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Information search in times of market uncertainty: an examination of aggregate and disaggregate uncertainty

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Information search in times of market uncertainty: an examination of aggregate and disaggregate uncertainty

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Abstract

Purpose – This study explores the association between individual investor information demand and two measures of market uncertainty – aggregate market uncertainty and disaggregate industry-specific market uncertainty. It extends the literature by being the first to empirically examine investor information demand and disaggregate market uncertainty.

Design/methodology/approach – This paper constructs a measure of information search by using the Google Search Volume Index and computes measures of aggregate and disaggregate market uncertainty using institutional investors' trading data from Ancerno Ltd. The relation between market uncertainty, as measured by trading disagreements among institutional investors, and information search is analyzed using an OLS (Ordinary Least Squares) regression model.

Findings – This paper finds that individual investor information demand is significantly and positively correlated with aggregate market uncertainty but not associated with disaggregated industry uncertainty. The findings suggest that individual investors may not fully incorporate all relevant uncertainty information and that ambiguity-related market pricing anomalies may be more associated with disaggregate market uncertainty.

Research limitations/implications – This study presents an examination of aggregate and disaggregate measures of market uncertainty and individual investor demand for information, shedding light on the efficiency of the market in incorporating information. A limitation of our study is that our data for market uncertainty is based on investor trading disagreement from Ancerno, Ltd. which is only available till 2011. However, we believe the implications are generalizable to the current time period.

Practical implications – This study provides the first concurrent empirical assessment of investor information search and aggregate and disaggregate market uncertainty. Prior research has separately examined information demand in these two types of market uncertainty. Thus, this study provides information to investors regarding the importance of assessing disaggregate component measures of the market.

Originality/value – This paper is the first to empirically examine investor information search and disaggregate market uncertainty. It also employs a unique data set and method to determine disaggregate, and aggregate, market uncertainty.

Keywords Market ambiguity, Uncertainty, Google Search Index, Institutional investors

Paper type Research paper

1. Introduction

Research provides evidence that uncertainty [1] surrounding financial information affects equity markets by influencing share prices, price fluctuations, postearnings announcement

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drift and stock returns (Jiang *et al.*, 2005; Zhang, 2006; Caskey, 2009). Investor aversion to uncertainty has been blamed, at least in part, for the seeming failure of the market to incorporate all relevant information, leading to adverse market effects (Dow and Werlang, 1992; Cao *et al.*, 2005; Epstein and Schneider, 2010). Research also finds that this behavioral bias against ambiguity generally increases individual investor demand for information (Mele and Sangiorgi, 2015; Hasan *et al.*, 2018).

Guidolin and Rinaldi (2010) analytically assess the 2007–2008 financial crisis and separate overall market uncertainty from the uncertainty associated with the underlying individual assets. They conclude that trading breaks down when the uncertainty related to the disaggregated individual components exceeds that of the aggregate market. In addition, the analytical models of Peng and Xiong (2006) reveal that individual investors tend to pay more attention to information regarding the broader market than to detailed, firm-specific information. Further, Caskey (2009) shows analytically that ambiguity-averse investors often prefer aggregate information signals to disaggregate signals even when disaggregate signals may be more informative. The nexus of these analytical studies is that market uncertainty can be separated into aggregate and disaggregate components and that investors appear to value and pay more attention to aggregate information than to specific disaggregate information. In addition, Hasan *et al.* (2018) find empirically that investors increase their information search in response to increased aggregate market uncertainty; however, research has yet to empirically examine investor information search in the context of disaggregate market uncertainty.

Accordingly, our study is the first to empirically examine the association between individual investor information demand and disaggregate market uncertainty. Specifically, we examine the intersection of Guidolin and Rinaldi's (2010) analytical work that separates an overall assessment of market uncertainty from uncertainty assessments of individual market components, Caskey's (2009) analytical work that finds ambiguity-averse investors may prefer aggregate information over more informative disaggregate information, Peng and Xiong's (2006) analytical work on investor attention to overall market information versus disaggregate component information and Hasan *et al.*'s (2018) empirical work on investor information search during overall market uncertainty. In order to do so, we present a novel measure of disaggregate industry-specific market uncertainty, allowing us to assess whether individual investor information search is differentially associated with aggregate market uncertainty or disaggregated industry-specific market uncertainty. Our study has implications for understanding investor information demand in times of market ambiguity – a timely and relevant topic given the uncertainty experienced with the financial crises and COVID-19 world health crisis.

Ambiguity is a result of unknown factors influencing a firm's information environment that are unable to be fully identified or estimated, even by sophisticated, informed investors (Knight, 1921; Epstein and Wang, 1994; Jiang *et al.*, 2005). Importantly, to test whether investors react to ambiguity in the market requires a proxy for ambiguity. While prior researchers have utilized disagreement among forecasters, or forecast dispersion as proxies for market uncertainty, we follow Hasan *et al.* (2018) and measure market ambiguity based on the trading disagreement of institutional investors. Specifically, we interpret institutional investors' trading patterns as reflective of market ambiguity when there is disagreement on the side (i.e. buy versus sell) of trading activity in the equity of a particular firm. Institutional investors are informed, sophisticated investors who have established connections, ability and resources to evaluate a firm's business operations and opportunities to accurately assess firm risk based on known factors. Therefore, disagreement in trading behavior among this investor group is likely due more from unseen factors and is reflective of higher levels of market ambiguity. We base our market ambiguity proxies on actual trading disagreement, which we believe provides a more direct and accurate reflection of the level of market ambiguity than other commonly used proxies (Jiang *et al.*, 2005; Zhang, 2006).

The aggregate market is comprised of firms operating in various industry sectors. We measure disaggregate market ambiguity by assessing the trading disagreement of industry-specialized institutional investors. We expect the trading behavior of industry-specialized institutional investors to reflect their superior understanding of a specific industry's market and prospects and to be better informed of the components of market information that affect that industry (Kacperczyk *et al.*, 2005) [2]. Therefore, trading disagreements among industry-specialized institutional investors are likely reflective of actual industry-specific ambiguity. We measure general aggregate market ambiguity by assessing the trading disagreement of nonspecialized institutional investors. We then examine how individual investor information demand surrounding earnings announcements, an event typically associated with high information demand, is associated with aggregate market and disaggregated industry ambiguity [3]. Following prior research (Drake *et al.*, 2012; Hasan *et al.*, 2018), we measure information demand from individual investors using the Daily Google Search Volume Index (SVI).

Our results for 2006–2010 earnings announcements provide evidence consistent with Peng and Xiong (2006) that individual information demand is positively related to aggregate market ambiguity but is not significantly associated with disaggregate market ambiguity. Our findings suggest that individual investors may not pay adequate attention to industry-specific ambiguity, and thus, the market may not fully incorporate all uncertainty information, and that ambiguity-related market pricing anomalies may be more related to disaggregate market uncertainty than aggregate market uncertainty (Cao *et al.*, 2005; Epstein and Schneider, 2010; Guidolin and Rinaldi, 2010). Our analysis includes control for factors that may influence information demand such as earnings surprises and abnormal returns, along with proxies for market uncertainty identified from prior research.

Our study extends the literature on demand for information under market uncertainty in several important ways. First, our work contributes to the literature seeking to understand the impact of information uncertainty on equity markets, which is linked to market anomalies such as postearnings announcement drift, unexpected share price swings, overreaction to accounting accruals and equity market breakdowns (Zhang, 2006; Guidolin and Rinaldi, 2010; Mele and Sangiorgi, 2015). We are the first, of which we are aware, to concurrently empirically examine investor information search and its association with both aggregate and disaggregate market ambiguity. We also develop a novel proxy for disaggregate market uncertainty based on trading behavior of industry specialist institutional investors. Finally, we add to research examining individual information demand through Internet channels.

2. Literature review and hypotheses

2.1 Market uncertainty

This study examines information acquisition in the context of market uncertainty, which we distinguish from risk using a classic economic perspective. As explained by Knight (1921), risk applies to situations where we do not know the outcome of a given situation but can accurately measure the odds of various outcomes. Ambiguity or uncertainty, on the other hand, applies to situations where we cannot know all the information we need in order to determine all outcomes. Therefore, while calculating risk is possible, directly calculating uncertainty is not possible (Knight, 1921). Market uncertainty refers to the interpretation of the information environment of the firm in the market. It is what Jiang *et al.* (2005) refer to as information uncertainty and Hasan *et al.* (2018) refer to as market ambiguity.

Prior research offers market uncertainty as an explanation for market anomalies and trading breakdowns (Bartov *et al.*, 2000; Epstein and Schneider, 2010; Guidolin and Rinaldi, 2013). For example, Jiang *et al.* (2005) study the relation between information uncertainty and stock returns and provide evidence that firms with an environment of high information uncertainty have lower returns and their stock prices adjust more slowly to the release of earnings information. Similarly, Zhang (2006) suggests that market uncertainty explains stock price under reaction to publicly released information such as earnings announcements and analyst forecast revisions. He posits that "greater information uncertainty produces relatively higher (lower) stock returns following bad (good) news" (Zhang, 2006, p. 109). Assigning stocks to portfolios, based on the level of uncertainty in the firm's information environment, and examining portfolio returns, he provides evidence that the market does not fully react to all available information and concludes that this incomplete reaction is associated with the level of market uncertainty.

Of particular relevance to our study is the theoretical work by Guidolin and Rinaldi (2010) who, after the 2007–2008 financial crisis, develop a model of trading and pricing risky assets under uncertainty that includes both aggregate (market wide) and disaggregate (asset-specific) uncertainty. They extend their model to include ambiguity aversion and conclude that market failures due to ambiguity aversion may occur when the combined ambiguity related to the disaggregate components exceeds the ambiguity of the overall market. These authors are some of the first to address the possible disparity between systemic uncertainty in the aggregate market, contrasted with the sum of the uncertainty of the disaggregated market components. Importantly, they also demonstrate that aggregate and disaggregate market uncertainty are two different constructs that can be separately identified and assessed.

2.2 Market uncertainty and information demand

Fama (1970) described market equilibrium as occurring when stock prices fully reflect all available information. However, the presence of uncertainty has been found to hinder market participants from fully incorporating all available information (Dow and Werlang, 1992; Cao *et al.*, 2005; Epstein and Schneider, 2010) calling into question the ability of the market to obtain equilibrium. Consistent with investors not fully incorporating all available information is Caskey (2009) who shows analytically that ambiguity-averse investors often prefer aggregate information signals to disaggregate signals even when disaggregate signals may be more informative. Therefore, with ambiguity-averse investors in the market, equilibrium prices may fail to impound all publicly available information, even if the information is diagnostic. Caskey (2009) argues that this finding provides an explanation for market anomalies such as postearnings announcement drift (Bernard and Thomas, 1989) and market price overreactions to accrual anomalies (Zhang, 2007).

In addition, Peng and Xiong (2006) analytically examine the relation between investor cognitive attention and information search on asset-price dynamics. They find that when investor attention is limited, investors attend to and process more information regarding the broader aggregate market than firm-specific, disaggregate information. They argue that their findings help explain important features observed in equity return co-movements that are otherwise difficult to explain with standard rational expectations models. Hence, even without the presence of uncertainty, investor attention is biased toward aggregate market information compared to disaggregate information, again suggesting that investors do not fully attend to, and equally process, all available information even if the information is directly relevant to the specific evaluation being performed (i.e. pricing a specific firm's equity).

While market ambiguity has not typically been included in traditional asset-pricing models, Mele and Sangiorgi (2015) propose a model that includes uncertainty. They conclude that uncertainty-averse investors will attempt to reduce their uncertainty by demanding more information. Consistent with this is the empirical work of Drake *et al.* (2012) who examine the factors influencing individual investor information demand around earnings announcements, a time of historically high information demand. They find a positive relationship between information demand and a firm's information asymmetry, suggesting information demand increases with uncertainty surrounding the firm [4]. Building on these studies, Hasan *et al.* (2018) consider the influence of market uncertainty on investor demand for information. Specifically, they examine a firm's information environment, arguing that individual investors will demand more information when confronted with greater market ambiguity, particularly during earnings announcement periods. Using institutional investor disagreement as a proxy for aggregate market uncertainty, Hasan *et al.* (2018) conclude that when faced with greater market uncertainty, individual retail investors increase their search for information on companies that have high quality, reliable financial information.

Hence, Hasan *et al.* (2018) demonstrate that increased market uncertainty is positively associated with investor information search. While Hasan *et al.* (2018) examine the association between investor information search and aggregate market uncertainty, they do not assess whether information search is associated with disaggregate market uncertainty (Guidolin and Rinaldi, 2010). Accordingly, we extend the literature to simultaneously examine the association between investor information search and (1) aggregate market uncertainty and (2) disaggregate market uncertainty.

Based on the analytical results of Guidolin and Rinaldi (2010) who demonstrate that aggregate market uncertainty and disaggregate market uncertainty are distinct constructs, and the analytical investor attention to information work of Peng and Xiong's (2006), combined with the empirical results of Hasan *et al.* (2018), we expect that individual investor information search would be greater when aggregate market uncertainty increases, and less or not significantly associated with disaggregate market uncertainty. Thus, since uncertainty related to disaggregate components of the market is informative to understand overall market dynamics, we empirically test whether investors attend to and process more aggregate market information than specific, disaggregate information, expecting that individual investor information search will reflect a pattern of reacting more when there is aggregate market uncertainty than when there is disaggregate market uncertainty. Since earnings announcements are associated with increased information search (Drake *et al.*, 2012; Hasan *et al.*, 2018), we utilize earnings announcements in order to empirically examine our hypotheses. Therefore, we examine our two main hypotheses (in null form):

H1. Individual investor information search around earnings announcements is not associated with aggregate market uncertainty.

H2. Individual investor information search around earnings announcements is not associated with disaggregate market uncertainty.

3. Sample and data

To obtain data on individual investor information demand, we follow prior research (Drake *et al.*, 2012; Da *et al.*, 2011; Hasan *et al.*, 2018) and download the Google SVI from *Google Trends* (previously *Google Insights for Search*) for the S&P 500 firms for the period from 2006 to 2010. Our sample consists of approximately 80% of the total US stock market as measured by market value [5]. Following prior research, we employ the SVI as a proxy for individual investors' demand for firm information. Google constructs the daily SVI for each term or string of terms searched using their web crawler software. We then search Google SVIs for a firm's TICKER symbol as the proxy for firm information demand since searching on a ticker symbol is "more likely to reflect searches for financial information than searches for nonfinancial information" (Drake *et al.*, 2012, p. 1009). All TICKER symbol searches are used even those resembling common words such as "CAT," the ticker symbol for Caterpillar Inc. While this poses a limitation to our method by potentially introducing noise in our information demand proxy, any noise introduced by picking up non-firm-related searches is likely to only weaken our ability to find our hypothesized relationships [6].

Google search data can be extracted for various windows of time. Following prior studies, we extract the daily search data and then scale our daily data by the maximum number of searches for that TICKER symbol within that calendar quarter. Specifically, we assign the date on which the search term had the maximum number of searches during the quarter an index value of 100 and then index the searches on other days of the quarter against that maximum. Extracting daily SVI by calendar quarter ensures we have at least one day for that calendar quarter when SVI is 100. Thus, SVIs for our study range from 0 to 100.

We compute our measures of general aggregate market ambiguity and disaggregate market ambiguity by using the daily institutional investors trading data from *Ancerno Ltd*. The *Ancerno Ltd.* database identifies each institutional investor with a unique investor code (*clientcode*) and investor-type identifier, enabling us to compute fund-level industry specialization metrics. Trade information such as company identifiers (e.g. TICKER symbol), execution date, share volume, share price and the direction of the trade (buy or sell) are included in the database. We include firms in our sample if more than three institutional investors in the *Ancerno Ltd.* database trade the company during the quarter. To protect privacy of their clients, *Ancerno Ltd.* stopped reporting unique investment fund identifiers (*clientcode*) in 2011. Google SVI data are readily available beginning in 2006. Hence, we begin the study in 2006 and stop with the last complete year of full data availability – 2010. After merging the *Ancerno Ltd.*, *Google Trends*, *CRSP*, *Compustat*, *Thomson Reuters* and *IBES* databases, the final sample consists of 1,139 distinct trading days, 423 distinct firms and 15,426 quarterly earnings announcement days during 2006–2010.

4. Research design

4.1 Google Search Volume Index

In order to compute the information demand from individual investors for each sample firm, 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 weekday t minus the average SVI for the same ticker on the same weekday over the prior 10 weeks, scaled by the average SVI for the same ticker on the same weekday over the prior 10 weeks. Thus, *ABN_SVI* represents the percentage change for information demand for each firm i on any given day t compared to the prior 10 weeks of the same weekday. Specifically,

$$ABN\_SVI_{i,t} = \frac{SVI_{i,t} - \sum_{w=-10}^{-1} SVI_{i,w}/10}{\sum_{w=-10}^{-1} SVI_{i,w}/10} \tag{1}$$

where $SVI_{i,t}$ is firm i's Google SVI on weekday t and $SVI_{i,w}$ is the same firm i's Google SVI on the same weekday over the prior week w (e.g. $w = -10$ means the same weekday 10 weeks before day t).

4.2 Industry trading specialization

Prior research has demonstrated that funds that concentrate in fewer industries earn higher returns than more diversified funds (Kacpercyzk *et al.*, 2005; Huij and Derwall, 2011) and that the industries chosen to specialize in are those that the fund believes they have an information advantage (Kacpercyzk *et al.*, 2005). Accordingly, instead of estimating industry concentrations (Huij and Derwall, 2011), we use actual *Ancerno Ltd.* trading data and expect that the volume of trading in an industry is largely representative of the fund's level of specialization in that industry. Therefore, we form an industry specialization metric,

$SPECMET_{f,i}$, computed as the ratio of each fund's yearly dollar trading volume (buys plus sells) in the two-digit industry, scaled by the fund's total dollar trading volume in that year [7]. Specifically,

$$SPECMET_{f,i} = \frac{\sum_{f,i}(BUY_{f,i} + SELL_{f,i})}{\sum_{f}(BUY_{f} + SELL_{f})} \tag{2}$$

where $BUY_{f,i}$ ($SELL_{f,i}$) is dollar value of shares purchased (sold) by the *Ancerno* fund *f* in industry *i* during the year, and BUY_f ($SELL_f$) is total dollar value of shares purchased (sold) by the *Ancerno* fund *f* during the same year [8]. Thus, our industry specialization metric represents the yearly percentage of total dollar trading activity of each fund in each two-digit SIC industry [9].

We then rank the *Ancerno Ltd.* funds based on the specialization metric, $SPECMET_{f,i}$, for each industry, in every year and then sort them into three equal groups of high, medium and low industry specialization. We then assign each fund a yearly specialization rank, *SPEC*, in each industry. We code them 1 if they are in the lowest tercile, 2 for the middle tercile and 3 for the most specialized funds in the top tercile of *SPECMET*. We then designate funds in the highest (lowest) specialization group, *SPEC* = 3 (*SPEC* = 1), as industry-specialized (unspecialized) funds and use them to determine disaggregate (aggregate) market uncertainty, as explained next.

4.3 General and specialized market uncertainty

Following prior literature (Chordia and Subrahmanyam, 2004; Hasan *et al.*, 2018), we use the amount of institutional investor buy and sell order imbalance to represent market uncertainty. Specifically, we consider the trading imbalance only among industry specialist funds (*SPEC* = 3) as reflective of industry-specific uncertainty and employ it as our proxy for disaggregate market uncertainty (*DISAGREE_SP*). Similarly, we employ the trading imbalance only among the nonindustry specialist funds (*SPEC* = 1) as reflective of more general market uncertainty and use it as our proxy for aggregate market uncertainty (*DISAGREE_GN*) [10]. We construct our *DISAGREE_SP* and *DISAGREE_GN* proxies as 1 minus the absolute value of order imbalance for firm *i* on day *t* within each *SPEC* group of funds. The order imbalance metric is computed as $(BUY_{i,t} - SELL_{i,t})/(BUY_{i,t} + SELL_{i,t})$, where BUY_{it} ($SELL_{it}$) is total dollar value of shares purchased (sold) by the respective *Ancerno Ltd.* investors in firm *i* on day *t*. Thus, our firm-day market uncertainty measures are computed as:

$$DISAGREE\_SP \Big/ DISAGREE\_GN = 1 - Abs\left(\frac{BUY_{i,t} - SELL_{i,t}}{BUY_{i,t} + SELL_{i,t}}\right) \tag{3}$$

Our measures of market uncertainty have a possible range of 0 (no disagreement) to 1 (perfect disagreement). For example, if total *BUY* = \$60 and total *SELL* = \$40 among the nonspecialized investors, *DISAGREE_GN* = 0.80, suggesting a relatively high level of market uncertainty since investors have a high level of disagreement regarding the information available about firm *i* circulating in the market on day *t*. Finally, we construct our market uncertainty metrics over multiple days by averaging the *DISAGREE_SP* (*DISAGREE_GN*) for the period between day *t-n* and day *t*. Following Hasan *et al.* (2018), we use a four-day average disagreement measure (*DISAGREE[–3,0]_SP or DISAGREE [–3,0]_GN*) for our analyses [11]. We perform our tests using earnings announcements as prior research (Drake *et al.*, 2012) finds that individual investor demand for information is significantly higher during earnings announcements than during other trading days [12].

To explore the relationship between our measures of market uncertainty and individual investor information demand, we follow the empirical models from Drake *et al.* (2012) and Hasan *et al.* (2018). Accordingly, we control for firm size (*SIZE*), institutional ownership (*INST_OWNERSHIP*), abnormal returns (|*ABN_RETURN*|), earnings surprises (*EARN_SURPRISE)*, analyst following (*ANALYST_FOLLOWING)* and dispersion in analyst earnings forecasts (*ANALYST_DISPERSION*). In addition to these control variables, we include factors that potentially explain individual investor demand for information in response to market ambiguity. Therefore, we include an earnings quality measure as determined by discretionary accruals (*ABS_DISC_ACCRUALS)* and an audit quality measure (*TOP4_AUDITOR*) indicating whether the company uses a Big 4 audit firm (KPMG, EY, PWC and Deloitte). Finally, liquidity measures, computed based on firm-level trading volume (*TURNOVER_FIRM*), industry-level turnover (*TURNOVER_IND*), market volatility (*VOLATILITY_MKT*) and the difference between daily bid and ask prices (*SPREAD*), are included as controls. To address our hypotheses, various forms of the following model are estimated. All variables are defined in Appendix.

$$\begin{aligned} ABN\_SVI[0] = {} & b0 + b1{*}DISAGREE[-3,0]\_GN + b2{*}DISAGREE[-3,0]\_SP + b3{*}SIZE \\ & + b4{*}TURNOVER\_FIRM + b5{*}TURNOVER\_IND \\ & + b6{*}VOLATILITY\_MKT + b7{*}|ABS\_RETURN| \\ & + b8{*}EARN\_SURPRISE + b9{*}ANALYST\_DISPERSION \\ & + b10{*}INST\_OWNERSHIP + b11{*}ANALYST\_FOLLOWING \\ & + b12{*}BIG4\_AUDITOR + b13{*}ABS\_DISC\_ACCRUALS \\ & + b14{*}SPREAD + b15{*}DUMMIES + e \end{aligned} \tag{4}$$

The main variables of interest are our measures of market uncertainty *DISAGREE_SP[–3, 0]* and *DISAGREE_GN[–3, 0]*. Based on prior research (Peng and Xiong, 2006; Caskey, 2009; Guidolin and Rinaldi, 2010; Hasan *et al.*, 2018), we expect to find a positive association between information demand (*ABN_SVI[0]*) and aggregate market uncertainty (*DISAGREE_GN[–3, 0]*), and reduced or no significant relationship between investor information demand and disaggregate, industry-specific market uncertainty (*DISAGREE_SP[–3, 0]*).

5. Results

Table 1 presents summary statistics showing that average abnormal demand for information, *ABN_SVI*, as measured by Internet searches around earnings announcements is positive (0.093) on any given earnings announcement day (p-value < 0.01). The average trading disagreement among institutional investors considered generalists and industry specialists around earnings announcements are 0.267 and 0.345, respectively, reflecting a considerable amount of disagreement among these investors [13]. Table 1 also indicates that our sample of firms consists of large companies with an average market capitalization (*MVE*) of $26.5bn having on average 76.1% institutional investor holdings, which is consistent with institutional ownership in the US market for large companies.

Table 2 presents the Pearson correlation coefficients for our variables and provides some understanding of unconditional relations. We find positive correlations, albeit weak, between

Table 1.
Summary statistics

#	Variable	*N*	Mean	Std. dev.	P1	P25	P50	P75	P99
[1]	*ABN_SVI[0]*	15,426	0.093	0.327	−0.722	−0.062	0.028	0.178	1.062
[2]	*ABN_SVI[+1,+3]*	15,426	0.077	0.289	−0.676	−0.052	0.023	0.142	1.039
[3]	*DISAGREE[−3,+0]_GN*	15,426	0.267	0.523	−2.165	0.082	0.263	0.455	2.093
[4]	*DISAGREE[−3,+0]_SP*	15,426	0.345	0.206	−0.091	0.202	0.340	0.479	0.840
[5]	*DISAGREE[−3,+0]_MF*	15,426	0.438	0.172	0.068	0.314	0.437	0.564	0.816
[6]	*DISAGREE[−3,+0]_PF*	15,426	0.319	0.261	−0.457	0.160	0.315	0.468	1.058
[7]	*DISAGREE[−3,+0]_MF_GN*	15,426	0.092	0.159	0.000	0.000	0.000	0.142	0.644
[8]	*DISAGREE[−3,+0]_MF_SP*	15,426	0.328	0.710	−2.129	0.139	0.325	0.511	2.752
[9]	*DISAGREE[−3,+0]_PF_GN*	15,426	0.060	0.105	0.000	0.000	0.000	0.081	0.462
[10]	*DISAGREE[−3,+0]_PF_SP*	15,426	0.222	0.390	−1.081	0.019	0.182	0.386	1.602
[11]	*MVE*	15,426	26.464	38.396	1.041	5.602	13.156	27.064	198.033
[12]	*TURNOVER_FIRM*	15,426	7.118	2.671	1.000	5.000	8.000	10.000	10.000
[13]	*TURNOVER_IND*	15,426	5.403	2.839	1.000	3.000	5.000	8.000	10.000
[14]	*VOLATILITY_MKT*	15,426	24.687	12.688	10.220	16.650	22.100	26.330	69.250
[15]	*|ABN_RETURN|*	15,426	0.023	0.023	0.000	0.006	0.015	0.032	0.086
[16]	*ANALYST_DISPERSION*	15,426	0.068	0.122	0.003	0.016	0.031	0.067	0.817
[17]	*INST_OWNERSHIP*	15,426	0.761	0.141	0.353	0.675	0.775	0.861	1.000
[18]	*ANALYST_FOLLOWING*	15,426	15.121	6.720	3.000	10.000	15.000	19.000	34.000
[19]	*TOP4_AUDITOR*	15,426	0.891	0.312	0.000	1.000	1.000	1.000	1.000
[20]	*ABS_DISC_ACCRUALS*	15,426	0.095	0.153	0.004	0.016	0.042	0.095	0.885
[21]	*SPREAD*	15,426	0.044	0.030	0.009	0.023	0.035	0.055	0.145
[22]	*EARN_SURPRISE*	15,426	0.248	0.469	0.029	0.034	0.095	0.225	2.883

Note(s): This table reports summary statistics for our sample of 15,426 earnings announcement firm-days with available data from Google Trends, Ancerno Ltd., IBES, COMPUSTAT and CRSP between January 1, 2006, and December 31, 2010. Variable definitions are provided in Appendix; We report actual market value of equity (*MVE*) instead of *SIZE*, which is calculated as a decile rank of *MVE*.

Table 2. Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) *ABN_SVI[0]*	1.000										
(2) *ABN_SVI[+1,+3]*	0.647*	1.000									
(3) *DISAGREE[−3+0]_GN*	0.039*	0.034*	1.000								
(4) *DISAGREE[−3+0]_SP*	0.031*	0.025*	0.002	1.000							
(5) *DISAGREE[−3+0]_MF*	0.080*	0.073*	0.060*	0.244*	1.000						
(6) *DISAGREE[−3+0]_PF*	0.052*	0.056*	0.037*	0.073*	0.061*	1.000					
(7) *DISAGREE[−3+0]_MF_GN*	0.192*	0.189*	0.150*	0.098*	0.275*	0.120*	1.000				
(8) *DISAGREE[−3+0]_MF_SP*	0.001	0.001	0.008	0.086*	0.050*	0.001	0.021*	1.000			
(9) *DISAGREE[−3+0]_PF_GN*	0.118*	0.114*	0.101*	0.081*	0.171*	0.153*	0.317*	0.015	1.000		
(10) *DISAGREE[−3+0]_PF_SP*	0.008	0.006	−0.030*	0.079*	0.016	0.132*	0.048*	−0.013	0.038*	1.000	
(11) *SIZE*	0.172*	0.161*	0.083*	0.196*	0.351*	0.134*	0.499*	0.030*	0.337*	0.053*	1.000
(12) *TURNOVER_FIRM*	−0.007	−0.002	0.013	0.022*	−0.003	−0.007	0.020*	−0.031*	0.064*	−0.001	0.015
(13) *TURNOVER_IND*	−0.007	−0.004	0.009	0.031*	−0.005	−0.014	−0.003	−0.016	0.048*	−0.007	0.010
(14) *VOLATILITY_MKT*	−0.004	−0.025*	0.029*	0.003	0.068*	−0.011	0.044*	0.003	0.042*	−0.005	−0.101*
(15) *|ABN_RETURN|*	0.080*	−0.004	−0.008	−0.026*	−0.018	0.003	−0.031*	0.004	0.005	0.003	−0.170*
(16) *ANALYST_DISPERSION*	−0.009	−0.019*	−0.014	0.045*	−0.007	−0.015	−0.022*	0.019*	−0.005	0.024*	−0.009
(17) *INST_OWNERSHIP*	−0.049*	−0.053*	−0.049*	−0.081*	−0.066*	−0.035*	−0.143*	−0.053*	−0.079*	−0.018	−0.380*
(18) *ANALYST_FOLLOWING*	0.215*	0.223*	0.050*	0.109*	0.215*	0.101*	0.361*	0.019*	0.230*	0.040*	0.521*
(19) *TOP_AUDITOR*	0.018	0.012	0.022*	0.011	0.014	0.024*	0.061*	0.001	0.034*	0.027*	0.040*
(20) *ABS_DISC_ACCRUALS*	0.050*	0.055*	0.007	0.033*	0.036*	0.021*	0.105*	0.019	0.075*	0.000	0.101*
(21) *SPREAD*	0.030*	−0.023*	−0.015	−0.035*	−0.029*	−0.022*	−0.085*	0.002	−0.024*	0.002	−0.279*
(22) *EARN_SURPRISE*	−0.006	−0.003	−0.051*	−0.013	−0.075*	−0.041*	−0.103*	0.031*	−0.071*	−0.016	−0.192*

Variables	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(12) *TURNOVER_FIRM*	1.000										
(13) *TURNOVER_IND*	0.864*	1.000									
(14) *VOLATILITY_MKT*	0.008	0.001	1.000								

(*continued*)

Table 2.

Variables	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(15) |*ABN_RETURN*|	−0.032*	−0.030*	0.234*	1.000							
(16) *ANALYST_DISPERSION*	−0.072*	−0.065*	0.081*	0.091*	1.000						
(17) *INST_OWNERSHIP*	−0.019	−0.013	−0.001	0.114*	−0.026*	1.000					
(18) *ANALYST_FOLLOWING*	−0.062*	−0.073*	−0.017	−0.015	0.040*	−0.057*	1.000				
(19) *TOP_AUDITOR*	−0.023*	−0.035*	−0.024*	0.011	−0.020*	−0.014	0.042*	1.000			
(20) *ABS_DISC_ACCRUALS*	0.074*	0.113*	−0.084*	−0.006	−0.031*	−0.029*	0.118*	−0.024*	1.000		
(21) *SPREAD*	−0.040*	−0.036*	0.538*	0.630*	0.166*	0.152*	−0.053*	0.005	−0.047*	1.000	
(22) *EARN_SURPRISE*	0.012	0.007	0.041*	0.125*	0.264*	0.047*	−0.030*	−0.015	−0.003	0.190*	1.000

Note(s): This table reports correlations between our sample variables. Variable definitions are provided in Appendix; *denotes coefficients that are significant at $p < 0.05$

abnormal information demand *(ABN_SVI[0])* and our disagreement measures (*DISAGREE[–3,0]_GN, 0.039; DISAGREE[–3,0]_SP, 0.031; DISAGREE[–3,0]_MF, 0.080* for all mutual funds*; DISAGREE[–3,0]_PF, 0.052* for all pension funds) (see Table 2).

We employ Model (4) to test our hypotheses using the two trading disagreement measures to capture general aggregate market uncertainty *(DISAGREE[–3,0]_GN)* and disaggregate market uncertainty *(DISAGREE[–3,0]_SP)*. First, we include each measure separately in our model to observe individual effects. Consistent with prior research, column 1 of Table 3 reveals that individual investor information demand around earnings announcements is positively associated with aggregate market uncertainty as reflected in the trading disagreements among generalist funds (0.015, $p < 0.01$). However, there is no significant association between individual investor information demand and disaggregate market uncertainty as reflected in the trading disagreements among the specialist funds reported in Column 2 (0.009, $p > 0.10$). When both measures of market uncertainty are included in the same regression (Column 3), we continue to find that aggregate market uncertainty *(DISAGREE[–3,0]_GN)* is positive and significant (0.015, $p < 0.01$), but disaggregate market uncertainty *(DISAGREE[–3,0]_SP)* is not significantly associated with individual investor information demand (0.009, $p > 0.10$) [14].

These results reject H1 as we find that individual investors significantly increase information search behavior when there is increased aggregate market uncertainty. Our finding for aggregate market uncertainty is consistent with prior research (Drake *et al.*, 2012; Hasan *et al.*, 2018) and suggests that investors increase their information needs when aggregate market uncertainty increases. In contrast, our results provide support for H2 since

Variables	(1) *ABN_SVI[0]*	(2) *ABN_SVI[0]*	(3) *ABN_SVI[0]*
DISAGREE[–3,+0]_GN	0.015*** (3.028)		0.015*** (3.016)
DISAGREE[–3,+0]_SP		0.009 (0.495)	0.009 (0.489)
SIZE	0.017*** (5.693)	0.017*** (5.440)	0.017*** (5.540)
TURNOVER_FIRM	0.014*** (3.621)	0.014*** (3.659)	0.014*** (3.647)
TURNOVER_IND	0.002 (0.720)	0.002 (0.716)	0.002 (0.694)
VOLATILITY_MKT	−0.000 (–1.362)	−0.000 (–1.324)	−0.000 (–1.476)
|ABN_RETURN|	0.871*** (3.370)	0.874*** (3.365)	0.870*** (3.357)
EARN_SURPRISE	0.006 (0.858)	0.005 (0.677)	0.006 (0.821)
ANALYST_DISPERSION	−0.098 (–1.714)	−0.099 (–1.678)	−0.100 (–1.715)
INST_OWNERSHIP	−0.119** (–2.574)	−0.121** (–2.582)	−0.120** (–2.594)
ANALYST_FOLLOWING	0.007** (2.548)	0.006** (2.558)	0.006** (2.571)
TOP_AUDITOR	0.011 (0.584)	0.012 (0.604)	0.011 (0.577)
ABS_DISC_ACCRUALS	0.011 (0.285)	0.010 (0.259)	0.011 (0.269)
SPREAD	−0.125 (–0.520)	−0.140 (–0.588)	−0.134 (–0.564)
Constant	−0.316*** (–4.567)	−0.320*** (–4.459)	−0.322*** (–4.480)
Observations	15,426	15,426	15,426
Adjusted *R*-squared	0.0983	0.0980	0.0986

Note(s): This table shows the association between investor information demand and market ambiguity around earnings announcements by using the following regression model; *ABN_SVI[0] = b0 + b1*DISAGREE[-3,0]_GN + b2*DISAGREE[-3,0]_SP + b3*SIZE + b4*TURNOVER_FIRM + b5*TURNOVER_IND + b6*VOLATILITY_MKT + b7*|ABS_RETURN| + b8*EARN_SURPRISE + b9*ANALYST_DISPERSION + b10*INST_OWNERSHIP + b11*ANALYST_FOLLOWING + b12*BIG4_AUDITOR + b13*ABS_DISC_ACCRUALS + b14*SPREAD + b15*DUMMIES + e*; Variables are defined in Appendix. All models include fixed effects for weekday, month, year and industry. Numbers in parentheses are *t*-statistics calculated using robust standard errors as per White (1980). Standard errors are also clustered by industries. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

Table 3. Market ambiguity and information search around earnings announcements

we find that individual investors do not significantly increase their information search behavior around earnings announcements when there is greater disaggregate market uncertainty. Our empirical findings are consistent with the analytical work of Peng and Xiong (2006) and Caskey (2009) who find investors pay less attention to disaggregated information compared to aggregate market information. Our extension to an empirical setting with uncertainty regarding the aggregate market and the disaggregate market reinforces these earlier results. In sum, our findings indicate that the type of market uncertainty, aggregate versus disaggregate, influences investor behavior and supports the concept of differences in information demand in these two market contexts by individual investors.

The results in Column 3 of Table 3 also reveal that investors demand more information for larger firms (*SIZE* coefficient of 0.017, $p < 0.01$), firms with higher share turnover (*TURNOVER_FIRM* coefficient of 0.014, $p < 0.01$), firms with higher absolute value of abnormal returns (|*ABN_RETURN*| coefficient of 0.870, $p < 0.01$) and those with greater analyst following (*ANALYST_FOLLOWING* coefficient of 0.006, $p < 0.01$). Individual investors demand less information when institutional ownership is high (*INST_OWNERSHIP* coefficient of −0.120, $p < 0.05$), possibly indicating fewer actual retail owners resulting in lower abnormal search activities from these investors.

5.1 Additional analyses

Research provides evidence of differential patterns in trading behavior based on the type of institutional investor (Bushee, 2001; Bushee and Goodman, 2007: Ramalingegowda, 2014). Thus, we calculate market uncertainty metrics based on the separate trading behavior of mutual funds (*DISAGREE[–3,0]_MF*) and pension funds (*DISAGREE[–3,0]_PF*) [15]. We then examine whether investor information search is differentially associated with our measures of aggregate and disaggregate market uncertainty, dependent on the type of institutional investor used as a proxy. Accordingly, we use the following model to investigate this issue:

$$\begin{aligned} ABN\_SVI[0] = {} & b0 + b1{*}DISAGREE[-3,0]\_MF\_GN + b2{*}DISAGREE[-3,0]\_MF\_SP \\ & + b3{*}DISAGREE[-3,0]\_PF\_GN + b4{*}DISAGREE[-3,0]\_PF\_SP \\ & + b5{*}SIZE + b6{*}TURNOVER\_FIRM + b7{*}TURNOVER\_IND \\ & + b8{*}VOLATILITY\_MKT + b9{*}|ABS\_RETURN| \\ & + b10{*}EARN\_SURPRISE + b11{*}ANALYST\_DISPERSION \\ & + b12{*}INST\_OWNERSHIP + b13{*}ANALYST\_FOLLOWING \\ & + b14{*}BIG4\_AUDITOR + b15{*}ABS\_DISC\_ACCRUALS \\ & + b16{*}SPREAD + b17{*}DUMMIES + e \end{aligned} \tag{5}$$

Consistent with our main results, we find, untabulated, that individual investor information demand is significantly positively associated with aggregate market uncertainty but not with disaggregate market uncertainty, as reflected in trading differences of both mutual funds and pension funds. Further, we find that individual investor information search is greater when aggregate market uncertainty is measured based on trading disagreements among generalist mutual funds rather than generalist pension funds [16]. Our results are also intuitive, in that mutual funds, being more active traders, would be expected to better reflect current market uncertainty than long horizon institutions like pension funds. These results further collaborate our findings regarding H1 and H2 and suggest that our findings are not overly dependent on the type of institutional investor (i.e. mutual funds or pension funds) chosen to proxy for market uncertainty.

In our main analyses, we examine abnormal information search around earnings announcements beginning with three days prior to the earnings announcement through the announcement day (*t*–*3*, *t*). It could be that individual retail investors do not anticipate earnings announcements and only begin searching for information once the announcement is made. To ensure that our findings are not sensitive to the assessment period analyzed, we examine abnormal information search during the period $t{+}1$, $t{+}3$ following the earnings announcement. Results, untabulated, of these analyses are substantively the same as those presented in Table 3, and all of our conclusions remain unchanged. Thus, our results appear robust to our specification of search days analyzed surrounding earnings announcements.

Additionally, in order to examine the impact of our lagged main variables of interest, we include *DISAGREE[*–*7,*–*4]_GN* and *DISAGREE[*–*7,*–*4]_SP* in our main empirical model and find, untabulated, that the lagged variables are not generally significantly associated with individual information demand. Consistent with the broad earnings announcement literature, we document heightened information search activity immediately around the announcement date (i.e. [–3, 0]).

It could be that the actual level of market ambiguity differentially effects the association between information demand and market uncertainty, particularly in times of high market ambiguity. Accordingly, we examine whether information search manifests differently when market ambiguity is relatively high. To examine this possibility, we partition our sample based on median and upper quartile levels of *DISAGREE_GN[*–*3,0]* and *DISAGREE_SP [*–*3,0]* and reestimate our regression models for these subsamples. Results, untabulated, of these reduced sample regressions are consistent with our main results that information search is significantly positively associated with aggregate market uncertainty but not significantly associated with disaggregate market uncertainty. These consistent results, at the highest levels of market ambiguity, further strengthen our main findings.

In sum, our main results and numerous additional tests consistently reveal that individual investor information demand around earnings announcements is strongest during periods of aggregate overall market ambiguity. However, consistent with the analytical work of Peng and Xiong (2006) and Caskey (2009), individual investor information demand is not significantly associated with more specific, disaggregated market ambiguity.

6. Conclusion

Market equilibrium is hypothesized to occur when stock prices fully reflect available information (Fama, 1970). Market anomalies occur when market participants fail to fully incorporate available information, leading to events like postearnings announcement drift, unexpected price swings and overreaction to accounting accruals (Jiang *et al.*, 2005; Zhang, 2006; Caskey, 2009). Prior research offers uncertainty as an explanation for some of these anomalies. Given the influence that market uncertainty exerts upon market participants, in this paper, we examine individual investor reactions to aggregate and disaggregate market ambiguity by examining their information search behavior. Research finds that investors increase their information demand when faced with market ambiguity (Hasan *et al.*, 2018) and react differentially to aggregate and disaggregate ambiguity (Caskey, 2009), as well as attend to aggregate and disaggregate information differently (Peng and Xiong, 2006). Based on these findings, we hypothesize that individual investors will significantly increase their search for information when faced with aggregate market uncertainty but would have a reduced or nonsignificant increase in information search when faced with disaggregate market uncertainty. Using the trading behavior of institutional investors, we develop proxies for aggregate market uncertainty and disaggregate industry-specific uncertainty and test these associations.

We provide evidence that individual investor information search behavior is significantly positively associated with aggregate market uncertainty but is not significantly associated with disaggregate market uncertainty. Our results support and further develop those of Drake *et al.* (2012), Hasan *et al.* (2018), Peng and Xiong (2006) and Caskey (2009) and imply that investors recognize and react to market uncertainty in its general aggregate form but not when the uncertainty is disaggregated (Guidolin and Rinaldi's, 2010), even if it is associated with the specific industries they are investing in. Thus, our findings provide further empirical insight into our understanding of investor use of information. The seeming inability of ambiguity-averse investors to incorporate disaggregated signals of uncertainty also provides interesting implications for future research.

For example, one area of research would be to study the behavior of firms and examine their supply of information during times of high aggregate and disaggregate market uncertainty. Do they provide more management guidance or have more press releases or conference calls during these times? Another research area would be to investigate how other market intermediaries and participants such as the media, regulators and analysts react to these different types of market uncertainty. Future research could ascertain whether our findings, using all industries, are stronger in some industries compared to others. Further, do specific overall market conditions facilitate the seeming lack of interest in disaggregated industry ambiguity? Do more sophisticated investors exhibit the same information demand associations with aggregate and disaggregate measures of market uncertainty as individual retail investors in this study? Future research addressing these and similar issues would further our understanding of the specific market conditions and types of market participants (i.e. types of investors, analysts, etc.) under which our results are the most salient or possibly absent.

Our use of proxies for individual information demand, the Google SVI, and for market uncertainty, institutional investor trading activity, may limit the generalizability of our study. Further, our industry specialization measure is a yearly measure based on only one year of trading and not over a longer establishment period and as such may not accurately identify industry experts. However, prior researchers have used the same or similar proxies, time frames and approaches, and we believe that our measures and choices are similarly reasonably unbiased and accurate representations of the underlying constructs. Accordingly, we believe our results provide further insight into investor behavior in the market. However, we encourage replication of our work, including the development of other proxies of investor information demand, and aggregate and disaggregate market uncertainty, as well as studies on the nexus of these two fundamental market axioms.

Notes

1. For purposes of this study, we use the terms uncertainty and ambiguity, and their derivations, interchangeably.
2. Research supports this assumption finding that fund managers with industry specific knowledge outperform managers who do not have such experience or knowledge (Huij and Derwall, 2011; Cici *et al.*, 2018).
3. Note that we are not assuming investors react to signals from institutional investor trading. We use trading disagreements of institutional investors as representative of the uncertainty that already exists in the aggregate and disaggregate market.
4. Drake *et al.* (2012) also find that information search decreases as investor distraction increases, consistent with Peng and Xiong's (2006) work on investor attention.

5. https://us.spindices.com/indices/equity/sp-500 (Last accessed April 8, 2017).
6. Of our final sample of 423 distinct ticker symbols, we consider 14 to be common words (e.g. CAT, MAT, TOY, etc.). If we exclude these 14 firms and reperform our analyses, the reduced sample results are substantively the same as the full sample and all of our conclusions remain unchanged.
7. We compute our specialization metric based on trading activity and not holdings at the end of the period since holdings may not reflect the amount of trading activity in the industry during the period. In that sense, our industry specialization metric is similar to Ekholm and Maury's (2014) Average Weight Index. Additionally, Ancerno Ltd does not provide data on institutional investor holdings.
8. The fund-level trading specialization metric is recomputed every year.
9. Since our industry specialization metric is computed as a percentage it is not biased by the fund size.
10. We remove funds with $SPEC = 2$ from our regression analyses.
11. This allows us to incorporate institutional investors' predisclosure information into the computation of the disagreement metric.
12. Earnings announcements are one of the most influential and extensively publicized corporate events, providing us an avenue to examine individual investor demand for information. Moreover, earnings announcements draw a significant amount of investor attention (Hirshleifer *et al.*, 2009) and hence a substantial market response takes place (see Kothari, 2001 for a review).
13. These two means are statistically different at $p < 0.01$.
14. We test the equality of both coefficients and find that they are not statistically different ($p < 0.10$).
15. Our final sample consists of 1,732 institutional investor firm-year observations (mutual funds $n = 597$; pension funds $n = 1{,}135$).
16. We test the equality of coefficients on mutual and pension fund generalists and find that they are significantly different at $p < 0.01$.

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Supplemental Results

The supplementary file is available online for this article.

Appendix

Variable name	Variable definition	Source
ABN_SVI[0]	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 prior 10 weeks, scaled by the average SVI for the same weekday over the prior 10 weeks	Google Trends
ABN_SVI[+1 + 3]	The average ABN_SVI over the three-day period subsequent to the earnings announcement	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 Ltd.
DISAGREE[–3,0]	Average of DISAGREE over the four-day period from *t*–3 to day *t*	Ancerno Ltd.
DISAGREE[–3,0]_GN	Average of DISAGREE over the four-day period from *t*–3 to day *t* for Institutional Investors with low specialization*	Ancerno Ltd.
DISAGREE[–3,0]_SP	Average of DISAGREE over the four-day period from *t*–3 to day *t* for Institutional Investors with high specialization*	Ancerno Ltd.
DISAGREE[–3,0]_PF	Average of DISAGREE over the four-day period from *t*–3 to day *t* for Pension Funds	Ancerno Ltd.
DISAGREE[–3,0]_MF	Average of DISAGREE over the four-day period from *t*–3 to day *t* for Mutual Funds	Ancerno Ltd.
DISAGREE[–3,0]_PF_GN	Average of DISAGREE over the four-day period from *t*–3 to day *t* for Pension Funds with low specialization*	Ancerno Ltd.
DISAGREE[–3,0]_PF_SP	Average of DISAGREE over the four-day period from *t*–3 to day *t* for Pension Funds with high specialization*	Ancerno Ltd.
DISAGREE[–3,0]_MF_GN	Average of DISAGREE over the four-day period from *t*–3 to day *t* for Mutual Funds with low specialization*	Ancerno Ltd.
DISAGREE[–3,0]_MF_SP	Average of DISAGREE over the four-day period from *t*–3 to day *t* for Mutual Funds with high specialization*	Ancerno Ltd.

Variable name	Variable definition	Source
MVE	Market value of shares outstanding (*PRC*SHROUT*), expressed in billions	CRSP
SIZE	Annual decile rank of MVE for each firm	
|ABN_RETURN|	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
ANALYST_DISPERSION	Standard deviation of forecasts made within 90 calendar days before the earnings announcement	IBES
TURNOVER_FIRM	Annual decile rank of turnover, which is calculated as annual trading volume scaled by shares outstanding [(*VOL/SHROUT*) *1000] for each firm	CRSP
TURNOVER_IND	Annual decile rank of turnover, which is calculated as annual trading volume in each industry scaled by shares outstanding [(*VOL/SHROUT*)*1000] for each industry	CRSP
VOLATILITY_MKT	It is measured using the market Volatility Index, which is a key measure of market expectations of near-term (30-day) volatility of the market as conveyed by S&P 500 stock index option prices	CBOE Indexes
INST_OWNERSHIP	Percentage of shares owned by institutional investors. Calculated quarterly	Thompson

(*continued*)

Table A1. Variable names and definitions

Variable name	Variable definition	Source
ANALYST_FOLLOWING	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
ABS_DISC_ACCRUALS	Absolute value of performance matched discretionary accruals as suggested by Kothari *et al.* (2005). Calculated yearly**	COMPUSTAT
SPREAD	(Askhi – Bidlo)/((Askhi + Bidlo)/2). Calculated daily	CRSP
EARN_SURPRISE	Absolute value of 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

Table A1.

***Calculation of Specialization Metric:**
We create an industry specialization metric for each investment fund in each year based on the fund's percentage total dollar trading volume in the specific two-digit industry SIC (i.e. 37 for automakers). Our specialization metric is computed as the ratio of each fund's dollar trading activity in the industry scaled by the fund's total dollar trading activity in that year (following Ekholm and Maury, 2014). Then, we rank institutional investors based on the specialization metric in every year and sort them into three groups of industry specialization. We identify funds at the lowest tercile of specialization as low specialization funds *(GENERALIST)* and funds at the highest tercile of specialization as high specialization funds *(SPECIALIST).*

****Calculation of Performance-Adjusted Discretionary Accruals following Kothari *et al.* (2005):**
We estimate Total Accruals using the following regression.

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

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. $1/\mathrm{TA}_{t-1}$: 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 *b*0, *b*1, *b*2, *b*3 and *b*4 for our sample separately for each two-digit SIC code. Next, we use the estimated coefficients to determine the expected performance adjusted accruals for each firm – the non-discretionary accruals. Then we take the difference between actual total accruals and the expected performance adjusted 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 the absolute value of discretionary accruals to proxy for earnings quality, where low (high) levels of absolute discretionary accruals (*ABS_DISC_ACCRUALS*) represents high (low) quality of earnings.

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