Journal of Accounting Research

DOI: 10.1111/j.1475-679X.2012.00443.x
Journal of Accounting Research
Vol. 50 No. 4 September 2012
Printed in U.S.A.

Investor Information Demand: Evidence from Google Searches Around Earnings Announcements

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Received 30 August 2010; accepted 10 January 2012

ABSTRACT

The objective of this study is to investigate factors that influence investor information demand around earnings announcements and to provide insights into how variation in information demand impacts the capital market response to earnings. The Internet is one channel through which public information is disseminated to investors and we propose that one way that investors express their demand for public information is via Google searches. We find that abnormal Google search increases about two weeks prior to the earnings announcement, spikes markedly at the announcement, and

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continues at high levels for a period after the announcement. This finding suggests that information diffusion is not instantaneous with the release of the earnings information, but rather is spread over a period surrounding the announcement. We also find that information demand is positively associated with media attention and news, and is negatively associated with investor distraction. When investors search for more information in the days just prior to the announcement, preannouncement price and volume changes reflect more of the upcoming earnings news and there is less of a price and volume response when the news is announced. This result suggests that, when investors demand more information about a firm, the information content of the earnings announcement is partially preempted.

1. *Introduction*

The SEC requires public companies to disclose "meaningful financial and other information to the public" to create a "common pool of knowledge for all investors to use" (SEC [2011]).[1] Hence, the objective of public disclosure is to provide stakeholders with useful information, which conceptually relates to the *supply* of accounting information. A large body of research examines the nature, quality, and timing of accounting disclosures, as well as the capital market consequences of changes in the supply of information. In this paper, we shift the focus to the *demand* for information. Our objective is to investigate factors that influence investor information demand and to provide insights into how variation in information demand impacts the capital market response to earnings.[2]

An implicit assumption made in the accounting and finance literature is that public information is effortlessly obtained and immediately processed by the market. For example, asset-pricing models assume both that the diffusion of public information is instantaneous and that investors act on the information immediately (Merton [1987]). However, this assumption ignores the operation of the various channels through which public information is disseminated to the market. Our investigation is motivated by the idea that public availability of information alone does not imply that information is instantaneously received by all market participants. Investors must also expend effort to obtain the information through various channels (e.g., press releases, business press, analysts, the Internet) and use the information—that is, the market must demand the information.

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[1] For more information, see http://www.sec.gov/about/whatwedo.shtml.

[2] We use the term "information demand" to capture an individual's desire for information about a particular firm in a general equilibrium setting. This definition is broader than the neoclassical economic view of demand wherein supply and demand are independent, and agents participating in a market demand utility-maximizing quantities of goods given prices and a wealth constraint. In our setting, the supply and demand for information are not independent and the information gathered in a Google search is relatively costless to acquire. We urge caution in overgeneralizing the usage of Google search volume as a proxy for information demand in settings other than a general equilibrium setting.

One important channel through which investors express their demand for public information is via Internet searches. The Google Search Volume Index (SVI) measures the extent to which a particular term or phrase is searched for using the Google Search engine. We collect daily SVI for the ticker symbols of S&P 500 firms to capture variation in investor information demand.[3] Our assumption is that a Google user who enters a ticker symbol into the search engine is looking for some piece of financial information about the firm. These data are an ideal proxy for information demand because the data reflect effort by the investor to obtain firm-specific information. To increase the likelihood that the search reflects demand for financial information, we employ a short-window event-study methodology around earnings announcements that removes the normal level of Google search volume during nonearnings announcement periods. This research design allows us to *directly* test for the impact of information demand on the market response to earnings news.

Our empirical analysis proceeds in two phases. In the first phase, we examine the timing and magnitude of Internet search around earnings announcements and the factors that influence Internet search. In the second phase, we examine the capital market implications of Internet search by testing whether Internet search is associated with the price discovery of earnings information.

Regarding the timing, we find that information demand through the Internet increases, on average, about two weeks prior to the earnings announcement. Abnormal search volume trends upward as the earnings announcement date approaches and then spikes markedly on the announcement date. At the earnings announcement, abnormal search volume is 13.2% greater than normal. This announcement-day spike is consistent with other observed "spikes" in the earnings announcement literature (e.g., Beaver [1968]). After the earnings announcement, search volume returns to normal levels after about two weeks. Our results suggest that investors begin to seek and process information in the days before the earnings announcement, during the announcement, and for weeks after the announcement.

To understand the magnitude of the spike in information demand at the earnings announcement and the factors that influence investor information demand, we estimate a series of models aimed at explaining within-firm abnormal search volume. We begin simply by regressing daily abnormal search volume on a broad set of explanatory variables. The explanatory variables fall into one of five classifications: Event Dates, Media Attention, News, Liquidity, and Distraction. Within the Event Dates

[3] We use tickers instead of company names to increase the likelihood that the user is an investor, rather than a user searching for other company information, such as products or store locations. For example, if we were to use "Bank of America" rather than its ticker, "BAC," we could not separate search for online banking, branch locations, or interest rates from search for financial information.

classification, we examine five specific events—earnings announcements, acquisition announcements, management forecast dates, analyst forecast dates, and dividend announcements—to benchmark the magnitude of information demand for earnings announcements against that for other public disclosures. We include the variables in the remaining classifications to identify (and control for) other firm-specific factors that may influence investors' demand for information via the Internet as they change over time.

We find that several factors are associated with investors' search via Google. Abnormal search volume is positively associated with variation in firm-specific press coverage and stock return magnitudes, which is consistent with the notion that the Internet serves as a complement to other news sources at providing information to investors. We also find that abnormal search volume in Google is negatively associated with liquidity, which suggests that investors demand more information via the Internet when trading in the security is more difficult. Finally, we find that abnormal Internet search is negatively associated with investor distraction, which suggests that investors seek less information when they are distracted by higher levels of competing earnings news.

Next, we explore the timing of abnormal search around corporate events for a given firm. We find evidence of pre-event increases in search volume; however, this increase is only observed for expected events (e.g., earnings announcements) and is nonexistent for unexpected events (e.g., acquisition announcements). On the event date, we find that earnings announcements and acquisition announcements are associated with the greatest spike in Google search volume. Management forecast dates, analyst forecast dates, and dividend announcement dates are also each associated with increased demand for information, but to a lesser degree than are earnings announcement dates. Following the event, the demand for information stays at abnormally high levels for earnings announcements, management forecasts, and acquisition announcements.

We also examine whether the timing of search around earnings announcements varies in the cross-section for firms with different attributes. We find that search volume is amplified around the earnings announcement for firms that, on average, are larger, have more analysts, have higher spreads, and have higher idiosyncratic volatility. One possible interpretation for these results is that investors search more when the search costs are relatively lower (stronger information environment) and when the potential search benefits are relatively higher (more uncertainty and idiosyncratic risk).

In total, our evidence from the first phase analyses provides new insights into the timing and drivers of investors' demand for information around earnings announcements. The finding that information demand increases before the earnings announcement and continues well after the announcement suggests that information diffusion is not instantaneous with the release of the earnings information, but rather that it is spread over several weeks surrounding the earnings announcement. Our findings also speak to the cost of acquiring information—the findings suggest that investors must expend effort to acquire public information around earnings announcements, and that they expend more effort when the potential returns to search are higher. These findings are consistent with the theoretical model in Grossman and Stiglitz [1980], in which information is reflected into price as individuals expend resources to obtain the information. Although these analyses are primarily exploratory, our novel data allow us to provide the first empirical evidence on the timing of, and factors that influence, the demand for information via the Internet around earnings announcements.

In the second phase, we investigate the impact of investor information demand on the association between market activity (returns and volume) around earnings announcements and earnings news. It may be that Internet search provides no useful information about upcoming earnings either because other information sources provide sufficient information to investors or because useful information is difficult to acquire via Internet search engines. If Internet information demand does have an impact on how the market reacts to earnings, we expect it to improve the speed at which the stock prices impound information. As a result, the increased stock price informativeness would partially preempt the information content of the earnings announcement.

We find that preannouncement returns are more highly associated with the upcoming earnings surprise when preannouncement search is higher. Similarly, we find that preannouncement trading volume is more positively associated with the absolute magnitude of the earnings surprise when preannouncement search is higher. Together, these results provide the first direct empirical evidence that the market reaction to earnings news is partially *preempted* when information demand is abnormally high in the predisclosure period and suggest that investor search activities in the predisclosure period are an important and incremental determinant of the market response to earnings.

In our final analysis, we switch the focus from the preannouncement period to the announcement period. We test whether preannouncement information demand results in a lower market reaction to the announcement of earnings information. We find that the earnings response coefficient (ERC) is lower when preannouncement abnormal search volume is higher. We also find that the association between announcement period trading volume and the absolute magnitude of the earning surprise is less positive when preannouncement search is higher. Together, this evidence suggests that the market reaction to earnings news is lower when preannouncement Internet search is higher. Finally, we find that the association between announcement period trading volume and the magnitude of the earnings surprise is more positive when announcement period search is higher. This suggests that high announcement period search reflects differences of opinion among investors, which results in significant increased trading volume, without significant changes in price.

In summary, we use a novel and direct measure of investors' information demand, Google search volume, to examine the pattern of information demand around earnings announcements, factors associated with information demand, and the impact of information demand on the market pricing of earnings. Broadly speaking, our evidence suggests that, when investors demand more information in the preannouncement period, market activity reflects more of the upcoming earnings information in the preannouncement period and the market response when earnings are ultimately announced is attenuated. Thus, we provide the first empirical evidence that investor information demand is positively associated with market efficiency with respect to earnings news. We emphasize that one cannot infer from our results that the simple act of searching in Google for information per se is what drives the increased efficiency in the market. Rather, our results imply that investors use Internet searches to acquire information already in the public domain that has not yet been fully impounded into prices, and that these searches for public information are triggered by an important corporate event (an earnings announcement).

The incorporation of earnings news into stock prices is fundamental to accounting research. Thus, the contribution of this study is to shed light on how investor information demand, expressed through Internet search, impacts the market response to earnings news. This study complements and extends the emerging literature that investigates the impact of Internet technologies in the capital markets (see, for example, Blankespoor, Miller, and White [2011], which investigates firms' use of Twitter). Given the increasing usage of Internet technologies to disseminate financial information, it is important to understand the impact of the Internet on the price discovery of earnings information. Our study provides initial evidence on this key information channel.

2. *Motivation and Related Literature*

2.1 MOTIVATION

For centuries, companies have been creating financial statements that are supplied to interested stakeholders. Financial accounting researchers have, in turn, developed a large body of research to understand how financial information is impounded into securities prices.[4] A key (but often implicit) assumption in much of theoretical and empirical capital market research is that public information is immediately and costlessly processed by market participants (e.g., Diamond [1985], Merton [1987], McNichols and Trueman [1994]). Under such an assumption, *how* public information gets to investors is not considered because it is not the focus of the investigation. In contrast, Grossman and Stiglitz [1980] assert that the amount of information in price depends upon the number of individuals who expend

[4] See Kothari [2001] and Dechow, Ge, and Schrand [2010] for surveys of this literature.

effort to become informed. Thus, as investors acquire and process public information, the "publicness" of that information increases.

Prior research has investigated some of the channels through which information reaches the market, such as financial reporting, security analysts, and management disclosures. In general, the findings in these papers suggest that these channels of information generally speed up price discovery. Our research augments some recent papers that investigate new channels through which the market acquires firm-specific information. Soltes [2009] investigates how variation in business press coverage affects firm-level market activity and finds that greater press coverage is associated with lower spreads, increased turnover, and lower idiosyncratic volatility. Bushee et al. [2010] similarly find that press coverage improves a firm's information environment, which reduces firm-level information asymmetry. Blankespoor, Miller, and White [2011] investigate managers' use of Twitter as a tool for voluntary disclosure. They find that firms with more "tweets" during news events have lower bid-ask spreads and greater depth.

In this paper, we examine an important channel through which investors acquire and process information—the Internet. The Internet is the largest aggregated source of information in the world. By making financial disclosures more accessible, the Internet has revolutionized the manner in which information is obtained by investors. Large financial Web sites, such as Yahoo Finance and Google Finance, collect and present financial statement and stock price information for interested investors. Banks and brokerages maintain extensive Web sites to supply investors with recommendations and tutorials for investing. In addition, regulators are now using the Internet as a primary channel of financial information dissemination (e.g., the SEC EDGAR database). Despite its prominence as a primary source of information to investors, very little is known about when and how much investors use the Internet to meet their demands for information and the consequences of such demand. Concurrent research, including Da, Engelberg, and Gao [2011] and this study, begin to address this void in the literature.

2.2 GOOGLE SEARCH LITERATURE

Concurrent research has begun to investigate the effects of Google search volume data in a variety of settings. Ginsberg et al. [2009] show that queries in Google for search terms related to the flu accurately estimate the level of influenza activity in different regions of the United States. That is, they use the demand for medical information to help understand how the flu spreads and how it can be tracked. Choi and Varian [2009] and Da, Engelberg, and Gao [2010] use Google SVI as a proxy for *customers'* demand for information. Specifically, Choi and Varian [2009] investigate the association between weekly Google SVI and monthly retail sales of automobiles and homes, as well as tourism. They find that the inclusion of Google SVI improves simple prediction models. Similarly, Da, Engelberg, and Gao [2010] find that search frequency is a leading indicator of firm performance. They use weekly search frequency for firm products (e.g., "Ipod," "Advil") and find that Google SVI is positively associated with news (revenue and earnings surprises) released in the subsequent earnings announcement.

An innovative study by Da, Engelberg, and Gao [2011] uses Google SVI on ticker symbols as a proxy for firm-specific investor attention. Their results show that, in an average week, Google SVI is positively associated with market capitalization, abnormal returns, turnover, and media attention. Their results are consistent with Google SVI acting as a more direct and timely proxy for attention than prior proxies, such as extreme returns, trading volume, and media attention.

Our study complements and extends these papers in two ways. First, we extend the literature using Google search volume to an information release context. This focus allows us to identify *which* information stimulates demand. That is, by examining information demand during a short period surrounding an information release, we are more likely to capture investors' actions of seeking information about that release. In contrast, Google search volume on an average day (or week as in Da, Engelberg, and Gao [2011]) is a novel proxy for investor attention to a specific firm, but it is more difficult to assess exactly what information the searcher is actually demanding. For example, a user on a given day may search for the ticker, MSFT, which yields millions of pages of general financial information for Microsoft. However, if the user is searching for that same ticker on the earnings announcement day, it is much more likely that they are searching for a specific type of financial information—earnings information—for Microsoft. Thus, an important distinction between our paper and previous papers is that Google search volume, within the context of an information release, is more likely to serve as a proxy for demand for specific information; whereas Google search volume in an everyday context is more likely to serve as a proxy for general investor attention.[5] This refinement has implications beyond accounting—financial economics has long looked at the market response to, and price discovery of, specific releases of information. Moreover, this distinction allows us to speak more directly about the diffusion of public information—as more investors gather information regarding a specific release of information, the more public the information becomes, which improves the price discovery process.

We also extend prior literature by providing direct evidence on the *timing* of information demand, which is possible because of our access to daily Google search volume (described below). Prior studies use weekly search data, which is the state of the art for broad samples. This extension helps us move beyond the initial question of whether investors pay attention to a security to understand *when* investors demand financial information.

[5] We acknowledge that investor information demand and investor attention are very similar and may be viewed as capturing the same underlying concept. If investors are looking for information about a stock, they are paying attention to it; conversely, if investors are paying attention to a stock, they are also likely looking for information about that stock.

Understanding the timing of information demand is important given that prior research suggests that information diffusion is immediate (e.g., Merton [1987]). This is an empirical question that can be assessed with these data, which we now describe.

3. Data and Research Design

3.1 GOOGLE SEARCH VOLUME AND SAMPLE

We obtain a proprietary database of investors' search activities on Google. Google Trends tracks and reports "... users' propensity to search for a certain topic on Google" to arrive at a number called the SVI.[6] Following Da, Engelberg, and Gao [2011], we identify a stock in Google using its ticker symbol. As Da, Engelberg, and Gao [2011] argue, ticker symbols (e.g., "MSFT") are less ambiguous than company names (e.g., "Microsoft," "Microsoft Inc.") and searches using ticker symbols as the search term are more likely to reflect searches for financial information than searches for nonfinancial information. SVI measures the number of daily searches for a particular ticker symbol and thus provides time-series variation in information search about a particular firm. Since tickers are firm specific and generally unique, this variable should provide a direct and timely proxy for investor information demand to a specific firm on a given day.

We obtain daily Google search volume for the tickers of the S&P 500 for the years 2005 to 2008. We use S&P 500 firms because these firms are the largest and most economically meaningful firms in the economy, and as such, they are more likely to have search data available from Google at the daily level.[7] One advantage of the S&P 500 sample is that it allows for variation in investor information demand, while holding relatively constant differences in the information environment, which is high for all S&P 500 firms. Our daily data are finer than the weekly SVI data used in prior research (e.g., Da, Engelberg, and Gao [2011]), which allows us to more directly isolate the search behavior of investors in short windows around earnings announcements. We employ the "fixed scaling" data so that the number of searches for a given term is scaled by the number of searches at a fixed point in time (generally when Google begins tracking the search data for the term). The fixed scaling is useful because it ensures that the "scalar" is unchanged over time. Due to our use of S&P 500 firms and because the SVI data for a particular search term is scaled by the number of searches for that term at a fixed point in time, the focus of our empirical analyses is on *within-firm* variation.

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[6] http://www.google.com/intl/en/trends/about.html

[7] We attempted to extract daily SVI for a sample of non–S&P 500 firms, but found null values of SVI for the majority of these firms. This issue is the result of insignificant search volume for the ticker. We also found that 42 of the S&P 500 firms had null values of SVI for the entire sample period. As such, we excluded these firms from our sample.

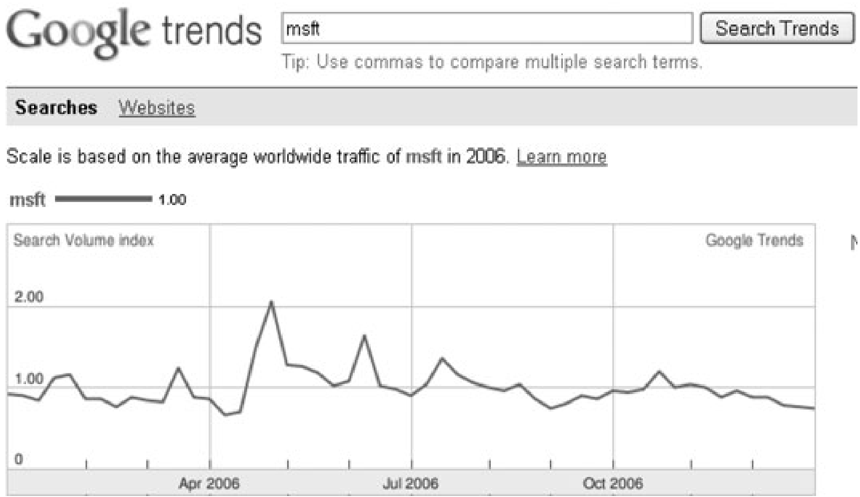

FIG. 1. Example of Google search volume for Microsoft's Ticker (MSFT) in 2006. This figure presents Google Search Volume Index for the ticker for Microsoft (MSFT) during 2006. Quarterly earnings announcements for Microsoft in 2006 occurred on January 26, April 27, July 20, and October 26. The figure is a screenshot of Google Trends, which can be found at http://www.google.com/trends.

Figure 1 provides a time plot of the SVI data from Google for "MSFT" (the ticker symbol for Microsoft Corporation) search volume in 2006. The figure shows that SVI is generally around 1.0 for the search term "MSFT," with occasional spikes and drops in investor search volume. An index level of 1.0 implies that the level of search on that particular day for a given firm is equal to the level of search when Google first started tracking the data for that firm (generally in 2004). Although we do not make statistical inferences from this figure, we note that it shows a consistent spike in Google search volume around Microsoft's quarterly earnings announcements in 2006.

Our sample consists of firms included in the S&P 500 at any point in time from 2005 to 2008. We require each firm to have Google search volume as well as coverage in Compustat, CRSP, I/B/E/S, and the 13F Thomson databases. The intersection of the Google search data with these databases results in a preliminary sample of 457 firms. Next, we follow Da, Engelberg, and Gao [2011] and remove 35 ticker symbols with potential alternative meanings (e.g., "CAT," "TOY," and "MAT"), which add noise to the analyses. These exclusions results in a final sample of 4,139 earnings announcements from 422 unique firms.

The use of Google search volume comes with several caveats. First, ideally, the data would reflect the actual count of the number of searches for a given search term. However, Google keeps that information private and instead provides an index of user's "propensity" to search for a particular term.[8] Google samples the data to determine how many searches have been made; by their own account, Google admits that the data are an approximation of the amount of search volume and may contain errors. Second, while the data reflect search by investors, we cannot observe the precise piece of information the investor demands or acquires. Third, we cannot observe who is doing the searching. It is possible that much of the search derives from retail investors, as suggested in Da, Engelberg, and Gao [2011]. Note that these issues add noise and imprecision to the data, which should make it more difficult to find results and draw inferences.[9] However, to the extent that the data are systematically biased in one of the above ways, we urge caution in interpreting our results and look forward to future research using finer data to help alleviate these concerns.

3.2 VARIABLES

To understand how Google search volume around information announcements varies from normal levels, we model the expected level of SVI. We note that there is variation in the raw SVI data across days of the week. Specifically, search volume is considerably lower on weekends than it is on weekdays. For example, the average raw SVI is 1.06 on Sunday and is 1.20 on Wednesday. To remove the influence of potential day-of-the-week effects, we estimate the expected level of SVI separately for each day of the week. Specifically, we calculate abnormal search volume (*AbSearch*) for firm i on day t as the raw SVI as provided by Google, minus the average raw SVI for the same day of the week k over the prior 10 weeks, scaled by the average raw SVI for the same day of the week k over the prior 10 weeks. Following Da, Engelberg, and Gao [2011], we use the natural logarithm of 1+*AbSearch* to normalize the distribution.

In short, *AbSearch* captures deviations from a firm- and weekday-specific benchmark. The adjustment for the expected level of search controls for search volume that is unrelated to the earnings announcement, increases the power of the statistical tests, and reduces the likelihood that correlated omitted variables are confounding the results. To make cross-sectional comparisons, we examine whether abnormal search around events varies for different types of firms (i.e., in the interactive form). This approach is consistent with the methodology in the trading volume literature in which within-firm abnormal volume is explained by time-varying, firm-specific characteristics (e.g., liquidity), using interactive variables to assess the

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[8] For details, see: http://www.google.com/intl/en/trends/about.html#7

[9] Some other minor concerns with the data are: (1) the search terms are in English only, (2) the data do not include search from other important search engines such as Yahoo and Bing, (3) the data do not include searches in other important search mechanisms, such as Google Finance, and (4) not all search terms are indexed by Google SVI.

influence of cross-sectional characteristics (e.g., firm size; see Bamber, Barron, and Stevens [2011] for a review of that literature).

We obtain returns data from CRSP and estimate abnormal returns (*AR*) by calculating the raw buy-and-hold return for a particular period (discussed in further detail below) and subtracting the buy-and-hold return to one of the benchmark portfolios formed based on size and book-to-market (5×5), consistent with Hirshleifer, Lim, and Teoh [2009].[10] We use I/B/E/S data to calculate unexpected earnings (*UE*) using two different expectation benchmarks. We define unexpected earnings following Hirshleifer, Lim, and Teoh [2009] based on analyst forecasts (*UEAF*) as the difference between actual earnings and the median analyst forecast measured over the 60-day period ending the day before the earnings announcement, scaled by stock price on the fiscal period end date. We also define unexpected earnings based on the earnings time-series (*UETS*) as the difference between actual earnings and actual earnings for the same quarter in the prior year (i.e., the seasonal change), scaled by stock price on the fiscal period end date.

The focus of many of our empirical tests is on the earnings announcement. We choose this corporate information event for four reasons. First, earnings announcements are (arguably) one of the most important, and widely publicized, corporate disclosure events for a firm because of their impact on security prices. Starting with Beaver [1968], a long line of empirical research provides evidence of a significant market reaction to earnings announcements (see, Kothari [2001] for a review). Second, earnings announcements are generally scheduled in advance (Chen and Mohan [1994]).[11] This scheduling allows investors to anticipate the date of the public disclosure, and, thus, facilitates the *timing* of information collection activities. Prior research investigates the behavior of market participants in the days leading up to an earnings announcement to draw inferences about the extent to which the market anticipates the earnings news. Third, our focus on earnings announcements allows us to investigate a relatively large number of events (four events per year, per firm) over our four-year sample period. Finally, the availability of proxies for market expectations of earnings allows us to calculate the "surprise" at the earnings announcement.

We include various control variables (discussed in further detail below) in our models using data obtained from the Compustat, CRSP, Thomson

[10] Firms are assigned to a particular size and book-to-market portfolio in June of each year.

[11] Financial Web sites often provide notice of upcoming earnings announcements for investors and some allow users to search for earnings announcement dates by ticker symbol. See, for example, http://biz.yahoo.com/research/ earncal/today.html. Thus a portion of Google search volume in the preannouncement period may relate to investors' efforts to learn the date of the upcoming earnings announcement. However, if search for earnings announcement dates was the primary driver of all search in the preannouncement period, we would expect to find no relation between Internet search and price discovery (i.e., it would bias against our results).

13F, Thomson SCD, and First Call databases. We also include press coverage data obtained from a proprietary database.[12] In the appendix, we provide definitions and data sources for all variables.

Our analyses focus on various event windows centered on the earnings announcement (denoted day 0). When abnormal search (*AbSearch*) is averaged or when abnormal returns (*AR*) are accumulated (buy-and-hold) over a particular window, we append the variable name to specify the window over which the variables are measured. For example, *AbSearch* $[-5, -1]$ denotes that abnormal search is averaged over the five-day period ending one day before the earnings announcement date and $AR[0, +1]$ denotes the buy-and-hold abnormal return over the two-day period beginning on the earning announcement date. While the majority of the windows we investigate are very short (within five days of the earnings announcement), we do investigate one longer pre-earnings announcement window that begins the day after the fiscal-quarter end date (denoted day *FQE*) and ends the day before the earnings announcement date.

3.3 DESCRIPTIVE STATISTICS

Table 1 presents descriptive statistics for the variables used in the empirical tests described in the next section. We find that the mean *AbSearch*$[FQE, -1]$ is 0.026, which indicates that investor search volume is 2.6% greater than normal over this period. We find that investor search in the five days just before the announcement, *AbSearch*$[-5, -1]$ is 4.3% greater than normal. At the earnings announcement, *AbSearch*$[0, +1]$, is 13.2% greater than normal. In table 2, we present Pearson (above diagonal) and Spearman (below diagonal) correlations. We draw our main inferences from the various multivariate analyses that directly follow, to which we now turn.

4. *Investor Information Demand*

In this section, we set up a series of models that investigate the timing and extent of investor demand for information, as proxied by abnormal search volume. In the first model, we examine the relation between abnormal search and a broad set of firm-specific, time-varying factors that explain investors demand for information. In the second model, we assess the timing of information demand by examining the relation between abnormal search and particular event dates (with a special focus on earnings announcements) and examine how search varies in the pre-event period, announcement period, and post-event period. In the third model, we examine the extent to which cross-sectional determinants explain variation in the Google search patterns around earnings announcements. Collectively,

[12] We thank Eugene Soltes for providing the press coverage data from Soltes [2009].

TABLE 1
Descriptive Statistics

Variable	Mean	Standard Deviation	10%	Q1	Median	Q3	90%
AbSearch[FQE,−1]	0.026	0.243	−0.073	−0.024	0.000	0.031	0.100
AbSearch[−5,−1]	0.043	0.280	−0.091	−0.037	0.007	0.063	0.166
AbSearch[0,+1]	0.132	0.449	−0.078	−0.025	0.027	0.109	0.346
AR[*FQE*,−1]	0.000	0.080	−0.080	−0.035	0.000	0.038	0.080
AR[−5,−1]	0.001	0.035	−0.031	−0.014	0.001	0.016	0.035
AR[0,+1]	0.003	0.067	−0.063	−0.028	0.001	0.033	0.073
Abvol[−5,−1]	1.112	2.762	−1.504	−0.696	0.445	2.245	4.508
Abvol[0,+1]	4.071	3.721	0.453	1.472	3.176	5.565	8.803
UEAF	−0.001	0.017	−0.002	0.000	0.000	0.002	0.003
UETS	−0.002	0.028	−0.007	0.000	0.002	0.004	0.007
Loss	0.048	0.213	0.000	0.000	0.000	0.000	0.000
Analyst Following	14.691	6.409	7.000	10.000	14.000	19.000	23.000
Institutional Ownership	0.766	0.136	0.589	0.692	0.775	0.843	0.924
Size	22,713	33,255	3,449	5,856	11,719	23,413	51,502
Book-to-Market	0.427	0.293	0.165	0.241	0.363	0.544	0.756
Earnings Persistence	0.489	0.434	−0.129	0.166	0.555	0.853	0.991
Earnings Volatility	0.214	0.362	0.035	0.059	0.109	0.208	0.448
Turnover	0.202	0.144	0.082	0.108	0.158	0.237	0.387
Spread	0.001	0.002	0.000	0.000	0.001	0.001	0.003
# Announcements	182	106	33	103	172	264	315
Management Forecast	0.0	0.1	0.0	0.0	0.0	0.0	0.0
# Analyst Forecasts	3.3	2.9	0.0	1.0	3.0	5.0	7.0
# News Articles[*FQE*,−1]	2.7	4.2	0.0	0.0	1.0	4.0	8.0
# News Articles[−5,−1]	0.6	1.1	0.0	0.0	0.0	1.0	2.0
# News Articles[0,+1]	0.6	0.7	0.0	0.0	0.0	1.0	2.0
N	4,133						

This table presents descriptive statistics for information search and control variables. The sample consists of 4,133 quarterly observations for S&P 500 firms over the period 2005 to 2008. Variable definitions are provided in the appendix. All variables, except returns, are winsorized at the 1st and 99th percentiles.

these analyses shed light on the drivers of investor information demand and provide an assessment of when that demand increases.

4.1 FACTORS ASSOCIATED WITH ABNORMAL SEARCH VOLUME

We begin by regressing daily abnormal search volume on a broad set of event date indicator variables and other explanatory variables based on information from financial reports, the market, analysts, and the media. We estimate the model using the full time-series of daily Google search data for our sample of S&P 500 firms.

TABLE 2

Pearson (Above) and Spearman (Below) Correlations

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	*AbSearch* [*FQE*, −1]		0.73	0.53	0.01	0.01	0.02	0.03	0.00	0.01	0.01	−0.02	0.00	0.03	−0.01	−0.01	0.03	−0.01	0.02	−0.02	−0.03	0.03	0.03	−0.01	0.00	−0.03
2	*AbSearch* [−5, −1]	0.51		0.58	0.02	0.01	0.03	0.06	0.03	0.01	0.01	−0.02	0.04	0.03	0.03	−0.04	0.04	−0.02	0.04	−0.02	−0.05	0.03	0.01	−0.02	0.00	−0.02
3	*AbSearch* [0, +1]	0.22	0.43		0.00	−0.01	0.02	0.03	0.10	0.00	0.01	−0.02	0.17	−0.01	0.21	−0.08	0.05	−0.05	0.11	−0.04	−0.08	0.00	0.02	0.09	0.10	0.08
4	*AR* [*FQE*, −1]	0.01	0.02	0.02		0.31	−0.07	−0.07	−0.09	0.01	0.06	−0.07	0.02	−0.04	0.00	0.00	0.00	−0.06	−0.08	−0.03	−0.02	0.03	−0.04	−0.03	−0.02	−0.03
5	*AR* [−5, −1]	−0.01	0.01	−0.01	0.33		−0.15	0.02	−0.03	0.08	0.09	−0.05	0.02	−0.03	0.01	−0.04	0.01	0.01	−0.04	−0.02	0.01	0.00	0.00	0.00	0.01	0.00
6	*AR* [0, +1]	0.01	0.02	0.02	−0.03	−0.09		0.03	−0.09	0.03	−0.02	−0.02	0.02	0.03	−0.02	0.03	0.02	0.00	0.02	0.00	−0.03	0.00	0.02	−0.01	−0.01	0.00
7	*Abvol* [−5, −1]	0.03	0.04	0.02	−0.07	0.01	0.00		0.40	−0.07	−0.10	0.04	−0.04	0.00	0.04	0.10	0.00	0.06	0.00	0.06	−0.08	0.02	0.10	0.04	0.08	0.04
8	*Abvol* [0, +1]	−0.02	0.03	0.10	−0.08	−0.04	−0.01	0.41		−0.03	−0.06	0.03	0.00	0.04	0.02	−0.03	−0.01	−0.01	−0.02	0.02	−0.13	−0.03	−0.08	0.01	0.03	0.06
9	*UEAF*	0.01	0.01	0.00	0.10	0.06	0.33	−0.05	−0.02		0.75	−0.45	0.08	−0.08	0.04	−0.28	−0.04	−0.26	−0.26	−0.09	0.03	0.01	0.00	−0.07	−0.07	−0.07
10	*UETS*	0.03	0.01	0.02	0.11	0.07	0.15	−0.04	0.00	0.42		−0.51	0.12	−0.10	0.04	−0.40	−0.03	−0.27	−0.27	−0.11	0.05	0.02	−0.01	−0.10	−0.10	−0.11
11	*Loss*	−0.01	−0.01	0.01	−0.06	−0.05	−0.04	0.03	0.01	−0.23	−0.24		−0.14	0.12	−0.08	0.34	−0.01	0.40	0.31	0.10	−0.05	−0.02	0.00	0.12	0.10	0.11
12	*Log* (1+*Analyst Following*)	−0.05	0.04	0.18	0.02	0.02	0.03	−0.02	0.02	0.02	0.10	−0.13		−0.11	0.35	−0.19	0.21	−0.06	0.00	−0.09	−0.13	−0.03	0.30	0.17	0.16	0.18
13	*Institutional Ownership*	0.04	0.03	−0.04	−0.04	−0.02	0.02	−0.01	0.04	0.03	0.02	0.10	−0.12		−0.29	0.03	0.05	0.10	0.33	0.07	0.06	−0.02	−0.01	−0.13	−0.12	−0.13

(Continued)

TABLE 2—*Continued*

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
14	*Rank of Size*	−0.05	0.03	0.20	0.01	0.02	0.00	0.07	0.02	−0.02	0.07	−0.17	0.50	−0.35		−0.10	0.05	0.04	−0.24	−0.11	−0.09	−0.02	0.16	0.48	0.46	0.33
15	*Rank of Book-to-Market*	0.02	−0.04	−0.08	−0.01	−0.03	−0.02	0.04	−0.08	0.04	−0.14	0.17	−0.16	−0.02	−0.15		−0.03	0.33	0.23	0.15	0.01	0.00	0.13	0.07	0.06	0.08
16	*Earnings Persistence*	0.01	0.02	0.06	0.00	0.01	0.01	0.00	0.01	−0.04	0.13	−0.03	0.23	0.07	0.14	−0.10		0.01	0.11	0.01	0.03	−0.06	0.10	−0.04	−0.01	−0.04
17	*Earnings Volatility*	0.05	−0.03	−0.08	0.00	0.02	−0.03	0.00	−0.08	0.09	0.04	0.26	−0.10	0.08	−0.09	0.42	−0.11		0.31	0.04	0.04	−0.02	0.22	0.18	0.13	0.10
18	*Turnover*	0.03	0.01	0.07	−0.02	−0.02	−0.01	−0.01	0.00	0.01	−0.02	0.21	−0.04	0.44	−0.38	0.04	0.09	0.27		0.13	−0.04	−0.04	0.13	−0.03	−0.01	0.02
19	*Spread*	0.02	−0.01	−0.03	−0.07	−0.03	−0.01	0.07	0.02	−0.01	−0.04	0.11	−0.11	0.10	−0.21	0.06	−0.02	0.06	0.18		0.05	0.01	0.01	−0.06	−0.05	−0.05
20	*Rank of # Announcements*	0.00	−0.03	−0.11	−0.02	0.01	−0.02	−0.08	−0.16	0.04	0.07	−0.04	−0.13	0.10	−0.09	0.05	0.03	0.09	−0.03	0.04		−0.02	0.11	−0.05	−0.10	−0.17
21	*Management Forecast*	0.05	0.04	0.01	0.03	0.00	0.00	0.01	−0.04	−0.02	0.02	−0.02	−0.03	−0.03	0.00	0.01	−0.05	−0.01	−0.04	0.02	−0.02		0.04	0.03	0.01	−0.01
22	*# Analyst Forecasts*	0.05	0.01	0.05	−0.01	0.01	0.00	0.10	−0.08	−−0.01	0.01	0.01	0.27	−0.05	0.27	0.19	0.05	0.29	0.11	0.01	0.09	0.06		0.18	0.10	0.08
23	*# News Articles* [*FQE*, −1]	−0.01	−0.02	0.08	−0.03	−0.01	−0.04	0.04	−0.03	−0.02	−0.06	0.12	0.13	−0.15	0.34	0.07	−0.08	0.08	−0.05	−0.04	−0.05	0.04	0.20		0.81	0.63
24	*# News Articles* [−5, −1]	−0.02	0.01	0.10	−0.02	0.00	−0.03	0.06	0.01	−0.02	−0.07	0.09	0.15	−0.12	0.31	0.03	−0.04	0.03	−0.06	−0.05	−0.10	0.02	0.12	0.72		0.57
25	*# News Articles* [0, +1]	−0.02	0.00	0.12	−0.03	−0.01	−0.01	0.03	0.06	−0.03	−0.07	0.10	0.17	−0.16	0.33	0.05	−0.05	0.05	−0.03	−0.05	−0.18	−0.01	0.11	0.64	0.52	

This table presents Pearson (above diagonal) and Spearman (below diagonal) correlations between firm-specific variables. The sample consists of 4,393 quarterly observations for S&P 500 firms over the period 2005 to 2008. Variable definitions are provided in the appendix. All variables, except returns, are winsorized at the 1st and 99th percentiles.

The first model is as follows:

$$
\begin{aligned}
AbSearch_{it} = {} & a_{\text{Week}} + a_1 \textit{Earnings Announcement}_{it} \\
& + a_2 \ \textit{Management Forecast Date}_{it} \\
& + a_3 \ \textit{Analyst Forecast Date}_{it} + a_4 \ \textit{Dividend Announcement}_{it} \\
& + a_5 \ \textit{Acquisition Announcement}_{it} \\
& + a_6 \ \#\, \textit{News Articles}_{it} + a_7 |\textit{Return}_{it}| \\
& + a_8 \ \textit{Turnover}_{it} + a_9 \textit{Bid} - \textit{Ask Spread}_{it} \\
& + a_{10} \ \textit{Rank of}\ \#\, \textit{Announcements}_t \\
& + a_{11} \ \textit{Rank of Size}_{it} + a_{12} \textit{Log}(1 + \textit{Analyst Following}_{it}) \\
& + a_{13} \ \textit{Rank of Book-to-Market}_{it} \\
& + a_{14} \ \textit{Institutional Ownership}_{it} \\
& + a_{15} \ \textit{Fourth Qtr}_{it} + e_{it}
\end{aligned}
\tag{1}
$$

where,

$AbSearch_{it}$ = Google SVI on day t for firm i less the average Google SVI for the same firm and weekday over the previous 10 weeks, all scaled by the average Google SVI for the same firm and weekday over the previous 10 weeks;
Earnings Announcement$_{it}$ = indicator variable set equal to one on day t if firm i announces earnings and to zero otherwise;
Management Forecast Date$_{it}$ = indicator variable set equal to one on day t if firm i issues a management forecast and to zero otherwise;
Analyst Forecast Date$_{it}$ = indicator variable set equal to one on day t if any analyst issues an earnings forecast for firm i and to zero otherwise;
Dividend Announcement$_{it}$ = indicator variable set equal to one on day t if firm i makes a dividend announcement and to zero otherwise;
Acquisition Announcement$_{it}$ = indicator variable set equal to one on day t if firm i makes an acquisition announcement and to zero otherwise;[13]
 # News Articles$_{it}$ = the number of news articles in the *Wall Street Journal*, the *New York Times*, *USA Today*, and the *Washington Post* that mention firm i on day t (Soltes [2009]);
$|Return_{it}|$ = absolute value of the raw stock return of firm i on day t;[14]
Turnover$_{it}$ = average monthly trading volume of firm i, scaled by the average number of shares outstanding over the one-year period ending on the most recent fiscal quarter end date;

[13] We obtain acquisition announcement dates from the Thomson SDC database.

[14] We also estimate model (1) using the signed, raw stock return and find that the coefficient on the signed stock return is insignificant in the model. However, our general inferences with respect to the relative magnitude of *AbSearch* on earnings announcements dates are unchanged. Additionally, we estimate model (1) using abnormal returns and find that our general inferences are unchanged as well.

Bid-Ask Spread$_{it}$ = the high-low estimate of bid-ask spread for firm i on day t, as in Corwin and Shultz [2011];
Rank of # Announcements$_t$ = the decile rank of the total number of firms announcing earnings on day t;
Rank of Size$_{it}$ = the decile rank of market-value of equity for firm i (Compustat PRCCQ $\times$ CSHOQ) measured as of the most recent fiscal quarter end;
Log(1 + Analyst Following$_{it}$*)* = the natural log of 1 plus the number of analysts in the last I/B/E/S consensus analyst earnings forecast prior to the earnings announcement;
Rank of Book-to-Market$_{it}$ = the decile rank of book-to-market (Compustat CEQQ/[PRCCQ $\times$ CSHOQ]) measured as of the most recent fiscal quarter end;[15]
Institutional Ownership$_{it}$ = the number of shares owned by institutional investors scaled by total shares outstanding measured as of the most recent fiscal quarter end; and
Fourth Qtr$_{it}$ = indicator variable set equal to one if day t is in the fourth fiscal quarter of firm i and to zero otherwise.[16]

The purpose of model (1) is twofold. First, we seek to benchmark the level of investor information demand at the earnings announcement to that for other corporate events. Second, we explore the extent to which changes in firm-specific factors influence the level of investor demand for information.

In model (1), we include a set of event date indicators to allow us to compare the coefficient magnitude of abnormal Google search volume on the earnings announcement date to that for other public announcements. The set of events we examine in addition to earnings announcements includes two other earnings-related events, the issuance of management forecasts and analyst forecasts, as well as two other corporate events, dividend announcements, and acquisition announcements.

In addition to the event date indicator variables just described, we select a set of time-varying, firm-specific factors, which we use to explain Internet search. We group these explanatory variables into the following four classifications: Media Attention (*# News Articles*), News (|*Return*|), Liquidity (*Turnover* and *Bid-Ask Spread*), and Distraction (*# Announcements*). We also include a set of controls, including *Rank of Size, Log*(1 + *Analyst Following*), *Rank of Book-to-Market, Institutional Ownership,* and *Fourth Quarter.*[17] In model (1), we use the raw *AbSearch* rather than the natural

[15] Following Hirshleifer, Lim, and Teoh [2009], we use the natural logarithm of one plus *Analyst Following*, and the decile ranks of *Size*, *Book-to-Market*, and *# Announcements* rather than the raw values of these variables.

[16] We include an indicator variable for the fourth quarter following Mendenhall and Nichols [1988],

[17] We note that these control variables are largely fixed across time and do not vary greatly in our sample of S&P 500 firms. We include them in model (1) as control variables for

logarithm of 1+*AbSearch* as the dependent variable to facilitate interpretation of the coefficients on the event indicator variables that represent percent increases in search above normal on that particular event date. However, when we estimate the model using the logged variable, we find that our statistical inferences are similar. We assess statistical significance using *t*-statistics based on standard errors clustered by firm to account for residual dependence across time. We include week fixed effects in the models to control for variation in *AbSearch* related to a particular period in time.[18]

Table 3 presents the estimation results for model (1). We find that, among the Event Date variables, acquisition announcements are associated with the highest abnormal search volume; the coefficient on *Acquisition Announcement* of 15.1% is significantly different from zero. The coefficient on *Earnings Announcement* of 8.6% is the next highest magnitude among the events analyzed and is also significantly positive. Even though the results of a coefficient equality test indicate that these two coefficients are insignificantly different from each other (F-statistic = 1.32; p-value = 0.25), we note that the magnitude of abnormal search for acquisition announcements is almost double that for earnings announcements. We find that the coefficients on *Management Forecasts, Analyst Forecasts,* and *Dividend Announcements* are 3.6%, 1.9%, and 1.1% respectively, each of which is significantly different from zero. The coefficient equality tests (unreported) indicate that search magnitude at earnings announcements is significantly greater than search magnitude on management forecast dates, analyst forecast dates, and on dividend announcement dates. This evidence suggests that earnings announcements are events that, on a relative basis, are associated with higher percent increases in investor search volume, on par with acquisition announcements.

With respect to the factors that influence investor information demand, we find that daily *AbSearch* is positively associated with media attention and news. Thus, we find that investors search for more information on days when the media and the market are relatively more focused on the firm. We also find that daily *AbSearch* is negatively associated with the liquidity of the firm's shares. To the extent that relatively lower liquidity proxies for higher information asymmetry (e.g., Leuz and Verrecchia [2000]), the evidence suggests that information demand is higher when information asymmetry is greater. Finally, we find that daily *AbSearch* is negatively associated with investor distraction. This result is consistent with the argument in Hirshleifer, Lim, and Teoh [2009] that investor attention is spread more

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completeness. Since our models are designed to exploit within-firm variation in abnormal search, we are less likely to detect a relation between these relatively constant variables and abnormal search if such a relation exists.

[18] In a sensitivity analysis, we estimate model (1) using firm fixed effects and time-clustered standard errors. This approach yields slightly smaller standard errors (i.e., stronger results) and does not change any of our general inferences.

TABLE 3
Factors Associated with Daily Abnormal Google Search

	Daily *AbSearch*	
Variables	Coefficient	Standard Error
Event Dates		
Earnings Announcements	0.086***	(0.011)
Management Forecast Date	0.036***	(0.011)
Analyst Forecast Date	0.019***	(0.003)
Dividend Announcements	0.011**	(0.005)
Acquisition Announcements	0.151**	(0.059)
Media Attention		
# News Articles	0.008***	(0.002)
News		
|Return|	0.695***	(0.088)
Liquidity		
Turnover	−0.049***	(0.014)
Bid-Ask Spread	0.037	(0.061)
Distraction		
# Announcements	−0.001***	(0.000)
Controls		
Rank of Size	−0.003	(0.006)
Log (1+*Analyst Following*)	0.003	(0.003)
Rank of Book-to-Market	−0.005	(0.004)
Institutional Ownership	0.016*	(0.009)
Fourth Qtr	0.013	(0.010)
Week Fixed Effects	Yes	
Firm Fixed Effects	No	
N	274,081	
Adj R-square	0.027	

This table presents the results of model (1), which models the time-varying, firm-specific factors that influence the demand for information. The dependent variable is the abnormal level of Google search volume for a firm's ticker symbol for each day in a time-series. Standard errors are presented in parentheses to the right of the coefficient estimates and are clustered by firm. The sample consists of S&P 500 firms from 2005 to 2008. Variable definitions are provided in the appendix. *, **, *** indicates statistical significance at the $p < 0.10$, 0.05, 0.01 level, respectively.

thinly when more firms announce earnings on a particular day. We also note that most of the (relatively) time-invariant control variables are insignificant in table 3.

4.2 THE TIMING OF INVESTOR DEMAND AROUND EARNINGS ANNOUNCEMENTS

We begin our next set of empirical tests by investigating the pattern of abnormal search volume around the earnings announcement. Figure 2 plots mean *AbSearch* from day −30 to day +30 relative to the earnings announcement on day 0. We also plot *AbSearch* over a similar window relative to a randomly selected day in the same calendar year for each observation.

Broadly speaking, we observe a clear, positive trend in Google search volume during the preannouncement period, a marked spike at the earnings announcement, followed by a negative time trend in the post-disclosure

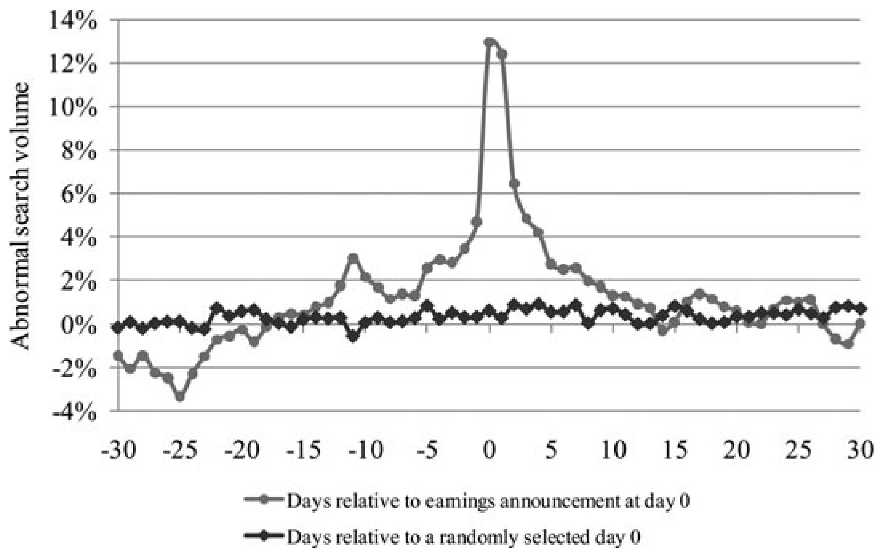

FIG. 2. Google search around earnings announcements and randomly selected days. In this figure, we plot abnormal Google search volume (*AbSearch*) around earnings announcements for sample firms. The figure is centered on the quarterly earnings announcement date, $t = 0$, and extends 30 trading days before and after that date. *AbSearch* is defined in the appendix and is measured in percentage points. For each event observation, we benchmark *AbSearch* around the earnings announcement event against *AbSearch* around a randomly selected event date from the same calendar year.

period. More specifically, in the preannouncement period we find that *AbSearch* increases nearly monotonically from −3.3% on day −25 to 4.7% on day −1. *AbSearch* becomes significantly positive (significance unreported) two weeks before the earnings announcement (on day −14). At the announcement, *AbSearch* increases to 13.2% on day 0, followed by 12.4% on day +1.[19] After the earnings announcement, we find that *AbSearch* gradually returns to a relatively stable level around 0%. The pattern of average *AbSearch* for the randomly selected days provides no clear trend over time, generally bouncing around 0% throughout the entire window. Taken together, the results in figure 2 suggest that investors demand more information about a firm as the earnings announcement date approaches. Although much of the prior literature assumes that information in the public domain is immediately accessed and processed by investors, these results suggest that investors begin to seek and process information in the days

[19] Although the spike in abnormal search at the announcement is dramatic, we note that the amount of search at the announcement is small relative to total search volume during the whole quarter. To put it into perspective, assume that normal daily search volume is 1 on average. Then the sum of *abnormal* search volume over days 0 and +1 of 25% (13.2% + 12.4%) is only 0.28% of total search volume for the quarter (25.6%/90). Ball and Shivakumar [2008] make a similar point regarding returns around earnings announcements.

before the earnings announcement, during the announcement, and for weeks after the announcement.

Next, we examine in multivariate analyses the timing of investor demand for information around corporate events. We focus on the time period just before, during, and after the event period for each of the corporate events described in model (1). We do this by creating indicator variables for the five-day period prior to the event (days [−5, −1]), the event date (day [0]), and for the five-day post-event period (days [+1, +5]). We construct these indicator variables separately for five announcements (earnings, management forecasts, analysts' forecasts, dividend announcements, acquisition announcements) and add them to model (1). The second model is as follows:

$$\begin{aligned}
AbSearch_{it} = \beta_{\text{Week}} &+ \beta_1 \textit{Earnings Announcement}\,[-5,-1]_t \\
&+ \beta_2\ \textit{Earnings Announcement}[0]_t \\
&+ \beta_3\ \textit{Earnings Announcement}\,[+1,+5]_t \\
&+ \beta_4\ \textit{Management Forecast Date}\,[-5,-1]_t \\
&+ \beta_5\ \textit{Management Forecast Date}\,[0]_t \\
&+ \beta_6\ \textit{Management Forecast Date}\,[+1,+5]_t \\
&+ \beta_7\ \textit{Analyst Forecast Date}\,[-5,-1]_t \\
&+ \beta_8\ \textit{Analyst Forecast Date}\,[0]_t \\
&+ \beta_9\ \textit{Analyst Forecast Date}\,[+1,+5]_t \\
&+ \beta_{10}\ \textit{Dividend Announcement}\,[-5,-1]_t \\
&+ \beta_{11}\ \textit{Dividend Announcement}\,[0]_t \\
&+ \beta_{12}\ \textit{Dividend Announcement}\,[+1,+5]_t \\
&+ \beta_{13}\ \textit{Acquisition Announcement}\,[-5,-1]_t \\
&+ \beta_{14}\ \textit{Acquisition Announcement}\,[0]_t \\
&+ \beta_{15}\ \textit{Acquisition Announcement}\,[+1,+5]_t + \beta_n\ \textit{Controls} + e \quad (2)
\end{aligned}$$

where,

Controls = a set of controls variables including *# News Articles*, *|Returns|*, *Rank of Size*, *Log*(1+*Analyst Following*), *Turnover*, *Bid-Ask Spread*, *Fourth Qtr*, *Rank of # Announcements*, *Institutional Ownership*, and *Rank of Book-to-Market*; and all other variables as defined above.

The purpose of model (2) is to investigate the timing of investor demand for various corporate announcements. Table 4 presents the estimation results for model (2). We find that only earnings announcements are associated with significant pre-event abnormal search ($\beta_1 = 0.013$, $p < 0.01$); the coefficients on the pre-event periods for the other events (β_4, β_7, β_{10}, β_{14}) are all insignificant. The advanced scheduling and public disclosure of earnings announcements dates by firms likely contributes to this increase.

TABLE 4
The Timing of Information Demand Around Corporate Events

		Daily *AbSearch*	
	Event	Coefficient	Standard Error
$\beta 1$	*Earnings Announcement*[−5, −1]	0.013***	(0.003)
$\beta 2$	*Earnings Announcement*[0]	0.092***	(0.011)
$\beta 3$	*Earnings Announcement*[+1, +5]	0.043***	(0.007)
$\beta 4$	*Management Forecast*[−5, −1]	0.013	(0.011)
$\beta 5$	*Management Forecast*[0]	0.035***	(0.009)
$\beta 6$	*Management Forecast*[+1, +5]	0.020**	(0.009)
$\beta 7$	*Analyst Forecast*[−5, −1]	0.003	(0.002)
$\beta 8$	*Analyst Forecast*[0]	0.013***	(0.002)
$\beta 9$	*Analyst Forecast*[+1, +5]	0.002	(0.002)
$\beta 10$	*Dividend Announcement*[−5, −1]	0.001	(0.005)
$\beta 11$	*Dividend Announcement*[0]	0.008	(0.005)
$\beta 12$	*Dividend Announcement*[+1, +5]	0.001	(0.005)
$\beta 13$	*Acquisition Announcement*[−5, −1]	0.001	(0.013)
$\beta 14$	*Acquisition Announcement*[0]	0.152**	(0.059)
$\beta 15$	*Acquisition Announcement*[+1, +5]	0.077**	(0.036)
	Controls		Yes
	Year-week fixed effects		Yes
	Firm clusters		Yes
	N	274,081	
	Adj *R*-square	0.031	
	Selected *F*-tests	*F*-stat	*p*-value
	Unexpected Event[−5, −1]: $\beta 4+\beta 7+\beta 13 = 0$	0.92	0.338
	Expected Event[−5, −1]: $\beta 1+\beta 10 = 0$	5.75	0.017
	Unexpected Event[+1, +5]: $\beta 6+\beta 9+\beta 15 = 0$	6.76	0.010
	Expected Event[+1, +5]: $\beta 3+\beta 12 = 0$	30.13	0.000

This table presents the results of model (2), which models factors that influence the demand for information as a function of different windows around corporate events. The dependent variable is the abnormal level of Google search volume for a firm's ticker symbol for each day in a time-series. Standard errors are presented in parentheses to the right of the coefficient estimates and are clustered by firm. The sample consists of S&P 500 firms from 2005 to 2008. Variable definitions are provided in the appendix. *, **, *** indicates statistical significance at the $p < 0.10, 0.05, 0.01$ level, respectively.

On the event dates, we find significant increases in abnormal search volume, which is consistent with the results presented in table 3. That is, we find positive and significant coefficients for each event with the exception of dividend announcements. Finally, we find that post-event search is abnormally high for earnings announcements ($\beta_3 = 0.043$, $p < 0.01$), management forecasts ($\beta_6 = 0.020$, $p < 0.05$), and acquisition announcements ($\beta_{15} = 0.077$, $p < 0.05$).

Tests of coefficient equality in model (2) provide two additional insights. First, events that are generally expected by the market (earnings and dividend announcements) generate abnormal levels of search before the event occurs (F-stat $= 5.75$, $p < 0.05$). In contrast, unexpected news announcements (analyst and management forecasts, acquisition announcements) do not generate abnormal demand before the event (F-stat $= 0.92$, $p > 0.10$). However, information demand *after* the announcement continues at abnormally high levels, for both unexpected events (F-stat = 6.76, $p < 0.05$) and expected events (F-stat = 30.13, $p < 0.01$).[20] Second, abnormal search following an earnings announcement is significantly higher than it is during the period before the earnings announcement (i.e., $\beta_3 > \beta_1$, $p < 0.01$). This finding is consistent with investors expending more effort to interpret released information than they do to prepare for an upcoming announcement.[21] In total, the evidence suggests that the timing of investor demand is different for different types of events. Moreover, information diffusion is not immediate for these events, but rather takes place in a window of days around the announcement.

4.3 CROSS-SECTIONAL DIFFERENCES IN THE TIMING OF INVESTOR DEMAND AROUND EARNINGS ANNOUNCEMENTS

In the third model, we further explore search patterns around earnings announcements by examining the extent to which differences in the cross-section of firms influence those patterns. We focus on the earnings announcement and examine abnormal search volume around earnings announcements within ranks of the following four, frequently used cross-sectional attributes: firm size, analyst following, bid-ask spreads, and idiosyncratic volatility. We identify firms as being high versus low in a particular attribute by using the highest quartile in the prior calendar quarter as a threshold.[22] The third model is as follows:

$$\begin{aligned} AbSearch_{it} = {} & \beta_{\text{Week}} + \beta_1 Earnings\,Announcement\,[.]_{it} + \beta_2 Attribute_{it} \\ & + \beta_3\,(Earnings\,Announcement\,[.]_{it}\;x\;Attribute_{it}) + \beta_n Controls \end{aligned} \tag{3}$$

where,

Earnings Announcement$[.]_{it}$ = event-day indicator variables set equal to one during the days before, during, and after (i.e., event days $[-5, -1]$, $[0]$, $[+1, +5]$, and zero otherwise;
$Attribute_{it}$ = one of four indicators variables defined as follows:
LargeFirms = indicator variable set equal to one if the market value of equity of the firm at the end of the prior quarter is in the highest quartile of the sample and to zero otherwise;

[20] Jin, Livnat, and Zhang [2011] also use the distinction between expected and unexpected events to examine investor information; specifically, they examine the relation between option-related measures and future returns to document whether option market participants have superior private information or superior information-processing abilities relative to equity market participants.

[21] We further note that the coefficient for each window around the earnings announcement is significantly different from the coefficient from every other window ($\beta_1 \neq \beta_2 \neq \beta_3$, $p <$ 0.01, results untabulated). Thus, pre-earnings announcement search, though above normal, is significantly lower than both announcement-period search and post-earnings announcement search.

[22] We note that the results are qualitatively similar if we use other thresholds of the four attributes, such as the upper tercile or above the median.

HighFollowing = indicator variable set equal to one if the average number of analyst following of the firm for the prior quarter is in the highest quartile of the sample and to zero otherwise;
LargeSpread = indicator variable set equal to one if the average bid-ask spread of the firm for the prior quarter is in the highest quartile of the sample and to zero otherwise;
HighIdio = indicator variable set equal to one if the average idiosyncratic volatility of the firm for the prior quarter is in the highest quartile of the sample and to zero otherwise;
Controls = a set of controls variables including *# News Articles*, *|Returns|*, *Turnover*, *Fourth Qtr*, *Rank of # Announcements*, *Institutional Ownership*, and *Rank of Book-to-Market* as defined above.

Table 5 presents the estimation results for model (3). We find that abnormal search in the pre-earnings announcement period is higher for larger firms. We also find that abnormal search at the earnings announcement and in the postannouncement period is higher for larger S&P 500 firms and for those with higher analyst following. It is also higher for firms with greater spreads and idiosyncratic volatility. One interpretation of these findings is that investors focus on their search on where the search costs are lowest (i.e., in firms with high information environments, as proxied by firm size and analyst following) and where the benefits from acquiring information are the highest (i.e., where information asymmetry is the highest, as proxied by high bid-ask spreads and idiosyncratic volatility). We are cautious in interpreting the results in such a fashion since (1) all of these firms are S&P 500 firms and there is less variation in these cross-sectional attributes than in a random sample of public firms and (2) these variables serve as proxies for numerous different constructs. Nevertheless, this analysis demonstrates that, even in a setting such as the S&P 500, investors' demand for information in the period around earnings announcements is different for different types of firms.

The results presented in tables 3 through 5 provide important insights into the drivers of investor information demand. We find that investors demand more information about a firm when there is relatively more news about the firm being disseminated to the market and during important corporate announcements such as acquisition announcements and earnings announcements. We find that investors are uniquely interested in gathering information at different times for different types of events and different types of firms. Having investigated the determinants of search, we now turn to investigate some of the market implications of increased search volume.

5. *The Effects of Abnormal Search on the Market Response to Earnings News*

In this section, we present the results of our second phase of analysis, which examines the effects of increased demand for information on the

TABLE 5

The Effects of Firm Characteristics on the Timing of Information Demand Around Earnings Announcements

	Daily *AbSearch*				
Variables	(1)	(2)	(3)	(4)	(5)
Earnings Announcement[−5, −1]	0.003	0.004	0.005	0.005	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Earnings Announcement[0]	0.031***	0.046***	0.064***	0.068***	0.002
	(0.006)	(0.008)	(0.011)	(0.012)	(0.007)
Earnings Announcement[+1, +5]	0.018***	0.021***	0.029***	0.031***	0.006
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)
LargeFirms	−0.006*				−0.004
	(0.003)				(0.003)
Earnings Announcement[−5, −1]* *LargeFirms*	0.018**				0.017*
	(0.009)				(0.009)
Earnings Announcement [0]* *LargeFirms*	0.180***				0.165***
	(0.036)				(0.033)
Earnings Announcement [+1, +5]* *LargeFirms*	0.085***				0.075***
	(0.021)				(0.019)
HighFollowing		−0.003			−0.002
		(0.003)			(0.003)
Earnings Announcement [−5, −1]* *HighFollowing*		0.014*			0.009
		(0.007)			(0.007)
Earnings Announcement[0]* *HighFollowing*		0.131***			0.082***
		(0.032)			(0.027)
Earnings Announcement[+1, +5]* *HighFollowin*		0.077***			0.053***
		(0.018)			(0.016)
LargeSpread			−0.006*		−0.006*
			(0.003)		(0.003)
Earnings Announcement[−5, −1]* *LargeSpread*			0.010		0.006
			(0.008)		(0.008)
Earnings Announcement [0]* *LargeSpread*			0.047**		0.039**
			(0.020)		(0.017)
Earnings Announcement[+1, +5]* *LargeSpread*			0.041***		0.032**
			(0.015)		(0.013)
HighIdio				−0.010***	0.011***
				(0.003)	(0.003)
Earnings Announcement[−5, −1]* *HighIdio*				0.010	0.009
				(0.007)	(0.007)
Earnings Announcement [0]* *HighIdio*				0.033*	0.031**
				(0.018)	(0.015)

(Continued)

TABLE 5—*Continued*

	Daily *AbSearch*				
Variables	(1)	(2)	(3)	(4)	(5)
Earnings Announcement [+1, +5]* *HighIdio*				0.030** (0.013)	0.022** (0.010)
Controls	Yes	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	244,871	244,871	244,871	244,871	244,871
Adj *R*-square	0.034	0.032	0.031	0.030	0.035

This table presents the results of model (3). The dependent variable is the abnormal level of Google search volume for a firm's ticker symbol for each day. Standard errors are presented in parentheses below the coefficient estimates and are clustered by firm. The sample consists of S&P 500 firms from 2005 to 2008. Variable definitions are provided in the appendix. *, **, *** indicates statistical significance at the $p < 0.10$, 0.05, 0.01 level, respectively.

market response to earnings news. As described above, we predict that, to the extent abnormal search volume for public information is useful, increased preannouncement search will accelerate the price discovery of earnings before the earnings are actually announced. We predict that, in turn, the information content of earnings will be partially preempted. We focus our analyses on three event windows: [*FQE*, −1], [−5, −1], and [0, +1]. For these analyses, we include day +1 in the earnings announcement event window ([0, +1]) to be consistent with the recommendations in Berkman and Truong [2009].

5.1 EVIDENCE FROM THE PREANNOUNCEMENT PERIOD

To examine whether increased investor demand accelerates the price discovery of upcoming earnings news, we examine whether the association between preannouncement abnormal returns and the subsequent earnings news is stronger when preannouncement search volume is relatively higher. Specifically, we estimate the following model:

$$AR\,[-5,-1] = \delta_0 + \delta_1\, UE + \delta_2\, AbSearch\,[.] + \delta_3 (UE \times AbSearch\,[.]) + \delta_x\, Controls + \delta_y\, (UE \times Controls) + e, \tag{4}$$

where,

Controls = a set of control variables including *Log*(1+*Analyst Following*), *Institutional Ownership*, *Rank of Size*, *Rank of Book-to-Market*, *Turnover*, *Fourth Qtr*, *Rank of # Announcements*, *# News Articles*[.] as defined previously, plus the following additional variables:
Earnings Persistence = First-order auto-correlation coefficient of quarterly earnings estimated over the four-year period ending on the fiscal end date;
Earnings Volatility = Standard deviation of seasonal earnings changes estimated over the four-year period ending on the fiscal end date;
Management Forecasts = indicator variable set equal to one if managers issue a forecast between the fiscal quarter end date and the earnings announcement date;

Forecast Revisions[.] = the count of the number of analyst earnings forecast revisions between the fiscal quarter end date and the earnings announcement date; and all other variables as defined previously.

In model (4), δ_3 is the coefficient of interest. A positive δ_3 provides evidence consistent with preannouncement price changes reflecting more future earnings news when preannouncement abnormal search is higher. Thus, model (4) is a variation of the future earnings response coefficient (FERC) models used to measure factors associated with current prices incorporating future earnings news (Lundholm and Myers [2002], Gelb and Zarowin [2002], Ayers and Freeman [2003]). With respect to the control variables, we control for factors that prior research finds to be associated with the market response to earnings news as measured by the earnings response coefficient (ERC).[23] Specifically, prior research finds that the ERC is associated with various firm characteristics including analyst following (Shores [1990]), firm size (Collins and Kothari [1989]), institutional ownership (Teoh and Wong [1993]), book-to-market (Collins and Kothari [1989]), and earnings persistence (Kormendi and Lipe [1987]). Following Hirshleifer, Lim, and Teoh [2009], we also include earnings volatility, share turnover, and the number of other firms reporting earnings on the same day. We include a measure of press coverage to control for the general level of news about the firm before the earnings announcement. Because the dependent variable is returns, we cluster standard errors at the industry-quarter level with industry defined by the Fama-French 17 industry classifications. (All remaining tests have either returns or trading volume as the dependent variable and also use this clustering method.)

Table 6 presents the estimation results for model (4). The heading of each column denotes the earnings expectations benchmark used to calculate *UE*. In columns (1) and (2) we present the results using *AbSearch*[*FQE*, −1] as the variable of interest, and in columns (3) and (4) we present the results using *AbSearch*[−5, −1] as the variable of interest. We include all the control variables and the interactions of the control variables with *UE* in all of the regressions, but we do not tabulate their coefficients for parsimony.

In table 6, columns (1) and (2), we find that the coefficient on the interaction *UE* × *AbSearch*[*FQE*, −1] is positive and significant using both earnings benchmarks ($\delta_3 = 2.795$, $p < 0.05$ in column (1) and $\delta_3 = 1.952$, $p < 0.01$ in column (2)). This result suggests that, when investors search for more information in the period between the end of the prior quarter and the day before the earnings announcement, price changes in the five-day period before the earnings announcement reflect more of the information content of the upcoming earning surprise. In columns (3) and (4), we find similar evidence for the five-day window ending just before earnings are

[23] Our set of control variables follows Hirshleifer, Lim, and Teoh [2009]. As in Hirshleifer, Lim, and Teoh [2009] we require a minimum of four observations to estimate *Earnings Persistence* and *Earnings Volatility*.

TABLE 6

The Association Between Preannouncement Abnormal Returns, the Earnings Surprise, and Abnormal Search

		$AR[-5, -1]$ Earnings Expectations Based on			
Variables	Pred	Analysts (1)	Time-Series (2)	Analysts (3)	Time-Series (4)
UE	+	−0.537	−0.608	−0.116	−0.222
		(0.484)	(0.369)	(0.408)	(0.291)
AbSearch[*FQE*, −1]	+/−			−0.000	−0.004
				(0.004)	(0.004)
UE × *AbSearch*[*FQE*, −1]	+			2.795**	1.952***
				(1.220)	(0.598)
AbSearch[−5, −1]	+/−			0.000	−0.001
				(0.003)	(0.003)
UE × *AbSearch*[−5, −1]	+			1.769***	1.614***
				(0.625)	(0.436)
Controls		Yes	Yes	Yes	Yes
UE × *Controls*		Yes	Yes	Yes	Yes
N		4,133	4,133	4,133	4,133
Adj *R*-square		0.050	0.047	0.051	0.057

This table presents the results of model (4). The control variables are as follows: *Log*(1+*Analyst Following*), *Institutional Ownership*, *Rank of Size*, *Rank of Book-to-Market*, *Earnings Persistence*, *Earnings Volatility*, *Turnover*, *Fourth Qtr*, *News Articles*[.], *Management Forecasts*, *# Forecast Revisions*[.], *Rank of # Announcements*[.]. Standard errors are presented in parentheses below the coefficient estimates and are clustered by time (calendar quarter) × industry (Fama-French 17 classifications). The sample consists of S&P 500 firms from 2005 to 2008. Variable definitions are provided in the appendix. *, **, *** indicates statistical significance at the $p < 0.10, 0.05, 0.01$ level, respectively. We use one-tailed tests when a direction is predicted.

announced—the coefficient on the interaction *UE* × *AbSearch*[−5, −1] is positive and significant using both earnings benchmarks ($\delta_3 = 1.769$, $p < 0.01$ in column (3) and $\delta_3 = 1.614$, $p < 0.01$ in column (4)). These results provide consistent evidence that preannouncement investor search moves prices in the direction of the upcoming earnings news, which is consistent with the Internet serving as an information channel through which the price discovery process is improved.

Next, we examine whether abnormal search volume in the preannouncement period impacts the relation between preannouncement abnormal trading volume and the upcoming earnings news. The volume tests are motivated by the idea, first championed by Beaver [1968], that volume reactions offer unique insights relative to those derived from pricing tests. Bamber, Barron, and Stevens [2011] explain that volume reactions capture changes in the expectations of individual investors, while price reactions capture changes in the expectations of the market as a whole. We estimate abnormal volume using daily trading data from CRSP. We calculate daily abnormal volume (*Abvol*) over our event windows as total trading volume during the event window minus the average trading volume for a 250-trading-day period ending on the quarter-end date, divided by the standard deviation of trading volume over that same 250-day estimation period.[24] We sum *Abvol* over the preannouncement period [−5, −1] and we estimate the following model:

$$Abvol\,[-5,-1] = \tau_0 + \tau_1|UE| + \tau_2 AbSearch\,[.] + \tau_3(|UE| \times AbSearch\,[.]) + \tau_x Controls + \tau_y(|UE| \times Controls) + e, \quad (5)$$

where,

$|UE|$ = absolute value of *UE*
Controls = a set of control variables including *Log*(1 + *Analyst Following*), *Institutional Ownership*, *Rank of Size*, *Rank of Book-to-Market*, *Earnings Persistence*, *Earnings Volatility*, *Turnover*, *Management Forecasts*, *# Forecast Revisions*, *Fourth Qtr*, *Rank of # Announcements*, and *# News Articles*[.] as defined previously.

Model (5) follows Bamber [1986] and [1987] in using the absolute value of the earnings surprise as a measure of news released at the announcement. We also include all control variables from model (4). Here, the coefficient of interest is τ_3. A significantly positive τ_3 indicates that the association between preannouncement trading volume and upcoming earnings news is stronger when preannouncement Internet search is higher.

Table 7 presents the estimation results for model (5). For the longer preannouncement period, we find an insignificant coefficient on the interaction term $|UE| \times AbSearch[FQE,-1]$ regardless of the earnings benchmark. However, we find that the coefficient on the interaction term $|UE| \times AbSearch[-5,-1]$ is positive and significant using both earnings benchmarks ($\tau_3 = 34.351$, $p < 0.05$ in column (3) and $\tau_3 = 31.199$, $p < 0.01$ in column (4)). Thus, we find evidence of a significant association between preannouncement volume and the magnitude of the earnings news, but only when the shorter of the two preannouncement windows ([−5, −1]) is used. This provides evidence that, when investors search for more information in the five days just before the earnings announcement, trading activity over that same five-day period is more highly associated with the magnitude of subsequent earnings news. This evidence is consistent with that presented in table 6 using stock returns.

Together, the evidence from the preannouncement period analyses suggests that market activity reflects more of the upcoming earnings news when Internet search in the days just before the earnings announcements is higher. This finding suggests that investor search via the Internet yields more timely price discovery of earnings information. In the next section, our focus shifts to the announcement period.

5.2 EVIDENCE FROM THE ANNOUNCEMENT PERIOD

We examine whether increased information demand via Internet search is associated with preemption of the information content of earnings news.

[24] The 250-trading-day window (one calendar year) is consistent with Bamber [1987].

TABLE 7

The Association Between Preannouncement Abnormal Volume, the Earnings Surprise, and Abnormal Search

		Abvol[−5, −1] Earnings Expectations Based on			
Variables	Pred	Analysts (1)	Time-Series (2)	Analysts (3)	Time-Series (4)
|*UE*|	+	2.771	13.574	19.549	17.160
		(31.366)	(23.121)	(30.728)	(19.383)
AbSearch[*FQE*, −1]	+/−	0.661*	0.691*		
		(0.392)	(0.405)		
|*UE*| × *AbSearch*[*FQE*, −1]	+	6.871	2.042		
		(47.081)	(33.422)		
AbSearch[−5, −1]	+ / −			0.665**	0.559**
				(0.270)	(0.269)
|*UE*| × *AbSearch*[−5, −1]	+			34.351**	31.199***
				(19.361)	(12.782)
Controls		Yes	Yes	Yes	Yes
|*UE*| × *Controls*		Yes	Yes	Yes	Yes
N		4,133	4,133	4,133	4,133
Adj *R*-square		0.035	0.038	0.038	0.042

This table presents the results of model (5). The control variables are as follows: *Log(*1+*Analyst Following), Institutional Ownership*, *Rank of Size*, *Rank of Book-to-Market*, *Earnings Persistence*, *Earnings Volatility*, *Turnover*, *Fourth Qtr, News Articles*[.], *Management Forecasts*, *# Forecast Revisions*[.], *Rank of # Announcements*[.]. Standard errors are presented in parentheses below the coefficient estimates and are clustered by time (calendar quarter) × industry (Fama-French 17 classifications). The sample consists of S&P 500 firms from 2005 to 2008. Variable definitions are provided in the appendix. *, **, *** indicates statistical significance at the $p < 0.10, 0.05, 0.01$ level, respectively. We use one-tailed tests when a direction is predicted.

To test this prediction, we examine whether the earnings response coefficient (i.e., the sensitivity of stock returns to earnings news) is lower when preannouncement search is higher. The distinction between this test and the previous one is the horizon over which abnormal returns, the dependent variable, is measured. In the previous set of tests, we examine abnormal returns in the period before the earnings announcement, whereas in this set of tests, we examine abnormal returns in the actual earnings announcement window. As with the models in tables 4 and 5, we examine search in the two preannouncement periods. We also include search during the announcement period to test whether the ERCs vary with announcement period search. We estimate the following model of the earnings response coefficient:

$$\begin{aligned} AR\,[0,+1] = {} & \omega_0 + \omega_1\, UE + \omega_2\, AbSearch\,[.,-1] \\ & + \omega_3 (UE \times AbSearch\,[.,-1]) + \omega_4\, AbSearch\,[0,+1] \\ & + \omega_5\, (UE \times AbSearch\,[0,+1]) + \omega_x\, Controls \\ & + \omega_y\, (UE \times Controls) + e, \end{aligned} \tag{6}$$

where,

Controls = a set of control variables including *Log*(1 + *Analyst Following*), *Institutional Ownership*, *Rank of Size*, *Rank of Book-to-Market*, *Earnings Persistence*, *Earnings Volatility*, *Turnover*, *Management Forecasts*, # *Forecast Revisions*, *Rank of* # *Announcements*, *Fourth Qtr*, and # *News Articles*[.], *AR* [−5, −1]as defined previously, and the following additional variables:
Loss = an indicator variable set equal to one if realized earnings are negative, and to zero otherwise; and all other variables as defined previously.

In model (6), the earnings response coefficient is ω_1, which measures the magnitude of the relation between stock returns and earnings. The coefficients of interest are ω_3 and ω_5. A significantly negative ω_3 provides evidence that announcement returns reflect less earnings news when preannouncement search is higher. Thus, a negative ω_3 is consistent with our prediction that preannouncement investor search results in preannouncement prices that partially preempt the information content of earnings. A significantly positive (negative) ω_5 provides evidence that announcement returns reflect less (more) earnings news when announcement search is higher. We include the same control variables as in model (4) (discussed above).[25] We also include an indicator for loss observations following Hayn [1995].

Table 8 presents the estimation results for model (6). Again, the heading of each column denotes the earnings expectations benchmark used to calculate *UE*. In columns (1) and (2), we present the results using *AbSearch*[*FQE*,−1] and in columns (3) and (4) we present the results using *AbSearch*[−5, −1]. Control variables and their interactions with *UE* are included in the models, but are not reported for parsimony.

In table 8, columns (1) and (2) we find evidence that preannouncement search during the full preannouncement period ([*FQE*, −1]) is associated with a lower ERC. Specifically, we find that the coefficient on the interaction term *UE* × *AbSearch*[*FQE*, −1] is negative and significant using both earnings benchmarks ($\omega_3 = -3.289$, $p < 0.10$ in column (1) and $\omega_3 = -2.477$, $p < 0.01$ in column (2)). In columns (3) and (4), we use the shorter preannouncement window, [−5, −1], and also find that the coefficient on the interaction term *UE* × *AbSearch*[−5, −1] is negative and highly significant using both earnings benchmarks ($\omega_3 = -3.818$, $p < 0.01$ in column (3) and $\omega_3 = -2.863$, $p < 0.01$ in column (4)). In all regressions, the ERC is positive and significant as expected. These results, together with those presented for the preannouncement period in tables 6 and 7, provide evidence consistent with our prediction that the information content of earnings is partially preempted when preannouncement Internet search is high.

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[25] In a sensitivity test (unreported), we follow Wilson [2008] and control for potential nonlinearity in the earnings-return relation (see, e.g., Freeman and Tse [1989], Lipe, Bryant, and Widener [1998]) by including $UE \times |UE|$ in model (5). We find results similar in magnitude and significance to those reported.

TABLE 8

The Association Between Announcement Abnormal Returns, the Earnings Surprise, and Abnormal Search

		$AR[0, +1]$ Earnings Expectations Based on			
Variables	Pred	Analysts (1)	Time-Series (2)	Analysts (3)	Time-Series (4)
UE	+	8.528***	3.027***	7.168***	2.287***
		(1.478)	(0.636)	(1.615)	(0.551)
AbSearch[*FQE*, −1]	+ / −	0.008	0.014		
		(0.008)	(0.009)		
UE × *AbSearch*[*FQE*, −1]	−	−3.289*	−2.477***		
		(2.223)	(1.043)		
AbSearch[−5, −1]	+ / −			0.007	0.009*
				(0.005)	(0.006)
UE × *AbSearch*[−5, −1]	−			−3.818***	−2.863***
				(1.364)	(0.809)
AbSearch[0, +1]	+ / −	0.002	0.002	0.000	0.000
		(0.006)	(0.006)	(0.006)	(0.006)
UE × *AbSearch*[0, +1]	+	−2.613**	−1.243	−0.699	0.183
		(1.211)	(1.000)	(1.034)	(0.632)
Controls		Yes	Yes	Yes	Yes
UE × *Controls*		Yes	Yes	Yes	Yes
N		4,133	4,133	4,133	4,133
Adj *R*-square		0.117	0.065	0.123	0.078

This table presents the results of model (6). The control variables are as follows: *Log(1+Analyst Following)*, *Institutional Ownership*, *Rank of Size*, *Rank of Book-to-Market*, *Earnings Persistence*, *Earnings Volatility*, *Turnover*, *Fourth Qtr*, *News Articles*[.], *Management Forecasts*, *# Forecast Revisions*[.], *Rank of # Announcements*[.], *Loss*. Standard errors are presented in parentheses below the coefficient estimates and are clustered by time (calendar quarter) × industry (Fama-French 17 classifications). The sample consists of S&P 500 firms from 2005 to 2008. Variable definitions are provided in the appendix. *, **, *** indicates statistical significance at the $p < 0.10, 0.05, 0.01$ level, respectively. We use one-tailed tests when a direction is predicted.

With respect to search during the announcement window, [0, +1], we find limited evidence that ERCs are significantly associated with announcement period search. We find a negative and significant coefficient on the interaction term *UE* × *AbSearch*[0, +1], but only when we simultaneously control for search during the longer preannouncement window and analyst forecasts are used as the earnings benchmark. Thus, we are cautious about drawing inferences regarding the association between ERCs and announcement period search. Overall, the results are consistent with the idea that, when investors demand more information in the preannouncement period, stock prices reflect more of that information in the preannouncement period and the market response when earnings are ultimately announced is attenuated.

In our final test, we investigate whether Internet search impacts the relation between announcement period trading volume and the magnitude of the earnings news. Specifically, we sum *Abvol* over the announcement period [0,+1] and estimate the following model:

$$\begin{aligned} Abvol\,[0,+1] = {} & \gamma_0 + \tau_1 |UE| + \gamma_2\, AbSearch\,[.,-1] \\ & + \gamma_3\,(|UE| \times AbSearch[.,-1]) + \gamma_4\, AbSearch\,[0,+1] \\ & + \gamma_5\,(|UE| \times AbSearch\,[0,+1]) \\ & + \gamma_x\, Controls + \gamma_y\,(|UE| \times Controls) + e, \end{aligned} \tag{7}$$

where,

Controls = a set of control variables including *Log*(1 + *Analyst Following*), *Institutional Ownership*, *Rank of Size*, *Rank of Book-to-Market*, *Earnings Persistence*, *Earnings Volatility*, *Turnover*, *Management Forecasts*, *# Forecast Revisions*, *Fourth Qtr*, *Rank of # Announcements*, and # *News Articles*[.] as defined previously.

In model (7) the coefficients of interest are γ_3 and γ_5. A significantly negative γ_3 indicates that the association between announcement period trading volume and the magnitude of the earnings news is weaker when *preannouncement* Internet search is higher. A significantly positive (negative) γ_5 provides evidence that the association between announcement period trading volume and the magnitude of the earnings news is stronger (weaker) when *announcement* Internet search is higher.

Table 9 presents the estimation results for model (7). We find that the coefficients on the interaction term $|UE| \times AbSearch[FQE, -1]$ are negative and significant using both earnings benchmarks ($\gamma_3 = -170.609$, $p < 0.01$ in column (1) and $\gamma_3 = -95.179$, $p < 0.01$ in column (2)). For the shorter preannouncement window, we find a negative and significant γ_3, but only when time-series forecasts are used as the earnings benchmark ($\gamma_3 = -38.499$, $p > 0.10$ in column (3) and $\gamma_3 = -25.574$, $p < 0.10$ in column (4)). Overall, we find significant results in three of the four regressions, which provide evidence consistent with those from the ERC model presented in table 8.

For announcement period search, measured over [0, +1], we find a positive and significant coefficient on the interaction term $|UE| \times AbSearch[0, -1]$ across all four models. This evidence is in contrast to the ERC model, where we found weak evidence of a negative association between ERCs and announcement period search. The evidence in table 9 suggests that high announcement period search reflects differences of opinion among investors, which results in significant increased trading volume, but insignificant or negative prices changes.

6. *Robustness and Alternate Tests*

Before concluding, we discuss the results of several untabulated robustness tests using alternative measures of Google search volume and variations in the specifications. To begin, recall that model (1) investigates factors associated with *AbSearch,* which is the variable used in prior research,

TABLE 9

The Association Between Announcement Abnormal Volume, the Earnings Surprise, and Abnormal Search

		Abvol[0, +1] Earnings Expectations Based on			
Variables	Pred	Analysts (1)	Time-Series (2)	Analysts (3)	Time-Series (4)
|*UE*|	+	72.322	58.778**	47.413	39.083
		(45.815)	(24.014)	(53.847)	(27.699)
AbSearch[*FQE*, −1]	+/−	−1.522***	−1.276***		
		(0.418)	(0.414)		
|*UE*| × *AbSearch*[*FQE*, −1]	−	−170.609***	−95.179***		
		(59.69)	(21.876)		
AbSearch[−5, −1]	+/−			−0.302	−0.241
				(0.311)	(0.316)
				(0.311)	(0.316)
|*UE*| × *AbSearch*[−5, −1]	−			−38.499	−25.574*
				(43.027)	(14.672)
AbSearch[0, +1]	+ / −	1.990***	1.840***	1.583***	1.465***
		(0.296)	(0.300))	(0.302)	(0.317)
|*UE*| × *AbSearch*[0, +1]	+	52.596*	36.380**	92.123**	47.837**
		(28.115)	(15.625)	(38.300)	(18.51)
Controls		Yes	Yes	Yes	Yes
|*UE*| × *Controls*		Yes	Yes	Yes	Yes
N		4,133	4,133	4,133	4,133
Adj *R*-square		0.052	0.051	0.047	0.045

This table presents the results of model (7). The control variables are as follows: *Log(1+Analyst Following), Institutional Ownership, Rank of Size, Rank of Book-to-Market, Earnings Persistence, Earnings Volatility, Turnover, Fourth Qtr, News Articles*[.], *Management Forecasts*, *# Forecast Revisions*[.], *Rank of # Announcements*[.], *Loss*. Standard errors are presented in parentheses below the coefficient estimates and are clustered by time (calendar quarter) × industry (Fama-French 17 classifications). The sample consists of S&P 500 firms from 2005 to 2008. Variable definitions are provided in the appendix. *, **, *** indicates statistical significance at the $p < 0.10$, 0.05, 0.01 level, respectively. We use one-tailed tests when a direction is predicted.

namely Da, Engelberg, and Gao [2011]. However, the residual from model (1) provides a measure of Internet search that, by construction, is unrelated to the other observable factors included in the model. We estimate the residual value and calculate the mean residual for each of our examination windows: [*FQE*, −1], [−5, −1], and [0, +1]. We find that this residual is highly correlated with *AbSearch* (correlation coefficient of approximately 0.78 for the two preannouncement windows, [*FQE*, −1] and [−5, −1], and a correlation coefficient of 0.95 for the announcement window, [0, +1]). When we estimate models (4) through (7) using the residual value instead of the raw *AbSearch* (results unreported), we find that all of our general inferences hold.

In addition to using the residual as a measure of search, we use the raw value of Google SVI (i.e., without any adjustments for the benchmark level of search volume) as the dependent variable in models (1) and (2). With this alternative measure, the event date indicators and all independent variables remain significant, with the exception of two variables, *Dividend*

Announcements and *Turnover*, in the estimation of model (1). Moreover, none of the control variables are significant under this specification. In estimating model (2) with the raw values of Google SVI, we find that all of the event date indicators for the time period before, during, and after the corporate events are positive and significant (one-tailed), save for the *Dividend Announcement*[.] dates. Again, none of the control variables are significant under this specification.

Finally, we performed many tests of robustness in models (1)–(7) including different fixed effects (e.g., firm, industry, time) and clustering the standard errors on different dimensions (e.g., firm and time), most of which are noted above in the footnotes. The results remain consistent across the board. We conclude from these tests that the timing and factors that explain Internet search activity around corporate events, and the impact of such on the market response to earnings news, are qualitatively the same regardless of the specification.

7. *Conclusion*

The results presented above provide empirical evidence on the nature and timing of investor demand for information, as well as the pricing consequences of increased investor demand for information around earnings announcements. The findings are summarized as follows: First, we find that investor information demand is positively associated with media attention and news, and negatively associated with investor distraction. Second, we find evidence of significant increases in investor demand around many corporate announcements. However, we find evidence of *pre*announcement increases in investor demand for earnings announcements only and that the increases are highest in those firms where the returns to search are most likely to be profitable. Third, we find that price changes and trading volume prior to earnings announcements reflect more of the upcoming earnings news when investors search for more information prior to the announcement. Fourth, we find that price changes at the earnings announcement are lower when investors search for more information prior to the announcement. Broadly, we conclude that the information content of earnings is partially preempted when investors' preannouncement search activities are high.

An important caveat is that we cannot observe the type of market participant that uses Google to search for information around earnings announcements. Da, Engelberg, and Gao [2011] argue that, since large institutional investors have access to better information sources, Google search likely measures the attention of retail investors. Consistent with this conjecture, their empirical tests provide evidence that weekly Google search captures the attention of individual traders who are "perhaps less sophisticated." However, our evidence that a portion of the information content of earnings news is preempted when Google search is high in the days just before the earnings announcement is inconsistent with the measure solely capturing the behavior of less sophisticated retail investors (or noise traders).

This limitation notwithstanding, this proxy does capture the act of seeking information, and, thus, can be used in other settings to further our understanding of how information demand impacts capital markets.

APPENDIX

Variable Definitions

Variable	Description	Source
# Announcements	The number of other firms announcing quarterly earnings on day t (in models (1) through (3)) or on the same day as the earnings announcement (in models (4) through (7)).	I/B/E/S
# Forecast Revisions	The count of the number of analyst earnings forecast revisions between the fiscal quarter end date and the earnings announcement date;	I/B/E/S
# News Articles [.]	Number of articles in the *Wall Street Journal*, the *New York Times, USA Today*, and the *Washington Post* that mention the firm on day t. When the variable is appended with an event window [*FQE*, −1], [−5, −1], or [0, +1], the number of articles is averaged over the specified window.	Soltes [2009]
|*Return*|	The absolute value of the raw daily stock return.	CRSP
AbSearch[.]	The natural logarithm of 1 + the average value of $AbSearch_{it}$ estimated over three windows, [*FQE*, −1], [−5, −1], or [0, +1], where day *FQE* is the first day after the quarter-end date and day 0 is the earnings announcement date.	Google Trends
$AbSearch_{it}$	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
Acquisition Announcement	Indicator variable set equal to one on an acquisition announcement date and to zero otherwise.	Thomson / SDC
Analyst Following	Number of analysts in the last I/B/E/S consensus analyst earnings forecast prior to the earnings announcement date	I/B/E/S
Analyst Forecast Date	Indicator variable set equal to one on an analyst forecast date and to zero otherwise.	I/B/E/S
AR[.]	Buy-and-hold abnormal returns estimated over two windows, [−5, −1] or [0,+1]. Abnormal returns are calculated as raw returns less the return on a benchmark portfolio matched to the firm based on quintiles of size and book-to-market. Firms are assigned to size and book-to-market portfolios in June of each year.	CRSP
Bid-Ask Spread	The Corwin and Schultz [2011] estimated daily bid-ask spread from daily high and low prices.	CRSP

Variable	Description	Source
Book-to-Market	Ratio of book value of common equity to market capitalization ($CEQQ/[PRCCQ \times CSHOQ]$) measured as of the fiscal quarter end date;	Compustat
Dividend Announcement	Indicator variable set equal to one on a dividend announcement date and to zero otherwise.	CRSP
Earnings Announcement	Indicator variable set equal to one on an earnings announcement date and to zero otherwise.	I/B/E/S
Earnings Persistence	First-order autocorrelation coefficient of quarterly earnings estimated over the past four years.	Compustat
Earnings Volatility	Standard deviation of the seasonal earnings changes over the past four years.	Compustat
Fourth Qtr	Indicator variable set equal to one for firms announcing fourth quarter earnings and to zero otherwise.	Compustat
Institutional Ownership	Shares held by institutional investors scaled by total shares outstanding (as reported in CRSP).	Thomson / CRSP
Log(1 + *Analyst Following*)	The natural logarithm of 1 + *Analyst Following*	I/B/E/S
Loss	Indicator variable set equal to one if realized earnings are negative and to zero otherwise.	I/B/E/S
Management Forecast Date	Indicator variable set equal to one on a management earnings forecast date and to zero otherwise.	FirstCall
Management Forecasts	Indicator variable set equal to one if managers issue a forecast between the fiscal quarter end date and the earnings announcement date and to zero otherwise.	First Call
Rank of # Announcements	The decile rank of the number of other firms announcing quarterly earnings on the same day as the earnings announcement	I/B/E/S
Rank of Book-to-Market	The decile rank of *Book-to-Market*, scaled to range between 0 and 1	Compustat
Rank of Size	The decile rank of *Size*, scaled to range between 0 and 1.	CRSP
Size	Market capitalization ($PRCCQ \times CSHOQ$) measured as of the fiscal quarter end date.	CRSP
Turnover	Average monthly trading volume, scaled by the average number of shares outstanding over the one year period ending on the fiscal quarter end date	CRSP
UE	Unexpected earnings defined using one of two definitions: *UEAF* = Difference between actual earnings and the median analyst forecast as reported in I/B/E/S, scaled by stock price at the fiscal end date as reported in CRSP. *UETS* = Difference between actual earnings and actual earnings for the same quarter in the prior year (seasonal change) as reported in I/B/E/S, scaled by stock price at the fiscal end date as reported in CRSP.	I/B/E/S
$\|UE\|$	Absolute value of *UE*.	I/B/E/S

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