR* -.00410, p<.05), and the higher the discretionary accruals (*DISC_ACCRUALS*

[11] Year, month, and weekday dummies are included in all regression models to control for time period effects. In addition, industry dummies are included to control for industry fixed effects. Heteroskedasticity adjusted robust standard errors (White 1980) are used in all models.

[12] While it is very unlikely that retail uninformed investors are influencing sophisticated institutional investors' behavior, we test for the presence of possible endogeneity by conducting a two-stage-least-square regression approach using model (2). The tenor of our main results strongly holds after controlling for potential endogeneity.

.00578, p<.10), the more information is demanded. Both results indicating the higher the perceived quality of the accounting information the lower the demand for information.

We also find that the higher the ownership of shares by institutional investors the lower the information demanded by individuals (*INST_OWNERS* -.0220, p<.01). Given there are fewer shares available to individual owners it follows there is less interest in those shares and thus less demand for information. Interestingly, our model (2) indicates a negative relation between the number of analysts following a company and the level of information demanded (*NUM_ANALYSTS* -.00121, P<.01). Since analysts are information intermediaries, the more analysts that follow a company the more information that should be available requiring less search activity by individual investors.

The results presented in Table 3 also suggest that demand for information is highest on Monday, evidenced by negative and significant (p<.01) coefficients on other weekdays. This is not surprising since the information revealed over the weekends may have a significant impact on investor beliefs, reflected in investors' information demand as they commute and return to work on Mondays. This is also consistent with prior research that observes higher trading volume from individual investors on Mondays (Lakonishok and Maberly 1990).

[Insert Table 3 here]

Table 3 presents the full sample analyses when we include all trading days in our sample. To examine the impact of market ambiguity on demand for information during earnings announcement periods, *H2*, we focus on earnings announcement days in our next analysis. Drake et al. (2012) show that information demand increases around earnings announcements. In this part of our analyses, we first provide evidence supporting Drake et al.'s (2012) findings and then gain finer intuitions about the type of earnings announcements that generate such increase in information demand. We modify equation (2) and employ the following empirical model:

$$ABN\_SVI = b_0 + b_1*DISAGREE[3, 0] + b_2*SIZE + b_3*RET + b_4*TURNOVER + b_5*ABS\_UE + b_6*DISPERSION + b_7*INST\_OWNERS + b_8*NUM\_ANALYSTS + b_9*TOP4\_AUDITOR + b_{10}*DISC\_ACCRUALS + b_{11}*SPREAD + e \quad (3)$$

where:

ABS_UE represents the absolute value of earnings surprise computed as the actual announced earnings minus the consensus (median forecast among the analysts), scaled by the consensus; and

DISPERSION is calculated as the standard deviation among analyst forecasts over the 90-day period before the earnings announcement.

Consistent with the previous analyses, weekday, month, and year dummies along with industry dummies are included in model (3). We include absolute earnings news (*ABS_UE*) based on consensus estimate to control for surprise from the actual earnings announcements, where consensus estimate is the median forecast among the analyst forecasts during the quarter prior to announcement. Prior evidence also indicates that greater divergence in analyst forecasts leads to higher monthly trading volume (Chordia et al. 2007) which may influence information demand. Thus, for the earnings announcement analysis, we include analyst forecast dispersion (*DISPERSION*) to control for pre-existing differences of opinion among analysts during the 90-day period before the announcement. This allows us to better interpret the influence of market ambiguity as measured by institutional investor trading activity, *DISAGREE*.

In order to observe the individual impact of our control variables on information demand by individual investors, we add the controls, one by one, in our empirical analysis by using equation (3). Results presented in column (9) of Table 4 clearly show that there is a positive, significant relation between demand for information and market uncertainty around earnings announcement days (*DISAGREE[-3, 0]* .0453, $p<.05$*)*. More importantly, comparing the magnitude of coefficients

on *DISAGREE[-3, 0]* between the full sample (.00883 in Table 3) and earnings announcement subsample (.0453 in Table 4) reveals that demand for information during earnings announcements is significantly higher than that during all trading days at p<.05 (more than 510 percent (.0453/.00883)). Interestingly, *NUM_ANALYSTS* reflects a positive coefficient in this model (.0103, p<.01) with the dispersion in analysts' forecasts exhibiting a significant, negative relation (*DISPERSION* -.0514, p<.01). This implies that, during earnings announcement periods, retail investors conduct more information searches on firms with high analyst following when market ambiguity is high i.e., there is high disagreement among institutional owners. This occurs in the presence of low disagreement in analysts' forecasts. The remaining control variables behave according to expectation.

[Insert Table 4 here]

While supportive of Drake et al.'s (2012) findings, the results in Table 4 do not provide us any substantially new intuitions beyond our main finding. In order to gain further insight into the effect of market ambiguity on information demand, we analyze whether key firm characteristics that influence the quality of the firm's information environment have any impact on investor information demand around earnings announcements. In Table 5, we run the following regression (i.e., equation (3)) for earnings announcement subsamples based on specific firm characteristics.

$$ABN\_SVI = b_0 + b_1*DISAGREE[-3, 0] + b_2*SIZE + b_3*RET + b_4*TURNOVER + b_5*ABS\_UE + b_6*DISPERSION + b_7*INST\_OWNERS + b_8*NUM\_ANALYSTS + b_9*TOP4\_AUDITOR + b_{10}*DISC\_ACCRUALS + b_{11}*SPREAD + e$$ [13]

The firm characteristics we use to form our earnings announcement subsamples are institutional ownership, analyst following, audit quality, and earnings quality. These characteristics may influence the information environment of the firm. Institutional ownership and analyst

[13] Column (5) & (6) exclude TOP4_AUDITOR as a control, since the subsample includes only observations with a Big-4 auditor.

following are market-based firm characteristics, while audit quality and earnings quality are characteristics influenced by firm choices. Since our sample is composed of large US firms, these firms tend to have high institutional ownership and analyst following as well as high audit and earnings quality.

Overall, we find that market ambiguity (*DISAGREE[-3, 0]*) is significant across each of our earnings announcement subsamples supporting our hypotheses that ambiguity is influencing information searches and providing further insight into the type of searches being conducted. Column (1) of Table 5 presents the results from the subsample of firms whose institutional ownership (*INST_OWNERS*) is less than median institutional ownership for our sample firms (column (2) shows results for the remaining observations in the subsample). Our results show that retail investors demand significantly more information around earnings announcements for firms experiencing market ambiguity when the firms have low institutional ownership (.0964) compared to firms with high institutional ownership (test of difference $p<.01$). This intuition is rather mechanical, since for firms with low (high) institutional ownership, retail ownership will be higher (lower) and as a consequence, information demand from retail investors should also be relatively higher (lower).[14]

Column (3) and (4) of Table 5 present the subsample of earnings announcements where the number of analysts following (*NUM_ANALYSTS*) is higher than the median (column (3)) and lower than the median (column (4)). Results show that retail investors demand significantly more information around earnings announcements as ambiguity increases for firms that have high analyst following (.0967) compared to firms with low analyst following (test of difference $p<.01$). This is consistent with the results presented in Table 4. Analysts are expert information intermediaries in

[14] Moreover, a test of difference of coefficient on *DISAGREE[-3, 0]* between low institutional ownership subsample of earnings announcements (.0964) and all earnings announcement sample (.0453) reveals that the impact of ambiguity on information acquisition is significantly different.

the market. Firms with higher analyst following have more publicly available information (Chordia et al. 2007). This provides more search opportunities for retail investors in times of market ambiguity.[15]

We turn now to characteristics that are a result of firm choices, audit quality and earnings quality. Almost 89% of our sample firms reported using a Big-4 auditor (*TOP4_AUDITOR*). The presence of a Big-4 auditor indicates higher reliability of the reported earnings. Therefore, we predict that retail investors having assurance that the financial information is reliable for investment decision-making purposes will be more likely to search for more information on firms with Big-4 auditors. Similarly, we predict that high earnings quality, as indicated by low absolute discretionary accruals (*DISC_ACCRUALS*), provides retail investors the impetus to search, as good quality information is available.

In particular, column (5) and column (6) of Table 5 show the regression results for the earnings announcement subsample for companies with a Big-4 auditor and non-Big-4 auditor, respectively. Our results show that retail investors demand significantly more information around earnings announcements as disagreement among institutional ownership increases for firms that report a Big-4 auditor (.0587) compared to firms with a non-Big-4 auditor (test of difference $p<.05$).[16] Similarly, we report the same inferences from the regression results in column (7) and column (8) for the quality of earnings subsamples; column (7) includes subsample of earnings announcements with discretionary accruals lower than median, i.e., high-quality earnings or high-quality financial information, and column (8) includes remaining observations with low-quality earnings. Firms with high-quality financial information, i.e., companies with absolute discretionary

[15] Furthermore, a test of difference of coefficient on *DISAGREE[-3, 0]* between high analyst following subsample of earnings announcements (.0967) and all earnings announcement sample (.0453) reveals that the impact of ambiguity on information acquisition is significantly different.

[16] In addition, a test of difference of coefficient on *DISAGREE[-3, 0]* between top-4 audit subsample of earnings announcements (.0587) and all earnings announcement sample (.0453) reveals that the impact of ambiguity on information acquisition is significantly different.

accruals (*DISC_ACCRUALS*) less than the median, generate more demand for information from retail investors (.0538). Overall, we find that retail investors demand more information around earnings announcements as disagreement among institutional ownership increases for firms that have high earnings quality compared to firms with low earnings quality. These results support our intuition that retail investors, when faced with ambiguity, will increase their search for information on companies that have high quality, reliable financial information.

[Insert Table 5 here]

5.3 Additional analysis

In this section of our analyses, we consider whether the structure of market ambiguity, i.e., the direction of informed investor disagreement, sell trades or buy trades, has a differential effect on individual investor information demand. In other words, we investigate a hitherto unexplored but interesting question, does the investor reaction differ if market uncertainty is driven by net selling activity versus net buying activity among institutional investors. Ahn, Kang and Ryu (2010) find that buyer-initiated trades usually have greater information content than seller-initiated trades. They also document that the asymmetry in information content between buy and sell initiated trades is generally attributable to institutional investors trading activities. Therefore, building on their research, we expect that demand for information by uninformed investors will be higher on days when market ambiguity is driven by selling activity (low information content days as per Ahn et al. 2010).

Interestingly, Table 1 reports an average *DISAGREE* of .446, implying that on average buy trades are either 3.48 times more than sell trades (net buying case) or vice versa (net selling case). To investigate the possibility of differential demand for information on net selling versus net buying days, we categorize our sample of trading days for each firm as net sell day versus net buy day

where a net sell day represents any trading day institutional investors sell more shares than they buy.

Next, we employ our main empirical model (2) to investigate whether demand for information is higher on net selling days and therefore only include trading days where selling activity is greater than buying activity (i.e., net selling>0). Our results, presented in Table 6, document positive, significant (p-value<.05) coefficients on *DISAGREE[-3, 0]* across all models. Focusing on the full model results presented in column 5 in Panel A of Table 6, the *DISAGREE[-3, 0]* coefficient is .0107 (p-value<.05), which is 1.21 times the coefficient we found in column 8 reflecting the full model in Table 3 (.00883). Examining the relation between demand for information and market ambiguity on net buying days, our results (untabulated) indicate a positive, but insignificant, coefficient on *DISAGREE[-3, 0]*.[17] This evidence indicates that information demand is stronger during days when net selling behavior drives market ambiguity compared to net buying days.

Turning to the earnings announcement period we identify the subsample of earning announcements around net selling days. Using this subsample we employ equation (3) and present the results in Panel B of Table 6. The coefficient on the *DISAGREE[-3, 0]* variable is positive and significant (.0652 in column 5, p<.05) indicating that retail investors demand more information when market ambiguity is driven by net selling activity during earnings announcement periods consistent with the results from our full sample.[18]

[Insert Table 6 here]

6. Conclusions and Limitations

[17] A test of difference of coefficient on *DISAGREE[-3, 0]* between subsamples from netsell and netbuy days reveals that the impact of ambiguity on information acquisition is significantly different.

[18] Comparing coefficient on the *DISAGREE[-3, 0]* from net selling days presented in column 5 in Panel B of Table 6, (.0652), reveals that it is 1.44 times the coefficient we found in column 9 in Table 4 (.0453).

In this paper, we examine the flow of information to individual investors in the U.S. capital market. We hypothesize that individual investors increase their information demand around the days when institutional investors' trading behavior reflects market uncertainty. We create a metric measuring institutional investor disagreement as a proxy for market ambiguity and employ the daily Google SVI on a particular security as a measure of demand for information by individual investors. We follow the construction of Drake et al. (2012) to capture the abnormal information demand from individual investors.

Overall, our results provide support for our hypotheses indicating that individual investors' demand for information is significantly related to market ambiguity, as measured by the disagreement among institutional investors, supporting the asset pricing model proposed by Mele and Sangiorgi (2015). We also find that individual investors demand significantly more information around earnings announcement days, as suggested by Drake et al. (2012). Further analyses show that firm characteristics influencing the quality of the firm's information environment (institutional ownership, analyst following, audit quality, and earnings quality) impact investor information demand around earnings announcements. These results support our intuition that retail investors, when faced with ambiguity, will increase their search for information on companies that have high quality, reliable financial information. Additional analyses indicate that individual investors also demand more information when market ambiguity, the disagreement among institutional investors, originates from net selling activities supporting the prior research (Ahn et al. 2010) finding that buyer-initiated trades have greater information content than seller-initiated trades.

We believe these results add to the literature examining capital market information flows. Our work provides additional support for the use of the Google SVI search data as a proxy for individual information demand. Further, our metric for market ambiguity provides an additional

measure of investor disagreement, one based on actual institutional investor trading behavior, thus, adding to the literature examining order imbalance.

Our research is subject to several limitations. First, as noted by other researchers (Drake et al 2012), the Google SVI search data which we use to measure individual information demand, is an approximation of the actual search volume and may contain errors so care should be taken when interpreting our results. Another limitation of our study is that we employ trading activities of mutual and pension funds from Ancerno that represent only a subset of the population of institutional investors. Accordingly, our inferences regarding the disagreement among institutions may not generalize beyond these types of institutional investors. However, as noted by Cready et al. (2014) Ancerno investors in our study account for roughly 10 percent of all CRSP trading volume. Finally, our sample period is limited to 2006–2010. We begin in 2006 since that is the first year we could collect daily ticker-search related data from Google and end in 2010 since that is the last year we had access to Ancerno data. Since our sample period captures data when there was most likely less Google search activity we believe our results would be stronger in an updated period. However, this is a limitation of our study and our results should be interpreted with this in mind.

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Appendix

Variable Name	Variable Definition	Source
ABN_SVI	The average value of raw Google Search Volume Index (SVI) for a given day t minus the average SVI for the same weekday over the past 10 weeks, scaled by the average SVI for the same weekday over the past 10 weeks.	Google Trends
DISAGREE	1 minus absolute value of order imbalance, order imbalance on day t is $(BUY_t – SELL_t)/(BUY_t + SELL_t)$.	Ancerno
DISAGREE[-3, 0]	Average of DISAGREE over the 4 day period from t-3 to day t.	
MVE	Market value of shares outstanding (*PRC* * *SHROUT*), expressed in billions.	CRSP
SIZE	Annual decile rank of MVE for each firm.	
RET	Absolute value of daily abnormal return; where abnormal return is calculated as return for stock i on day t minus value weighted CRSP index return for the market, *ABS(RET - VWRETD).*	CRSP
TURNOVER	Annual decile rank of turnover, which is calculated as annual trading volume scaled by shares outstanding [(*VOL/SHROUT*)*1000] for each firm.	CRSP
INST_OWNERS	Percentage of shares owned by institutional investors. Calculated quarterly.	Thompson
NUM_ANALYSTS	Number of total analysts following for each firm. Calculated quarterly.	IBES
TOP4_AUDITOR	Indicator variable: takes a value of 1 if the external auditor is a top 4 auditor, 0 otherwise, defined as EY, PWC, Deloitte and KPMG. Calculated annually.	AUDIT ANALYTICS
DISC_ACCRUALS	Absolute value of performance matched discretionary accruals as suggested by Kothari, Leone, and Wasley (2005). Calculated yearly.	COMPUSTAT
SPREAD	(Askhi – Bidlo)/((Askhi + Bidlo)/2). Calculated daily.	CRSP
UE	Actual earnings minus consensus scaled by consensus, (*ACTUAL - MEDEST)/MEDEST* where *MEDEST* is median forecast among the analysts during the quarter prior to earnings announcement.	IBES
ABS_UE	Absolute value of *UE*.	
DISPERSION	Standard deviation of forecasts made within 90 calendar days before the earnings announcements.	IBES

Calculation of Performance-Matched Discretionary Accruals following Kothari, Leone, and Wasley (2005):

We estimate Total Accruals using the following regression.

$$TAC = b0 + b1*1/TA_{t-1} + b2*(ChgSALES - ChgREC) + b3*PPE + b4*ROA + error$$

All variables are scaled by beginning of year total assets (except ROA) to control for heteroscedasticity.

TAC: Total accruals, computed as net profit after tax before extraordinary items less cash flows from operations. $1/TA_{t-1}$: Inverse of beginning of year total assets; ChgSALES: Change in net sales revenue; ChgREC: Change in net receivables; PPE: Gross property, plant, and equipment; and ROA: Return on assets.

First, we estimate the coefficients for b0, b1, b2, b3, and b4 for our sample. Next, we use the estimated coefficients to determine firm level performance matched non-discretionary accruals for each firm. Then we take the difference between total accruals and performance matched non-discretionary accruals to calculate discretionary accruals for each firm. Extreme levels of discretionary accruals, both high and low, are considered as signals for low quality earnings. Hence, we take absolute value of discretionary accruals to proxy for earnings quality, where low (high) levels of absolute discretionary accruals (DISC_ACCRUALS) represents high (low) quality of earnings.

Figure 1: Healy and Palepu model of financial and information flows in a financial market **(**Healy and Palepu 2001, p. 408.)

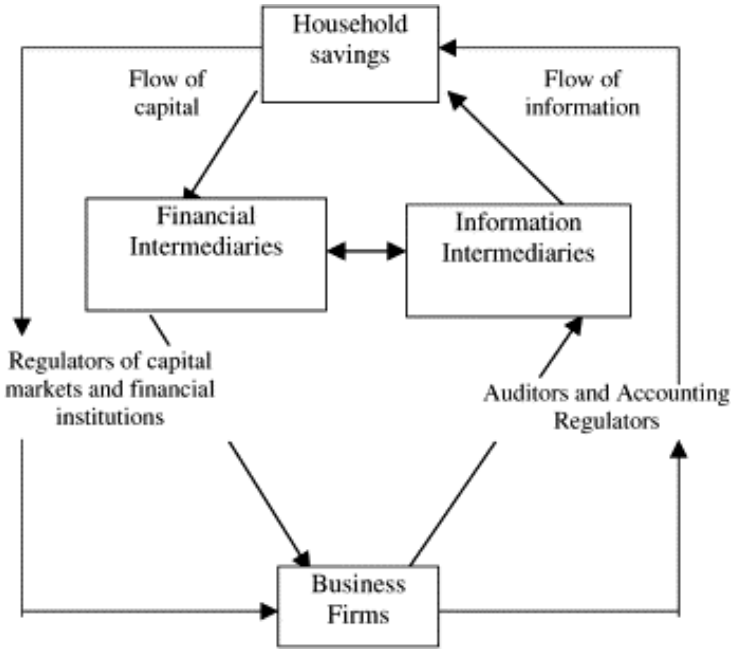

Figure 2: The following figure shows the average abnormal SVI for each decile rank of investor disagreement, where decile rank of disagreement over a 4-day period from t-3 to t is a proxy for the uncertainty in the market.

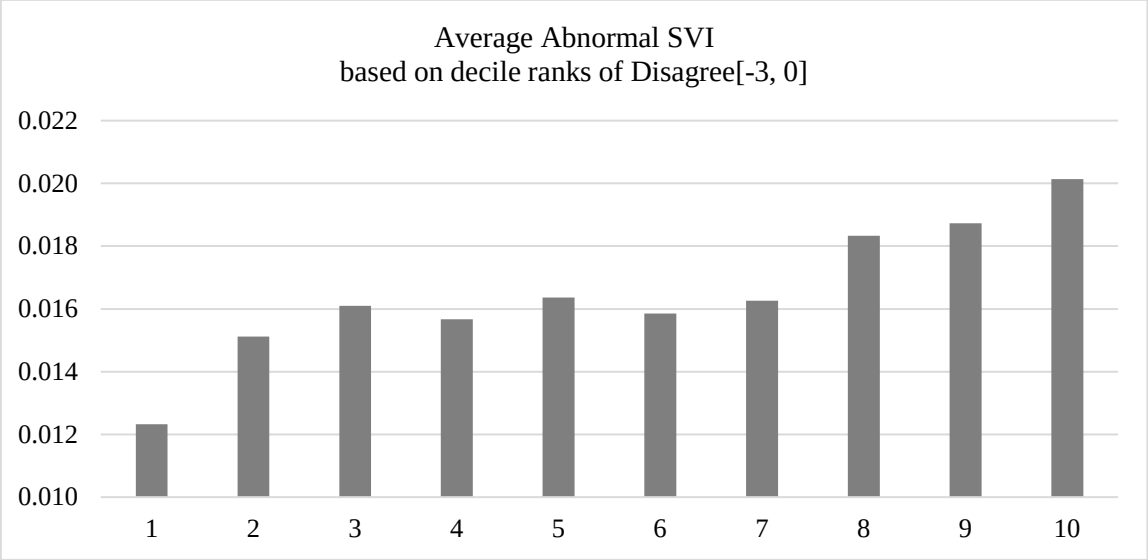

Figure 3: The following figure shows the average abnormal SVI around earnings announcements (EA) for each decile rank of investor disagreement, where decile rank of disagreement over a 4-day period from t-3 to t is a proxy for the uncertainty in the market.

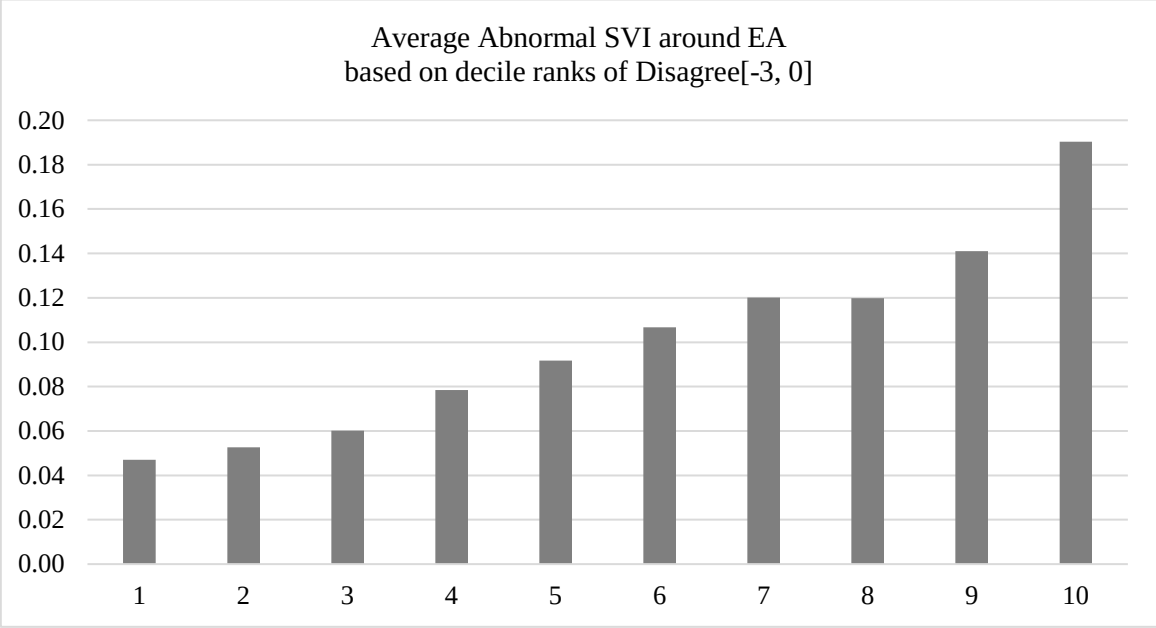

Table 1: Summary Statistics

Variable	N	Mean	P1	P25	P50	P75	P99
ABN_SVI	463,659	0.016	-1.000	-0.100	-0.001	0.100	1.053
DISAGREE[-3, 0]	463,659	0.446	0.055	0.319	0.449	0.575	0.830
MVE[a]	463,659	21.288	0.543	3.680	8.775	20.725	196.948
RET	463,659	0.014	0.000	0.004	0.009	0.018	0.086
TURNOVER[b]	463,659	0.013	0.002	0.006	0.009	0.015	0.066
INST_OWNERS	463,659	0.769	0.291	0.682	0.787	0.877	1.000
NUM_ANALYSTS	463,659	13.804	2.000	9.000	13.000	18.000	34.000
TOP4_AUDITOR	463,659	0.888	0.000	1.000	1.000	1.000	1.000
DISC_ACCRUALS	463,659	0.093	0.004	0.018	0.043	0.095	0.897
SPREAD	463,659	0.033	0.007	0.017	0.025	0.039	0.146
ABS_UE	20,947	0.281	0.000	0.037	0.103	0.255	3.000
DISPERSION	20,947	0.073	0.003	0.017	0.032	0.067	0.792

Table 1 reports summary statistics for a sample of 463,659 firm-days with available data from Google Trends, Ancerno, IBES, COMPUSTAT, and CRSP between January 1, 2006 and December 31, 2010. Variable definitions are provided in the Appendix.

Notes: [a]We report actual market value of equity (MVE) instead of SIZE, which is calculated as a decile rank of MVE. [b]We report actual annual turnover for each stock instead of turnover rank (TURNOVER), which is used in our analyses and calculated as the decile rank of turnover.

Table 2: Pearson Correlations

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
[1]	ABN_SVI	1										
[2]	DISAGREE[-3, 0]	**0.004**	1									
[3]	SIZE	**0.003**	**0.357**	1								
[4]	RET	**0.045**	**-0.040**	**-0.162**	1							
[5]	TURNOVER	**0.036**	**-0.054**	**-0.259**	**0.382**	1						
[6]	INST_OWNERS	**-0.006**	**-0.035**	**-0.337**	**0.056**	**0.315**	1					
[7]	NUM_ANALYSTS	**-0.004**	**0.232**	**0.533**	**-0.021**	**0.160**	**-0.046**	1				
[8]	TOP4_AUDITOR	**-0.003**	**0.014**	**0.038**	-0.001	**0.010**	**-0.015**	**0.048**	1			
[9]	DISC_ACCRUALS	0.002	**0.042**	**0.095**	**-0.029**	**0.004**	**-0.025**	**0.122**	**-0.021**	1		
[10]	SPREAD	**0.035**	**-0.032**	**-0.235**	**0.668**	**0.444**	**0.093**	**-0.024**	-0.001	**-0.050**	1	
[11]	ABS_UE[a]	-0.003	**-0.090**	**-0.201**	**0.125**	**0.176**	**0.033**	**-0.044**	**-0.020**	0.001	**0.196**	1
[12]	DISPERSION[b]	-0.013	**-0.019**	**-0.017**	**0.093**	**0.101**	**-0.035**	**0.021**	-0.008	**-0.026**	**0.156**	**0.246**

Table 2 reports Pearson correlations between the indicated variables for our population of 463,659 firm-days between January 1, 2006 and December 31, 2010. Variable definitions are provided in the Appendix.

Note: [a] Correlation coefficients for ABS_UE are based on Earnings Announcement sample only. [b] Correlation coefficients for DISPERSION are based on available observations for Earnings Announcement sample only. Bold coefficients are significant at p<.05.

Table 3: Investor Information Demand and Market Ambiguity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DISAGREE[-3, 0]	0.0117***	0.00910***	0.00771**	0.00919***	0.00909***	0.00909***	0.00908***	0.00883***
	(4.07)	(3.00)	(2.54)	(3.05)	(2.99)	(2.99)	(2.99)	(2.89)
SIZE		0.00123***	0.00184***	0.00146***	0.00340***	0.00340***	0.00339***	0.00345***
		(6.13)	(8.83)	(6.50)	(11.91)	(11.91)	(11.88)	(11.98)
RET		0.999***	0.794***	0.768***	0.744***	0.745***	0.743***	0.705***
		(20.41)	(15.58)	(15.16)	(14.79)	(14.80)	(14.79)	(12.20)
TURNOVER			0.00312***	0.00341***	0.00412***	0.00412***	0.00413***	0.00402***
			(14.67)	(15.77)	(18.69)	(18.70)	(18.70)	(17.80)
INST_OWNERS				-0.0248***	-0.0224***	-0.0225***	-0.0226***	-0.0220***
				(-5.87)	(-5.25)	(-5.26)	(-5.27)	(-5.18)
NUM_ANALYSTS					-0.0012***	-0.0012***	-0.00121***	-0.00121***
					(-10.81)	(-10.73)	(-10.80)	(-10.81)
TOP4_AUDITOR						-0.00416**	-0.00407**	-0.00410**
						(-2.45)	(-2.39)	(-2.41)
DISC_ACCRUALS							0.00592*	0.00578*
							(1.75)	(1.71)
SPREAD								0.0505
								(1.43)
TUESDAY	-0.00748***	-0.00742***	-0.00847***	-0.00859***	-0.00862***	-0.00863***	-0.00863***	-0.00864***
	(-4.71)	(-4.67)	(-5.32)	(-5.40)	(-5.42)	(-5.42)	(-5.42)	(-5.43)
WEDNESDAY	-0.0104***	-0.0104***	-0.0115***	-0.0116***	-0.0117***	-0.0117***	-0.0118***	-0.0118***
	(-6.52)	(-6.53)	(-7.21)	(-7.29)	(-7.38)	(-7.39)	(-7.39)	(-7.39)
THURSDAY	-0.00630***	-0.00683***	-0.00783***	-0.00792***	-0.00801***	-0.00802***	-0.00802***	-0.00809***
	(-3.88)	(-4.21)	(-4.82)	(-4.88)	(-4.94)	(-4.94)	(-4.94)	(-4.98)
FRIDAY	-0.00630***	-0.00541***	-0.00633***	-0.00643***	-0.00654***	-0.00654***	-0.00654***	-0.00658***
	(-3.81)	(-3.27)	(-3.83)	(-3.89)	(-3.96)	(-3.96)	(-3.96)	(-3.99)
Constant	0.0502***	0.0284***	0.0101*	0.0294***	0.0186***	0.0228***	0.0225***	0.0215***
	(10.64)	(5.66)	(1.96)	(4.75)	(3.00)	(3.47)	(3.42)	(3.26)
Observations	463659	463659	463659	463659	463659	463659	463659	463659
Adj-R^2	0.006	0.008	0.009	0.009	0.009	0.009	0.009	0.009

Table 3 presents coefficients estimates from the following regression model:

$ABN\_SVI = b_0 + b_1*DISAGREE[-3, 0] + b_2*SIZE + b_3*RET + b_4*TURNOVER + b_5*INST\_OWNERS + b_6*NUM\_ANALYSTS + b_7*TOP4\_AUDITOR + b_8*$
$DISC\_ACCRUALS + b_9*SPREAD + b_{10}*DUMMIES + e$

Variable definitions are provided in the Appendix.

*Note: All columns include fixed effects for weekday, month, year, and industry. Numbers in parentheses are t-statistics calculated using robust standard errors as per White (1980). ***, **, and * denote statistical significance at the 1%, 5% and 10% levels respectively.*

Table 4: Investor Information Demand and Market Ambiguity around Earnings Announcements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DISAGREE[-3, 0]	0.205***	0.0558***	0.0424**	0.0441**	0.0507***	0.0424**	0.0424**	0.0426**	0.0453**
	(10.80)	(2.95)	(2.28)	(2.32)	(2.67)	(2.27)	(2.27)	(2.28)	(2.44)
SIZE		0.0279***	0.0313***	0.0324***	0.0309***	0.0157***	0.0157***	0.0157***	0.0148***
		(20.78)	(22.39)	(22.42)	(20.56)	(8.99)	(8.99)	(9.03)	(8.59)
RET		1.890***	1.093***	1.118***	1.063***	1.215***	1.217***	1.208***	1.457***
		(10.97)	(5.56)	(5.48)	(5.22)	(6.07)	(6.08)	(6.07)	(5.78)
TURNOVER			0.0182***	0.0196***	0.0211***	0.0136***	0.0136***	0.0137***	0.0149***
			(11.89)	(12.07)	(13.15)	(9.85)	(9.84)	(9.88)	(10.69)
ABS_UE			0.00522	0.00945	0.00845	0.00679	0.00677	0.00666	0.00793
			(0.85)	(1.46)	(1.31)	(1.06)	(1.06)	(1.04)	(1.22)
DISPERSION				-0.0513***	-0.0573***	-0.0548***	-0.0549***	-0.0552***	-0.0514***
				(-2.85)	(-3.21)	(-3.02)	(-3.03)	(-3.04)	(-2.81)
INST_OWNERS					-0.0976***	-0.110***	-0.110***	-0.110***	-0.116***
					(-3.91)	(-4.40)	(-4.40)	(-4.42)	(-4.62)
NUM_ANALYSTS						0.0103***	0.0104***	0.0103***	0.0103***
						(10.94)	(10.97)	(10.78)	(10.76)
TOP4_AUDITOR							-0.00527	-0.00468	-0.00398
							(-0.55)	(-0.49)	(-0.42)
DISC_ACCRUALS								0.0349	0.0364
								(1.24)	(1.28)
SPREAD									-0.448**
									(-2.56)
Constant	-0.0995***	-0.284***	-0.422***	-0.439***	-0.367***	-0.304***	-0.299***	-0.302***	-0.290***
	(-3.37)	(-8.53)	(-10.73)	(-10.84)	(-8.06)	(-7.22)	(-6.90)	(-6.94)	(-6.63)
Observations	20947	20947	20947	20947	20947	20947	20947	20947	20947
Adj-R^2	0.024	0.049	0.056	0.059	0.059	0.071	0.071	0.071	0.071

Table 4 presents coefficients estimates from the following regression model:

$ABN\_SVI = b_0 + b_1*DISAGREE[-3, 0] + b_2*SIZE + b_3*RET + b_4*TURNOVER + b_5*ABS\_UE + b_6*DISPERSION + b_7*INST\_OWNERS + b_8*NUM\_ANALYSTS + b_9*TOP4\_AUDITOR + b_{10}*DISC\_ACCRUALS + b_{11}*SPREAD + e$

Variable definitions are provided in the Appendix. WEEKDAY_DUMMIES for Tuesday, Wednesday, Thursday, and Friday are included.

*Note: All columns include fixed effects for weekday, month, year, and industry. Numbers in parentheses are t-statistics calculated using robust standard errors as per White (1980). ***, **, and * denote statistical significance at the 1%, 5% and 10% levels respectively.*

Table 5: Investor Information Demand and Market Ambiguity around Earnings Announcements: Earnings Announcement Days Split into Sub-samples Based on Key Firm Characteristics

	INST_OWNERS		NUM_ANALYSTS		TOP4_AUDITOR		DISC_ACCRUALS	
	Low	All Others	High	Low	Big-4	Non-Big-4	High Quality	Low Quality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DISAGREE[-3, 0]	0.0964***	-0.00263	0.0967***	-0.00644	0.0587***	-0.0352	0.0538**	0.0336
	(3.57)	(-0.10)	(3.17)	(-0.32)	(2.98)	(-0.65)	(2.42)	(1.15)
SIZE	0.0135***	0.0163***	0.0283***	0.0154***	0.0129***	0.0294***	0.00970***	0.0214***
	(5.71)	(6.07)	(10.31)	(6.60)	(7.25)	(4.97)	(4.44)	(8.30)
RET	1.884***	1.126***	2.053***	0.380*	1.392***	2.004***	1.038***	1.772***
	(5.18)	(3.21)	(4.90)	(1.83)	(5.20)	(2.88)	(3.94)	(4.20)
TURNOVER	0.0171***	0.0130***	0.0280***	0.00794***	0.0151***	0.0128***	0.00900***	0.0220***
	(8.22)	(6.95)	(11.70)	(4.85)	(10.21)	(3.21)	(5.19)	(9.84)
ABS_UE	0.0208**	-0.00166	0.00651	0.00177	-0.00983*	0.136***	0.0217**	-0.00446
	(2.25)	(-0.18)	(0.51)	(0.35)	(-1.92)	(3.53)	(2.15)	(-0.56)
DISPERSION	-0.108***	0.0325	-0.102***	0.0722**	-0.0511***	0.0651	-0.0661***	-0.0220
	(-3.97)	(1.42)	(-5.14)	(2.02)	(-2.70)	(0.91)	(-3.46)	(-0.66)
INST_OWNERS	-0.186***	0.148	-0.107**	-0.0118	-0.116***	-0.0201	-0.0748***	-0.156***
	(-4.52)	(1.35)	(-2.13)	(-0.49)	(-4.35)	(-0.29)	(-2.81)	(-3.77)
NUM_ANALYSTS	0.0142***	0.00613***	0.0188***	-0.00518***	0.0112***	0.00165	0.00521***	0.0136***
	(11.59)	(3.95)	(11.23)	(-3.85)	(11.06)	(0.65)	(5.08)	(9.48)
TOP4_AUDITOR	-0.0217	0.00390	0.0118	-0.0195*			-0.00641	0.00157
	(-1.48)	(0.34)	(0.77)	(-1.68)			(-0.49)	(0.12)
DISC_ACCRUALS	0.0771**	-0.000344	0.0653	-0.0299	0.0346	0.0502	-0.837***	-0.0141
	(2.46)	(-0.01)	(1.58)	(-1.14)	(1.07)	(0.97)	(-2.59)	(-0.41)
SPREAD	-0.752***	-0.203	-0.763**	0.211	-0.405**	-0.690	-0.178	-0.656**
	(-3.16)	(-0.80)	(-2.49)	(1.40)	(-2.16)	(-1.53)	(-1.02)	(-2.18)
Constant	-0.284***	-0.438***	-0.795***	-0.0579	-0.276***	-0.347***	-0.171***	-0.384***
	(-4.35)	(-3.34)	(-8.51)	(-1.45)	(-6.20)	(-3.47)	(-2.69)	(-5.83)
Observations	10542	10405	11354	9593	18544	2403	10486	10461
Adj-R2	0.116	0.034	0.100	0.018	0.072	0.136	0.042	0.093

Table 5 presents coefficients estimates from the following regression model:

$$ABN\_SVI = b_0 + b_1*DISAGREE[-3, 0] + b_2*SIZE + b_3*RET + b_4*TURNOVER + b_5*ABS\_UE + b_6*DISPERSION + b_7*INST\_OWNERS + b_8*NUM\_ANALYSTS + b_9*TOP4\_AUDITOR + b_{10}*DISC\_ACCRUALS + b_{11}*SPREAD + e$$

Variable definitions are provided in the Appendix. WEEKDAY_DUMMIES for Tuesday, Wednesday, Thursday, and Friday are included. Column (1) shows regression results for the subsample of earnings announcement days for companies with low institutional ownership (INST_OWNERS<Median), while column (2) shows regression results for the remaining observations from earnings announcement subsample. Column (3) shows regression results for the subsample of earnings announcement days for companies with high analyst following (NUM_ANALYSTS>Median), while column (4) shows regression results for the remaining observations from earnings announcement subsample. Column (5) shows regression results for the subsample of earnings announcement days for companies with a top-4 auditor (TOP4_AUDITOR=1), while column (6) shows regression results for the remaining observations from earnings announcement subsample. Thus, Column (5) & (6) exclude TOP4_AUDITOR indicator variable as a control. Column (7) shows regression results for the subsample of earnings announcement days for companies with low absolute discretionary accruals (DISC_ACCRUALS<Median), i.e., high quality of reported earnings, while column (8) shows regression results for the remaining observations from earnings announcement subsample.

*Note: All columns include fixed effects for weekday, month, year, and industry. Numbers in parentheses are t-statistics calculated using robust standard errors as per White (1980). ***, **, and * denote statistical significance at the 1%, 5% and 10% levels respectively.*

Table 6 Panel A: Investor Information Demand and Market Ambiguity on Net Selling Days

	(1)	(2)	(3)	(4)	(5)
DISAGREE[-3, 0]	0.0112***	0.0106**	0.00970**	0.0114**	0.0107**
	(2.63)	(2.37)	(2.18)	(2.56)	(2.38)
SIZE		0.000936***	0.00157***	0.00306***	0.00323***
		(3.31)	(5.35)	(8.09)	(8.40)
RET		1.066***	0.857***	0.827***	0.728***
		(13.93)	(10.87)	(10.63)	(8.81)
TURNOVER			0.00318***	0.00419***	0.00391***
			(10.59)	(13.76)	(12.57)
INST_OWNERS				-0.0269***	-0.0252***
				(-4.32)	(-4.12)
NUM_ANALYSTS				-0.00118***	-0.00119***
				(-7.88)	(-7.89)
TOP4_AUDITOR				-0.00126	-0.00133
				(-0.53)	(-0.56)
DISC_ACCRUALS				0.00117	0.000846
				(0.25)	(0.18)
SPREAD					0.130**
					(2.55)
TUESDAY	-0.00558**	-0.00559**	-0.00662***	-0.00683***	-0.00684***
	(-2.48)	(-2.48)	(-2.94)	(-3.04)	(-3.05)
WEDNESDAY	-0.00915***	-0.00906***	-0.0101***	-0.0107***	-0.0107***
	(-4.06)	(-4.01)	(-4.47)	(-4.77)	(-4.78)
THURSDAY	-0.00581***	-0.00625***	-0.00712***	-0.00739***	-0.00756***
	(-2.60)	(-2.80)	(-3.19)	(-3.32)	(-3.40)
FRIDAY	-0.00529**	-0.00429*	-0.00520**	-0.00545**	-0.00554**
	(-2.35)	(-1.90)	(-2.30)	(-2.43)	(-2.46)
Constant	0.0614***	0.0406***	0.0202***	0.0331***	0.0303***
	(8.78)	(5.40)	(2.61)	(3.42)	(3.13)
Observations	227905	227905	227905	227905	227905
Adj-R^2	0.007	0.009	0.009	0.010	0.010

Panel A of Table 6 presents coefficients estimates from the following regression model:

$$ABN\_SVI = b_0 + b_1*DISAGREE[-3, 0] + b_2*SIZE + b_3*RET + b_4*TURNOVER + b_5*INST\_OWNERS + b_6*NUM\_ANALYSTS + b_7*TOP4\_AUDITOR + b_8*DISC\_ACCRUALS + b_9*SPREAD + b_{10}*DUMMIES + e$$

Variable definitions are provided in the Appendix.

*Note: All columns include fixed effects for weekday, month, year, and industry. Numbers in parentheses are t-statistics calculated using robust standard errors as per White (1980). ***, **, and * denote statistical significance at the 1%, 5% and 10% levels respectively.*

Panel B: Investor Information Demand and Market Ambiguity on Net Selling days around Earnings Announcements

	(1)	(2)	(3)	(4)	(5)
DISAGREE[-3, 0]	0.224***	0.0816***	0.0705**	0.0637**	0.0652**
	(8.05)	(2.96)	(2.56)	(2.38)	(2.44)
SIZE		0.0262***	0.0310***	0.0134***	0.0130***
		(14.97)	(16.38)	(6.03)	(5.81)
RET		1.572***	0.738***	0.817***	0.931***
		(7.55)	(3.00)	(3.39)	(3.27)
TURNOVER			0.0207***	0.0153***	0.0159***
			(9.55)	(8.18)	(8.33)
ABS_UE			0.0163*	0.0122	0.0127
			(1.84)	(1.40)	(1.44)
DISPERSION			-0.0280	-0.0365	-0.0346
			(-0.95)	(-1.24)	(-1.17)
INST_OWNERS				-0.140***	-0.143***
				(-4.15)	(-4.20)
NUM_ANALYSTS				0.0104***	0.0104***
				(8.21)	(8.21)
TOP4_AUDITOR				0.00529	0.00541
				(0.44)	(0.45)
DISC_ACCRUALS				0.0345	0.0350
				(0.90)	(0.92)
SPREAD					-0.204
					(-1.01)
Constant	-0.0924*	-0.275***	-0.462***	-0.303***	-0.298***
	(-1.90)	(-5.09)	(-7.27)	(-4.60)	(-4.49)
Observations	10620	10620	10620	10620	10620
Adj-R^2	0.025	0.047	0.058	0.073	0.073

Panel B of Table 6 presents coefficients estimates from the following regression model:

$$ABN\_SVI = b_0 + b_1*DISAGREE[-3, 0] + b_2*SIZE + b_3*RET + b_4*TURNOVER + b_5*ABS\_UE + b_6*DISPERSION + b_7*INST\_OWNERS + b_8*NUM\_ANALYSTS + b_9*TOP4\_AUDITOR + b_{10}*DISC\_ACCRUALS + b_{11}*SPREAD + e$$

Variable definitions are provided in the Appendix. WEEKDAY_DUMMIES for Tuesday, Wednesday, Thursday, and Friday are included.

*Note: All columns include fixed effects for weekday, month, year, and industry. Numbers in parentheses are t-statistics calculated using robust standard errors as per White (1980). ***, **, and * denote statistical significance at the 1%, 5% and 10% levels respectively.*