Googling for Information around Earnings Announcements

Michael S. Drake  
*Fisher College of Business*  
*The Ohio State University*  
2100 Neil Avenue  
*Columbus, OH 43210*  
614-292-2451  
mdrake@fisher.osu.edu

Darren T. Roulstone†  
*Fisher College of Business*  
*The Ohio State University*  
2100 Neil Avenue  
*Columbus, OH 43210*  
614-292-1822  
roulstone.1@osu.edu

Jacob R. Thornock  
*Foster School of Business*  
*University of Washington*  
Box 353200, Seattle, WA 98195  
206-543-7913  
thornocj@uw.edu

August 2010

†Corresponding author. We thank Cory Cassell, Rebecca Files, Ed Maydew, James Myers, Stephanie Rasmussen, Lynn Rees, Andy Van Buskirk, and workshop participants at The Ohio State University for comments and suggestions. We thank Yung-Yu Chen for assistance in acquiring Google search data and Eugene Soltes for graciously sharing his press coverage data. The financial support of the Fisher College of Business and Foster School of Business is gratefully acknowledged.
ABSTRACT

This paper examines the impact of investor information acquisition on the market response to earnings news. Prior research in this area has been hampered by inadequate proxies for investor information acquisition. We propose a direct measure of information acquisition, Google search volume, and examine how the market response to earnings news varies with investor search before and during the earnings announcement. We find that abnormal Google search increases about two weeks prior to the earnings announcement and then spikes markedly at the announcement with an order of magnitude at least as large as that of other important corporate events (e.g., acquisition announcements). When investors search for more information in the days just prior to the announcement, pre-announcement price changes reflect more of the upcoming earnings news and there is less of a price response when the news is announced. This finding suggests that when investors gather more information about a firm, the information content of the earnings announcement is partially preempted.

Key Words: Information Acquisition, Earnings Announcements, Information Content
1. Introduction

This paper examines the impact of investor information acquisition on the market response to earnings news. Theoretical research demonstrates that the market response to earnings disclosures is a function of investors’ preannouncement information and their interpretations of the announcement news (e.g., Kim and Verrecchia [1991], [1997]). In the preannouncement period, investors with rational expectations gather information when the expected profit from trading on that information is positive (McNichols and Trueman [1994]). As investors gather and trade on information prior to earnings announcements, market prices begin to partially reveal that information. As a consequence, there is less of a price reaction when the information is announced because a greater portion of the information content of the earnings news is anticipated.

Although the empirical literature on the market response to earnings is well developed, we understand very little about how information gathering in the period before and during the announcement affects this response. This gap in the literature is in large part due to the lack of data on investors’ information acquisition since these activities are difficult to observe empirically. Prior studies use firm characteristics such as firm size (Atiase [1985]), analyst following (Dempsey [1989]), and institutional ownership (El-Gazzar [1998]) as indirect proxies for information acquisition. In this study, we propose a direct measure of investor’s acquisition of information—Google search volume for a firm’s ticker. Using this measure of information acquisition, we investigate whether upcoming public disclosures induce information acquisition in the form of Google searches and whether pre-disclosure information acquisition affects the market response to earnings news. That is, we are interested in examining the effects on earnings’ information content when investors “google” for information prior to, and at the time
of the earnings announcement. Our analyses should be of interest to regulators and academics who seek to understand the capital market effects of investor information collection efforts.

We collect daily Google Search Volume Index (SVI) for S&P 500 firms. SVI measures the number of daily searches for a particular ticker symbol, and thus provides time-series variation in information acquisition for a specific firm. We use Google search volume to proxy for investor information acquisition activities because it captures investors’ direct actions—that is, it measures the extent to which investors physically type a ticker symbol into the Google search engine in order to gather information on the firm. We use tickers instead of company names to increase the likelihood that an investor is searching for financial information, rather than searching for other company information, such as products or store locations. Since Google is an efficient tool to gather stock price information, it is possible that the average investor is merely using Google to find out the current stock price. To increase the likelihood that investors are searching for information about impending earnings announcements, we employ a short-window event-study methodology and we remove the normal level of Google search volume during non-earnings announcement periods. This research design increases the likelihood that the variation in investor search is associated with the release of earnings news and allows us to directly test the effects of information acquisition on the market response to earnings news.

We find that investors increase their information search activities about two weeks prior to the earnings announcement. This increase in abnormal search volume in the pre-announcement period is consistent with the theoretical prediction in McNichols and Trueman

---

1 We view our use of S&P 500 firms as conservative as these firms are all likely to have strong information environments. Thus, our inferences are more likely to be driven by variation in search and less likely to be confounded by variation in the information environments of the firms.

2 For example, if we were to use “Bank of America” rather than its ticker, “BOA,” we could not separate search for online banking, branch locations, or interest rates from search for financial information.
[1994] that impending public disclosures stimulate private information acquisition. Abnormal search volume in Google continues to trend upward as the earnings announcement date approaches and then spikes markedly on the announcement date. The announcement-day spike is consistent with other observed “spikes” in the earnings announcement literature (e.g., Beaver [1968]).

When we compare the magnitude of abnormal Google search at the earnings announcement date to that for other public disclosures – such as management forecasts, analyst forecasts, dividend announcements, and acquisition announcements – we find that earnings announcements and acquisition announcements are associated with the greatest spike in search volume (11.9 percent and 15.2 percent higher than normal, respectively). Management forecasts, analyst forecasts and dividend announcements are associated with lower search volume than are earnings announcements.

Next, we investigate cross-sectional variation in abnormal search around earnings announcements. We find that pre-announcement abnormal search is higher for firms with greater abnormal return magnitudes (i.e., when there is more news), for relatively smaller S&P 500 firms with lower turnover, for firms with management forecasts subsequent to quarter-end, for firms in the fourth quarter, and for less “crowded” earnings announcement dates (pre-announcement period search volume is decreasing in the number of firms announcing earnings the same day). We find similar results for announcement period (days 0 and +1 relative to the announcement day) abnormal search volume. However, for this window we also find that announcement period abnormal search is higher for firms with lower book-to-market ratios (glamour firms), higher earnings volatility, and for firms with relatively fewer analyst earnings
revisions subsequent to quarter-end. We control for all of these factors in our subsequent analyses.

We conduct two analyses to test whether investors’ efforts in collecting information cause pre-announcement price changes to anticipate the content of the impending announcement. First, we examine whether the ratio of the absolute value of announcement period returns to the absolute value of pre-announcement period returns (labeled the “returns ratio”) is negatively associated with abnormal search volume over the pre-announcement period. Using two different pre-announcement search windows (all days from quarter-end to -1, and all days from -6 to -1, both relative to the announcement date) we find negative and statistically significant associations between the returns ratio and pre-announcement abnormal search. Second, we examine whether the association between pre-announcement abnormal returns and the subsequent earnings surprise is stronger when pre-announcement search is relatively higher. We find that the association between pre-announcement returns and the earnings surprise is more positive when pre-announcement search is higher. Taken together, these findings provide consistent empirical evidence that the market reaction to earnings news is partially preempted when information acquisition is abnormally high. Given that our models control for elements of the information environment of the firm (i.e., size, analyst coverage and forecasts, institutional ownership, management forecast, press coverage), this result suggests that investor search activities in the pre-disclosure period are an important and incremental determinant of the market response to earnings.

Finally, we test whether pre-announcement information collection results in a lower price reaction to the announcement of earnings information. We find that the earnings response coefficient (ERC) is lower when pre-announcement abnormal search volume is higher. This
finding suggests that differences in investor search activities in the days just before the earnings announcement affect the market’s response to earnings at the announcement. We also find some evidence that greater investor search at the earnings announcement is associated with a lower ERC. Thus the market impounds relatively less information into prices on the earnings announcement date for firms that have greater levels of abnormal search during the announcement period, perhaps because greater search activity at the announcement indicates the market needs additional information to process the earnings news.

We perform additional tests to examine how information search affects the relation between earnings news and trading volume and the relation between earnings news and post-announcement returns. We find some evidence that pre-announcement trading volume is more highly associated with the absolute magnitude of the upcoming earnings surprise when investors are searching for more information. However, we also find that trading volume at the announcement is positively associated with the absolute magnitude of the earnings surprise when abnormal search during the announcement period is high (in contrast to returns where ERC’s lessen with abnormal search). Finally, we find no evidence of abnormal search volume affecting post-earnings announcement drift.3

In summary, we use a novel and direct measure of investor’s information acquisition, Google search volume, to examine when investors acquire information around earnings announcements. Some researchers (e.g., Diamond [1985]) argue that mandatory disclosures of public information substitute for private information, which reduces the incentive to acquire private information. Others, such as McNichols and Trueman [1994] argue that anticipated public disclosures increase the expected profitability of pre-disclosure trading for informed

---

3 We note, however, that our sample of large firms (S&P 500 members) is not an optimal setting for attempting to test such a relation.
investors, and thus increase the incentives to invest in private information acquisition. Our data allows us to weigh in on this question by providing empirical evidence that upcoming public disclosures stimulate investor information acquisition and that these collected efforts by investors impact the market’s response to earnings. This study also contributes to the literature which investigates the impact of emerging technologies in the capital markets (see, for example, Blankespoor et al. [2010] which investigates firms’ use of Twitter). Finally, this study contributes a new proxy for investors’ information acquisition activity, which can be used in other settings.

One important caveat is that we cannot observe the type of market participant that uses Google to search for information around earnings announcements. Da et al. [2009] 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 finding 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 unsophisticated retail investors (or noise traders).

2. Literature Review and Motivation

The literature regarding the interplay between public information disclosures and the acquisition of private information provides the primary motivation for our empirical tests. We use search volume data from Google as our proxy for information acquisition and the earnings
announced as our disclosure setting. In this section, we discuss research relevant to each of these elements. We conclude the section by stating our empirical predictions.

2.1. Private Information Acquisition

A long line of theoretical research examines the relation between public disclosure and private information acquisition (see, e.g., Grossman and Stiglitz [1980], Gonedes [1980], Verrecchia [1982], Diamond [1985], Lundholm [1988], Bushman [1991], Alles and Lundholm [1993]). This literature is important to regulators and academics who seek to understand the incentives to acquire private information and to understand the capital market effects of information collection efforts. Grossman and Stiglitz [1980] demonstrate that, in a rational market without noise, investors have no incentive to acquire information because prices fully reveal that information to others. Verrecchia [1982] shows that when price only partially reveals traders’ private information, traders have an incentive to acquire information and that this incentive increases as the cost of acquiring information decreases and as the noise in price increases. An important addition to this literature is the consideration of private information acquisition when there are public disclosures (such as earnings announcements) providing information to all traders. Diamond [1985] shows that when public and private signals are observed contemporaneously, the public signal acts as a substitute for the private signal. This suggests that public disclosure reduces the incentive to invest in costly private information collection. In contrast to this finding in Diamond [1985], McNichols and Trueman [1994] demonstrate that, when investors are allowed to acquire and trade on information in advance of a public disclosure, the upcoming public signal stimulates private information acquisition in the pre-announcement period. They show that investors’ private information collection efforts “cause the pre-announcement price change to anticipate the public signal’s information content.”
Further, because pre-announcement price changes reflect more information about the impending public signal, they show that there is less of a market reaction to the news when it is announced.\textsuperscript{5}

Empirical tests of the effect of private information acquisition around public disclosures have been limited by the lack of an available proxy for information acquisition. Researchers have generally used variation in firm characteristics such as size, analyst following, or institutional ownership to proxy for variation in pre-disclosure private information acquisition (Atiase [1985]; Dempsey [1989]; El-Gazzar [1998]).\textsuperscript{6} The theoretical motivation establishing the link between these characteristics and private information acquisition is based on the incentives to acquire information and the costs of doing so. Atiase [1985] argues that private information search incentives are positively associated with firm size because firms with greater market capitalization provide greater potential benefits to acquiring private information and make it easier for informed traders to conceal their trades. Dempsey [1989] argues that analysts choose to follow firms which yield the highest benefit from private information, conditional on the cost of private information search; thus, analyst following will be positively correlated with private information acquisition. Finally, El-Gazzar [1998] argues that institutional owners have an incentive to develop private information because their investments are so large. All of these papers report evidence consistent with size, analyst following, and institutional ownership being correlated with private information acquisition. In contrast to these studies, our analyses use a more direct proxy for investors’ information search.

\textsuperscript{4} See proof of Proposition 4 in McNichols and Trueman [1994].
\textsuperscript{5} See proof of Proposition 5 in McNichols and Trueman [1994].
\textsuperscript{6} We control for all of these variables in the empirical tests that follow.
2.2. Google search frequency

One of the contributions of our study is the introduction to the literature of a new empirical proxy for information acquisition. We use search volume data from Google to proxy for investor information acquisition activities. We select this proxy for several reasons. First, Google SVI represents investors’ direct actions—that is, it measures the extent to which investors physically type a ticker symbol into the Google search engine in order to gather information on the firm. Second, the measure is timely. SVI is measured each day, which, combined with a short-window event-study methodology, increases the likelihood that the variation in investor search is associated with the release of earnings news and not with some other event or news. Third, as noted is Da et al. [2009], the internet is likely the most common medium to gather information and Google is the most common search engine used on the internet.  

Concurrent research in economics and finance has used Google search volume data in a variety of settings. Two papers, Choi and Varian [2009] and Da et al. [2010] use Google SVI as a proxy for customer’s 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 inclusion of Google SVI improves simple prediction models. Similarly, Da et al. [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 (revenues, earnings) released in the subsequent earnings announcement. More similar to the present study, Da et al. [2009] use Google SVI on ticker symbols as a proxy for investor’s demand for information, and more

---

7 For example, in May 2010, 72% of all searches on the internet were made via Google. http://www.hitwise.com/us/datacenter/main/dashboard-10133.html
specifically, as a proxy for investor attention. They find that weekly Google SVI is positively associated with other common proxies for attention including market capitalization, turnover, analyst following, and media attention; however, variation in these alternative proxies explains less than 10 percent of the variation in search frequency. They conclude that Google SVI is a more direct and timely proxy for attention than prior proxies.  

2.3. *Earnings announcements*

The public disclosure event investigated in this study is the earnings announcement. We choose this setting 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). While low R-squares from returns/earnings regressions cast some doubt on the informativeness of earnings announcements (e.g., Lev [1989]), a recent study (Basu et al. [2010]) finds that earnings announcements dominate other information events in terms of informativeness. Moreover, Landsman and Maydew [2002] find that the market reaction to earnings announcements is increasing over time.  

Second, earnings announcements are generally scheduled in advance (Chen and Mohan [1994]). The scheduling allows investors to anticipate the date of the public disclosure, and thus, facilitates the *timing* of information collection activities. Prior research investigates the

---

8 Our study differs from these concurrent studies in two important ways. First, we are primarily interested in how private information acquisition impacts the market reaction to earnings news (that is, the returns / earnings relation). Second, we are the first study to our knowledge to use *daily* Google SVI data.

9 Francis, Schipper and Vincent [2002] find that while the market response to earnings announcements has increased, the increased reaction is associated with other concurrent information releases, such detailed income statements.

10 Financial websites often provide notice of upcoming earnings announcements for investors and some allow users to search for earnings announcement dates by ticker symbol. See, e.g., [http://biz.yahoo.com/research/earn/cal/today.html](http://biz.yahoo.com/research/earn/cal/today.html)
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. For example, Christophe et al. [2004] examine short selling activity in the five days prior to the earnings announcement and find that short-selling during this period is motivated by the content of the upcoming earnings disclosure. Third, the use of earnings announcement 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 and to investigate variation in search related to the earnings surprise.

2.4. Empirical Predictions

The theoretical results in McNichols and Trueman [1994] provide the basis for the empirical predictions in this study. As discussed above we use daily Google search volume data around earnings announcements to test the following predictions:

Prediction 1: Private information acquisition in the pre-earnings announcement period increases as the announcement date approaches.

Prediction 2: Pre-earnings announcement returns reflect more future earnings news when pre-announcement private information acquisition is higher.

Prediction 3: Announcement returns reflect less earnings news when pre-announcement private information acquisition is higher.

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 Search Volume Index (SVI). Following Da et al. [2009], we identify a stock in Google using its ticker symbol. As Da et al. [2009] 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 rather than searches for non-financial information. In our dataset, 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 attention for 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&P500 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. Our daily data are finer than the weekly SVI data used in prior research (e.g., Da et al., [2009]), 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 keyword is scaled by the number of searches at a fixed point in time (generally when Google begins tracking the search data for the keyword).

Figure 1 is a screenshot of the SVI data provided by Google for a search of ‘MSFT’ (the ticker symbol for Microsoft Corporation) 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

---

12 We have attempted to pull SVI for a subset of smaller firms, which often yields null values of SVI for these smaller firms. This issue is likely the result of insignificant search volume for the ticker.
13 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 presents SVI based on fixed scaling. For details, see: http://www.google.com/intl/en/trends/about.html#7
volume. Although we do not make statistical inferences from this figure, we note that it shows a consistent spike in Google search volume around the 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 also require each firm to have Google search data, and coverage in Compustat, CRSP, IBES, and the 13F Thomson databases. The intersection of the Google search data with these databases results in a preliminary sample of 486 firms. Next, we follow Da et al. [2009] 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 451 firms and 4,393 earnings announcements, which we use in the analyses which follow.

3.3 Variables

To understand how Google search volume around information announcements varies from normal levels, we need to model the expected level of SVI. We note that there is variation in the raw SVI data across days of the week: search 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. In the regression analyses that follow, we use the natural logarithm of \(1 + AbSearch\) to normalize the distribution. This calculation provides us with a measure capturing deviations from a benchmark that is specific to a particular day of the week.
We obtain returns data from CRSP and calculate abnormal returns ($AR$) using prediction errors from a market model regression of firm raw returns on the CRSP value-weighted index return. At the end of each fiscal quarter, we estimate the market model parameters using returns over the past 250 trading days. We use these parameter estimates to calculate buy-and-hold abnormal returns over various event windows (discussed in further detail below).

We use IBES data to calculate unexpected earnings ($UE$) using two different expectation benchmarks. We define unexpected earnings 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 at the fiscal-end date. This definition of unexpected earnings is consistent with that in Hirshleifer et al. [2009]. We 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 at the fiscal-end date.

We focus our analyses on three event windows. Two of these windows are in the pre-announcement period and one is for the announcement itself. The first pre-announcement period begins the day after the fiscal-quarter end date (denoted day $FQE$) and ends the day before the earnings announcement date (denoted day $-1$). The second pre-announcement period consists of the 5-day period that begins six days before the earnings announcement date (denoted day $-6$) and ends on day $-1$. The announcement period begins on the earnings announcement date (denoted day $0$) and ends on the following day (denoted day $+1$). This earnings announcement window is consistent with the recommendations in Berkman and Truong [2009]. We append the $AbSearch$ and $AR$ variable names to specify the window over which the variables are measured.
For example, $AbSearch[FQE,-1]$, $AbSearch[-6,-1]$, or $AbSearch[0,+1]$ denote the three estimation windows as defined above.

We include various control variables (discussed in further detail below) in our models using data obtained from the Compustat, CRSP, Thomson 13F, Thomson SCD, and First Call databases. We also include press coverage data obtained from a proprietary database.\textsuperscript{14} In Appendix A, we provide definitions and data sources for all variables.

3.4 Descriptive Statistics

In Table 1 we present descriptive statistics for the variables used in the empirical tests described in the next section. We find that the mean $AbSearch[FQE,-1]$ is 0.025, which indicates that investor search is 2.5 percent greater than normal over this period. We find that investor search in the 5 days just before the accounting, $AbSearch[-6,-1]$ is 4.1 percent greater than normal. At the earnings announcement, $AbSearch[0,+1]$, is 12.6 percent greater than normal. This upward trend in the descriptive statistics for $AbSearch$ across the three windows provides preliminary evidence consistent with Prediction 1. We find that the sample consists of large firms (with high analyst following and institutional ownership), which is not surprising given our use of S&P 500 member firms.

In Table 2 we present Pearson (above diagonal) and Spearman (below diagonal) correlations among our variables. Pre-announcement search volume, $AbSearch[FQE,-1]$, is positively associated with institutional ownership, earnings volatility, and management forecasts, and negatively associated with analyst following and size. Abnormal search around the earnings announcement, $AbSearch[0,+1]$, is positively associated with analyst following, size, earnings persistence, turnover, the number of analyst forecasts and the amount of pre-announcement

\textsuperscript{14} We thank Eugene Soltes for providing the press coverage data from Soltes [2009].
press coverage and is negatively associated with institutional ownership, book-to-market, earnings volatility, and the number of contemporaneous earnings announcements.

4. Results

4.1. Abnormal Search Volume Around Earnings Announcements

We begin our empirical tests by investigating the pattern of abnormal search volume around the earnings announcement. In Figure 2, we plot 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 time trend during the pre-announcement period, a marked spike at the earnings announcement, followed by a negative time trend in the post-disclosure period. More specifically, in the pre-announcement period we find that $AbSearch$ increases nearly monotonically from -3.3 percent on day -25 to 4.5% on day -1. $AbSearch$ becomes significantly positive (t-stats unreported) two weeks before the earnings announcement (on day -14). At the announcement, $AbSearch$ increases to 12.3 percent on day 0, followed by 11.6 percent on day +1. After the earnings announcement, we find that $AbSearch$ gradually returns to a relatively stable level around 0 percent. The pattern of average $AbSearch$ for the randomly selected days provides no clear trend over time, generally bouncing around 0 percent throughout the entire window. Taken together, the results presented in Figure 2 suggest that investors seek more information about a firm as the earnings announcement date approaches, consistent with Prediction 1.
4.2. Abnormal Search Volume at Earnings Announcements Relative to Other Announcements

Figure 2 reveals a marked spike in investor search on the earnings announcement date. In this subsection we compare this level of \( AbSearch \) to that at other information revelation dates for the firm. The purpose of this analysis is to estimate the relative magnitude of the earnings announcement search spike.

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. We estimate the relative magnitudes of \( AbSearch \) on these event dates by regressing daily \( AbSearch \) on a set of indicator variables which are set to 1 on the date that the corresponding event takes place, and to zero otherwise. Specifically we estimate the following model:\(^\text{15}\)

\[
AbSearch_{it} = \sigma_{Firm} + \sigma_1 Earnings \: Announcement_i + \sigma_2 Management \: Forecast_i \\
+ \sigma_3 Analyst \: Forecast_i + \sigma_4 Dividend \: Announcement_i \\
+ \sigma_5 Acquisition \: Announcement_i + \sigma_6 ABS(Return) + \epsilon 
\]

(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 ten weeks, scaled by the average Google SVI for the same firm and weekday over the previous ten weeks;

\( Earnings \: Announcement \) = indicator variable set equal to one on an earnings announcement date and to zero otherwise;

\(^\text{15}\) In model (1), we use the \( AbSearch \) rather than the natural logarithm of \( 1 + AbSearch \) as the dependent variable to facilitate the interpretation of the coefficients. When we estimate the model using the logged variable, we find that our statistical inferences are similar.
Management Forecast = indicator variable set equal to one on a management forecast date and to zero otherwise;

Analyst Forecast = indicator variable set equal to one on an analyst earnings forecast date and to zero otherwise;

Dividend Announcement = indicator variable set equal to one on a dividend announcement date and to zero otherwise;

Acquisition Announcement = indicator variable set equal to one on an acquisition announcement date and to zero otherwise;\textsuperscript{16} and

\( \text{ABS(\text{Return})} \) = absolute value of the raw stock return on day \( t \).\textsuperscript{17}

We estimate model (1) with and without \( \text{ABS(\text{Return})} \) in the model to test whether our inferences are changed by controlling for magnitude of the news announced on that day.\textsuperscript{18} We include firm fixed effects to control for unobserved variation in search frequency across firms.

For model (1), and for all of our subsequent models, we assess statistical significance using \( t \)-statistics based on standard errors clustered by time (calendar quarter) and industry (Fama French 17 classification).

In Table 3, we present the estimation results for model (1). We find that acquisition announcements are associated with the highest abnormal search volume; the coefficient on Acquisition Announcement of 15.2 percent is strongly significantly different from zero. The coefficient on Earnings Announcement of 11.9 percent is the next highest magnitude among the events analyzed and is also significantly positive. However, the results of a coefficient equality test (unreported) indicates that these two coefficients are insignificantly different from each other (F-stat = 0.94). We find that the coefficient on Management Forecasts, Analyst Forecasts, and

\textsuperscript{16} We obtain acquisition announcement dates from the Thomson SDC database.

\textsuperscript{17} For our sample of large firms, there were only 12 dividend initiations during the sample period; as a result, we do not include an event indicator for the announcement of a new dividend.

\textsuperscript{18} 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 respected 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.
Dividend Announcements are 8.5 percent, 3.9 percent and 2.4 percent respectively. The coefficient equality tests (unreported) indicate that search magnitude at earnings announcements is significantly greater than search magnitude on analyst forecast dates and on dividend announcement dates. When we include Abs(Return) in the model we find that its coefficient is positive and significant. However, though its inclusion attenuates the coefficient magnitudes of the event indicator variables slightly, the relative ranking among the event dates is unchanged. This evidence suggests that earnings announcements are events that, on a relative basis, are associated with high levels of investor search, on par with acquisition announcements.

4.3. Abnormal search volume and firm characteristics

Next we examine which firm characteristics are associated with AbSearch over our three estimation windows. We estimate the following model:

\[
\text{AbSearch}_{t} = \alpha_{\text{Firm}} + \alpha_{1-3} \text{Abs}(	ext{AR}_{t}) + \alpha_{4} \log(1+\text{Analyst Following}) + \alpha_{5} \text{Institutional Ownership} + \alpha_{6} \text{Rank of Size} + \alpha_{7} \text{Rank of Book-to-Market} + \alpha_{8} \text{Earnings Persistence} + \alpha_{9} \text{Earnings Volatility} + \alpha_{10} \text{Turnover} + \alpha_{11} \text{Management Forecast} + \alpha_{12} \#\text{Analyst Forecasts} + \alpha_{13} \text{Fourth Qtr} + \alpha_{14} \text{Rank of #Announcements} + \alpha_{15} \#\text{News Articles}_{t} + e
\]

(2)

Where,

\(\text{AbSearch}_{t}\) = AbSearch estimated over one of three different windows: [FQE,-1], [-6,-1], and [0,+1];

\(\text{Abs}(	ext{AR}_{t})\) = the absolute value of AR estimated over one of three different windows: [FQE,-1], [-6,-1], and [0,+1];

\(\log(1+\text{Analyst Following})\) = the natural log of 1 plus the number of analysts in the I/B/E/S consensus analyst earnings forecast;

\(\text{Institutional Ownership}\) = proportion of the firm owned by institutional investors as reported by the Thomson 13f database;
**Rank of Size** = the decile rank of market-value of equity (Compustat PRCCQ x CSHOQ);

**Rank of Book-to-Market** = the decile rank of book-to-market (Compustat CEQQ / [PRCCQ x CSHOQ]);

**Earnings Persistence** = first-order autocorrelation coefficient of quarterly earnings estimated over the past four years;

**Earnings Volatility** = standard deviation of the seasonal earnings changes over the past four years;

**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;

**Management Forecast** = indicator variable set equal to one if managers issue a forecast between the fiscal quarter end date and the earnings announcement date;

**#Analyst Forecasts** = the count of the number of analyst earnings forecast revisions between the fiscal quarter end date and the earnings announcement date;

**Fourth Qtr** = indicator variable set equal to one for the fourth quarter and to zero otherwise;

**Rank of # Announcements** = the decile rank of the number of other firm announcing earnings on the same day as the earnings announcement;19 and

**# News Articles[...]** = the number of news articles in the *Wall Street Journal*, the *New York Times*, *USA Today*, and the *Washington Post* that mention the firm in each event window (Soltes, 2009).

In model (2), we include the absolute value of abnormal returns to control for the magnitude of news announced during the period as well as various other firm characteristics.20, 21

---

19 We use the decile ranking of the variable following Hirshleifer et al. [2009].

20 We exclude two variables from model (2), *Dividend Announcement* and *Acquisition Announcement*, that are in model (1) because these events appear infrequently during our event windows. However, in a sensitivity test (unreported) we control for these events by including an indicator variable if a dividend or acquisition announcement occurs during our event window and find virtually no change in the estimation results.

21 Following Hirshleifer et al. [2009], we use the natural logarithm of one plus *Analyst Following*, and the decile ranks of *Size* and *Book-to-Market* rather than the raw values of these variables, and we require a minimum of four observations to estimate *Earnings Persistence* and *Earnings Volatility.*
Because the dependent variables, $AbSearch[,\ldots]$, may be correlated across time for a particular firm, we include firm fixed-effects in the models.

We present the estimation results for model (2) in Table 4. In columns (1) and (2), we use pre-announcement Google search volume over $[FQE,-1]$ and $[-6,-1]$ as the dependent variables, respectively. In column (1), we find that $AbSearch[FQE,-1]$ is positively associated with the magnitude of news during the period ($\alpha_1 = 0.071; p < 0.01$). We also find that $AbSearch[FQE,-1]$ is significantly higher for relatively smaller S&P 500 firms, with lower share turnover, and for firms issuing management forecasts. Finally, we find that $AbSearch[FQE,-1]$ is higher in the fourth quarter and is lower when the time period is “less crowded” with other approaching earnings announcement dates. In column (2), using $AbSearch[-6,-1]$ as the dependent variable, we find similar association for $Turnover$, $Management Forecasts$, and $Fourth Quarter$. In contrast to the results presented in the first column, we find that the coefficients on $Rank of Firm Size$, $Rank of \# Announcements$, and $Abs(AR[-6,-1])$ are no longer significant.

In Table 4, column (3), we use announcement period abnormal search, $AbSearch[0,+1]$, as the dependent variable. Here we find that the coefficient on announcement period abnormal returns is positive and significant, suggesting that investors search for more information when more news is announced. We find that announcement period abnormal search is higher for firms with lower book-to-market ratios (i.e., glamour firms), higher earnings volatility, lower turnover, and fewer analyst forecast revisions. We also find that announcement period abnormal search is higher in the fourth quarter and on less crowded earnings announcement dates. Overall, the results of Table 4 suggest that several firm characteristics associated with the firm’s information environment are significantly associated with investor information acquisition via Google.
4.4. Abnormal Search and the Market Response to Earnings News

In this section, we conduct two tests of Prediction 2, which investigates whether pre-earnings announcement returns reflect more future earnings news when pre-announcement private information acquisition is higher.

4.4.1 Evidence from Return Ratios

In the first test, we follow prior literature (e.g., Atiase [1985], Dempsey [1989]) and calculate the ratio of the mean absolute value of abnormal returns calculated over \([0,+1]\) to the mean absolute value of abnormal returns calculated over two pre-announcement windows, \([FQE,-1]\) and \([-6,-1]\). We label these return ratios \(RR[FQE,-1]\) and \(RR[-6,-1]\) respectively. In words, the return ratios measure the amount of new information impounded into price at the earnings announcement relative to the amount of new information impounded into price in the pre-announcement period. For example, in our sample, the average firm has a \(RR[FQE,-1]\) of 2.471 as reported in Table 1. This suggests that the average earnings announcement in our sample conveys two-and-a-half times more information to the market than the average amount of information conveyed during the pre-announcement period.

We examine the association between return ratios and \(AbSearch\) using the following model:

\[
RR[.] = \beta_0 + \beta_1 AbSearch[.] + \beta_x Controls + e
\]  

(3)

Where,

\(Controls\) = a set of control variables including \(Log(1+Analyst Following)\), \(Institutional Ownership\), \(Rank of Size\), \(Rank of Book-to-Market\), \(Earnings Persistence\), \(Earnings Volatility\), \(Turnover\), \(Management Forecasts\), \#Analysts Forecasts, \(Fourth Qtr\), \(Rank of # Announcements\), and \#News Articles[...], as defined previously.
In model (3), the coefficient of interest is $\beta_1$. A significantly negative $\beta_1$ provides evidence consistent with Prediction 2 that relatively more information is impounded into price in the pre-announcement period relative to the announcement period for firms with higher pre-announcement AbSearch.

We include control variables in Model (3) that prior studies find to be associated with the market response to earnings. We control for $\log(1 + \text{Analyst Following})$ because Dempsey (1989) finds that analyst following is negatively associated with the price response to earnings news. He argues that analysts consider the costs and benefits of information search about a particular firm when making the coverage decision, and thus, analyst following provides information about the search incentives of analysts. We control for Institutional Ownership because El-Gazzar [1998] finds that institutional holdings are negatively associated with the price response to earnings. The intuition is that institutional investors have strong incentives to search for information prior to the announcement of earnings because of their fiduciary responsibilities and large resource base. We control for Rank of Size because Atiase (1985) finds that firm size is positively associated with the extent to which pre-earnings announcement stock prices reflect earnings information. This evidence is consistent with the idea that market participants have a greater incentive to be informed when market capitalization is high. We control for Rank of Book-to-Market because Collins and Kothari [1989] find that growth is positively associated with the price response to earnings. We control for Management Forecasts and for # Analyst Forecasts because these forecasts provide information about upcoming earnings announcements. We control for # News Articles[...] because press coverage may also be associated with the information environment of the firm. Prior research suggests that a more rich information environment reduces the market response to earnings news (Dempsey [1989],
We therefore expect negative coefficients on \( \log(1 + \text{Analyst Following}) \), \( \text{Institutional Ownership} \), \( \text{Rank of Size} \), \( \text{Rank of Book-to-Market} \), \( \text{Management Forecasts} \), \#\text{Analyst Forecasts} \), and \#\text{News Articles} \). Finally, we also include the other control variables included in model (2); however we make no predictions about the direction of their associations with \( \text{AbSearch} \).

In Table 5 we present the estimation results for model (3). In column (1) we use \( \text{RR}[\text{FQE}, -1] \) as the dependent variable. Consistent with Prediction 2, we find that the coefficient on pre-announcement abnormal search, \( \text{AbSearch}[\text{FQE}, -1] \), is negative and significant (\( \beta_1 = -0.170, p < 0.05 \)). This suggests that relatively more information is impounded into price in the pre-announcement period relative to the earnings announcement period for firms with higher pre-announcement \( \text{AbSearch} \). Also consistent with expectations, we find a negative and significant coefficient on \( \text{Rank of Size} \), \( \text{Rank of Book-to-Market} \), \( \text{Management Forecasts} \), and \#\text{Analysts Forecasts} \). However, contrary to our expectations, we find that the coefficients on \( \log(1 + \text{Analyst Following}) \) and \( \text{Institutional Ownership} \) are positive and significant. This difference from prior literature is likely attributable to our use of very large firms (S&P 500 members). In Table 5, columns (2) and (3), we use \( \text{RR}[-6,-1] \) as the dependent variable and find more evidence consistent with Prediction 2. Specifically, we find that the coefficients on \( \text{AbSearch}[\text{FQE}, -1] \) and \( \text{AbSearch}[-6,-1] \) in columns (2) and (3) respectively are both negative and significant. We also find similar associations and significance levels for the control variables in columns (2) and (3) as we observed in column (1). Thus, our findings suggest that when investors search for more information in the days just prior to the announcement, pre-announcement price changes reflect more of the upcoming earnings news, consistent with the theoretical prediction in McNichols and Trueman [1994].
4.4.2 Evidence from Pre-Announcement Returns

Next we examine whether the association between pre-announcement abnormal returns and the subsequent earnings news is stronger when pre-announcement search is relatively higher. Specifically, we estimate the following model:

\[
AR[-6,-1] = \delta_0 + \delta_1 UE + \delta_2 AbSearch[.] + \delta_3 (UE x AbSearch[.]) \\
+ \delta_4 Controls + \delta_5 (UE x Controls) + e,
\]

(4)

Where,

\[ Controls \]

a set of control variables including \( \log(1 + \text{Analyst Following}) \), Institutional Ownership, Rank of Size, Rank of Book-to-Market, Earnings Persistence, Earnings Volatility, Turnover, Management Forecasts, \#Analysts Forecasts, Fourth Qtr, Rank of \# Announcements, and \# News Articles[. . .] as defined previously.

In model (4), the coefficient of interest is \( \delta_3 \). A significantly positive \( \delta_3 \) provides evidence consistent with Prediction 2 that pre-announcement price changes reflect more future earnings news when pre-announcement private information acquisition 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).\(^{22}\)

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 et al. [2009] we also include

\(^{22}\) Our set of control variables follows Hirshleifer et al. [2009].
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 for the firm before the earnings announcement.

We present the estimation results for model (4) in Table 6. 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 $AbSearch[-6,-1]$ as the variable of interest. While we include all the control variables and the interactions of the control variables with $UE$ in all of the regressions, we do not tabulate their coefficients for parsimony.

In Table 6, columns (1) and (2), we find that the coefficient on $AbSearch[FQE,-1]$ is positive and significant, but only when the earnings time series is used as the earnings benchmark ($\delta_3 = 1.314, p < 0.01$ in column (2)). This suggests that when investors search for more information in the pre-announcement period, price changes in the five-day period before the earnings announcement reflect more of the information content of the earning surprise. In columns (3) and (4), we find that the coefficient on $AbSearch[-6,-1]$ is positive and significant using both earnings benchmarks ($\delta_3 = 1.087, p < 0.10$ in column (3) and $\delta_3 = 1.062, p < 0.05$ in column (4)). Overall, the Table 6 results support the prediction that investor search preemptively moves prices in the direction of the upcoming earnings news.

4.4.3 Evidence from Earnings Response Coefficients

In this section, we conduct tests of Prediction 3, which is that announcement returns reflect less earnings news when pre-announcement information acquisition is higher. Specifically, we estimate the following model of the earnings response coefficient:
\[ AR[0,+1] = \omega_0 + \omega_1 UE + \omega_2 AbSearch[.] + \omega_3 (UE \times AbSearch[.]) + \omega_x Controls + \omega_y (UE \times Controls) + e, \]  

(5)

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, #Analysts Forecasts, Rank of # Announcements, Fourth Qtr, and # News Articles[.,.] as defined previously.

In model (5), the coefficient of interest is \( \omega_3 \). A significantly negative \( \omega_3 \) provides evidence consistent with Prediction 3 that announcement price changes reflect less earnings news when pre-announcement private information acquisition is higher. We include the same control variables as in model (4) (discussed above).23

We present the estimation results for model (5) in Table 7. 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 \( AbSearch[FQE,-1] \), in columns (3) and (4) we present the results using \( AbSearch[-6,-1] \), and in columns (5) and (6) we present the results using \( AbSearch[0,+1] \) as the variable of interest. Control variables are included in the models, but are not reported for parsimony.

In Table 7 columns (1) and (2) we find some evidence that pre-announcement search is associated with a lower ERC. Specifically, we find that the coefficient on the interaction term \( UE \times AbSearch[FQE,-1] \) is negative and significant using both earnings benchmarks (\( \omega_3 = -4.133, p < 0.10 \) in column (1) and \( \omega_3 = -2.499, p < 0.05 \) in column (2)). In columns (3) and (4),

---

23 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 et al. [1998]) by including \( UE \times abs(UE) \) in model (5). In addition, we include an indicator for loss observations following Hayn [1995]. In both cases, we find results similar in magnitude and significance to those reported.
we use the shorter pre-announcement window, [-6,-1], and the evidence is again consistent across our two proxies for unexpected earnings. The coefficient on the interaction term $UE \times AbSearch[-6,-1]$ is negative and significant using both earnings benchmarks ($\omega_3 = -3.517, p < 0.05$ in column (3) and $\omega_3 = -1.914, p < 0.05$ in column (4)). This evidence is consistent with Prediction 3. Finally, in columns (5) and (6) we find some evidence that announcement search, [0,+1], is negatively associated with the market response to earnings news. When we use analysts forecasts as the earnings expectations benchmark, we find a negative and significant coefficient on the interaction term $UE \times AbSearch[0,+1]$ ($\omega_3 = -2.462, p < 0.10$ in column (5)).

Overall, the results are consistent with our predictions. Investors increase search activities in response to upcoming earnings announcements, which suggests that earnings announcements stimulate private information acquisition of information rather than substituting for it. Further, when investors gather more earnings information in the pre-disclosure period, stock prices reflect more of that information in the pre-announcement period. As a result, when abnormal search volume in Google is high before earnings are announced, the information content of the earnings announcement is partially preempted.

5. Additional Analyses

We present the results of two additional analyses in this subsection. The first analysis uses trading volume as a measure of investor reaction to earnings news; the second examines post-earnings announcement drift. We do not tabulate the results of these analyses for parsimony.
5.1 Abnormal Search and Trading Volume

Following McNichols and Trueman [1994], our main analyses focus on the impact of information acquisition on price reactions or changes in the expectations of the market as a whole around earnings announcements. However, it may also be the case that information acquisition impacts the expectations of individual investors, without changing the market’s overall valuation assessment (Bamber et al. [2010]). We test this idea by investigating how the association between trading volume and earnings news varies with differences in the information search activities of investors around earnings announcements.

We estimate abnormal volume using trading data from CRSP. We calculate daily abnormal volume ($Abvol$) over our event windows as total trading volume 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 estimate period. We sum $Abvol$ over two event windows, $[-6,-1]$ and $[0+1]$, and we estimate the following model:

$$
Abvol[.] = \tau_0 + \tau_1 Abs(UE) + \tau_2 AbSearch[.] + \tau_3 (Abs(UE) \times AbSearch[.]) + \tau_4 Controls + \tau_5 (Abs(UE) \times Controls) + e,
$$

(6)

Where,

- $Abvol[.] = Abvol$ estimated over one of two different windows: $[-6,-1]$, and $[0+1]$;
- $Abs(UE) = $ absolute value of $UE$
- $Controls = $ a set of control variables including $Log(1 + Analyst Following)$, $Institutional Ownership$, $Rank of Size$, $Rank of Book-to-Market$, $Earnings Persistence$, $Earnings Volatility$, $Management Forecasts$, $#Analysts Forecasts$, $Fourth Qtr$, $Rank of # Announcements$, and $# News Articles[..]$ as defined previously.
In model (6), we follow Bamber [1986] and [1987] and use the absolute value of the earnings surprise as a measure of news released at the announcement. We also include all control variables from model (5). When Abvol[-6,-1] is the dependent variable in model (6), we find that the coefficient on the interaction term Abs(UE) x AbSearch[-6,-1] is positive and significant, but only when the earnings time series is used as the earnings benchmark. This provides some evidence that when investors search for more information in the pre-announcement period, trading activity over that same five-day period is more highly associated with the magnitude of subsequent earnings news. Announcement–period volume however, is not associated with pre-announcement search: when Abvol[0,+1] is the dependent variable in model (6), the coefficient on the interaction term Abs(UE) x AbSearch[-6,-1] is insignificant using both earnings benchmarks.

When we estimate the model using announcement period search as our proxy for information acquisition, we find that the coefficient on the interaction term Abs(UE) x AbSearch[0,+1] is positive and significant using both earnings benchmarks. This suggests that when investors search for more information at the announcement, trading activity at the announcement is more highly associated with the magnitude of the earnings news. These results, together with the main analyses, suggest that information acquisition activities of investors impact both the expectations of individual traders, and the expectation of the market as a whole.

5.2 Abnormal Search and Post-Earnings Announcement Drift

Prediction 3 postulates that announcement returns reflect less earnings news when pre-announcement private information acquisition is higher. A natural follow-up question is whether the relation between earnings news and post-announcement returns is also affected by
information search. Here we investigate whether abnormal search around the earnings announcement has a negative impact on post-earnings announcement drift, i.e., the association between earnings surprises and subsequent returns (Bernard and Thomas [1989] and [1990], Foster et al. [1984]). Given that our sample consists of very large firms and the evidence in prior studies that the magnitude of drift is lower (or non-existent) for large firms (Bernard and Thomas [1989]), our setting is not ideal for testing the relation between AbSearch and drift. However, as a preliminary test, we estimate model (5) using, as the dependent variable, buy and hold abnormal returns calculated over the 60 day period starting on day +2 relative to the earnings announcement date. We find that the coefficient on the interaction term $\text{UE} \times \text{AbSearch}$ is insignificant using both earnings benchmarks and all three estimation windows: $[FQE,-1], [-6,-1], \text{or } [0, +1]$. Thus, there is no evidence that greater information search, prior to and at the earnings announcement, is associated with the relation between earnings surprises and long-term returns.

6. Conclusion

The results presented above provide empirical evidence consistent with the theoretical predictions in McNichols and Trueman [1994] and are summarized as follows: First, we find that investors search for more firm-specific information as earnings announcement dates approach. Second, we find that price changes prior to earnings announcements reflect more of the upcoming earnings news when investors search for more information prior to the announcement. Third, 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

---

24 The sixty day horizon is consistent with Berkman and Truong [2009] and Hirshleifer et al. [2009].
information content of earnings is partially preempted when investors’ pre-announcement search activities are high.

Our findings contribute to the literatures on information search and the market reaction to public disclosures. We provide a new proxy for investors’ search activities and show that its effects are incremental to the traditional proxies used in the prior literature. We acknowledge that a limitation of this proxy is that it does not capture the specific information the Google user seeks or the identity of the user. 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 acquisition impacts the capital markets.
## APPENDIX A
### Variable Definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td># Analyst Forecasts</td>
<td>The count of the number of analyst earnings forecast revisions between the fiscal quarter end date and the earnings announcement date;</td>
<td>I/B/E/S</td>
</tr>
<tr>
<td># Announcements</td>
<td>The number of other firms announcing quarterly earnings on the same day as the earnings announcement.</td>
<td>I/B/E/S</td>
</tr>
<tr>
<td># News Articles [...]</td>
<td>Number of articles about sample firms over three time periods, [FQE,-1], [-6,-1], or [0,+1], as defined above.</td>
<td>Soltes (2009)</td>
</tr>
<tr>
<td>Abs(Return)</td>
<td>The absolute value of the raw daily stock return.</td>
<td>CRSP</td>
</tr>
<tr>
<td>AbSearch[...]</td>
<td>The natural logarithm of 1 + the average value of AbSearch&lt;sub&gt;t&lt;/sub&gt; estimated over three windows, [FQE,-1], [-6,-1], or [0,+1], where day FQE is the first day after the quarter-end date and day 0 is the earnings announcement date.</td>
<td>Google Trends</td>
</tr>
<tr>
<td>AbSearch&lt;sub&gt;t&lt;/sub&gt;</td>
<td>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 ten weeks, scaled by the average SVI for the same weekday over the past ten weeks.</td>
<td>Google Trends</td>
</tr>
<tr>
<td>Acquisition Announcements</td>
<td>Indicator variable set equal to one on an acquisition announcement date and to zero otherwise.</td>
<td>Thomson / SDC</td>
</tr>
<tr>
<td>Analyst Following</td>
<td>Number of analysts in the I/B/E/S consensus analyst earnings forecast</td>
<td>I/B/E/S</td>
</tr>
<tr>
<td>Analyst Forecast Announcements</td>
<td>Indicator variable set equal to one on an analyst forecast revision date and to zero otherwise.</td>
<td>I/B/E/S</td>
</tr>
<tr>
<td>AR[...]</td>
<td>Buy and hold abnormal returns estimated over three windows, [FQE,-1], [-6,-1], or [0,+1]. Abnormal returns are calculated using prediction errors from a market model regression of firm raw returns on the CRSP value-weighted index return. Market model parameters are estimated using returns from the 250 trading days ending on the fiscal-end date.</td>
<td>CRSP</td>
</tr>
<tr>
<td>Book-to-Market</td>
<td>Ratio of book value of common equity to market capitalization (CEQQ / [PRCCQ x CSHOQ]);</td>
<td>Compustat</td>
</tr>
<tr>
<td>Dividend Announcements</td>
<td>Indicator variable set equal to one on a dividend announcement date and to zero otherwise.</td>
<td>CRSP</td>
</tr>
<tr>
<td>Earnings Announcements</td>
<td>Indicator variable set equal to one on an earnings announcement date and to zero otherwise.</td>
<td>I/B/E/S</td>
</tr>
<tr>
<td>Earnings Persistence</td>
<td>First-order autocorrelation coefficient of quarterly earnings estimated over the past four years.</td>
<td>Compustat</td>
</tr>
<tr>
<td>Earnings Volatility</td>
<td>Standard deviation of the seasonal earnings changes over the past four years.</td>
<td>Compustat</td>
</tr>
<tr>
<td>Fourth Qtr</td>
<td>Indicator variable set equal to one for firms announcing fourth quarter earnings and to zero otherwise.</td>
<td>Compustat</td>
</tr>
<tr>
<td>Institutional Ownership</td>
<td>Shares held by institutional investors scaled by total shares outstanding</td>
<td>Thomson</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

33
<table>
<thead>
<tr>
<th><strong>Log(1+Analyst Following)</strong></th>
<th>The natural logarithm of $1 + \text{Analyst Following}$</th>
<th>I/B/E/S</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Management Forecast Announcements</strong></td>
<td>Indicator variable set equal to one on a management earnings forecast date and to zero otherwise.</td>
<td>First Call</td>
</tr>
<tr>
<td><strong>Management Forecasts</strong></td>
<td>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.</td>
<td>First Call</td>
</tr>
<tr>
<td><strong>Rank of # Announcements</strong></td>
<td>The decile rank of the number of other firms announcing quarterly earnings on the same day as the earnings announcement</td>
<td>I/B/E/S</td>
</tr>
<tr>
<td><strong>Rank of Book-to-Market</strong></td>
<td>The decile rank of Book-to-Market, scaled to range between 0 and 1</td>
<td>Compustat</td>
</tr>
<tr>
<td><strong>Rank of Size</strong></td>
<td>The decile rank of Size, scaled to range between 0 and 1.</td>
<td>CRSP</td>
</tr>
<tr>
<td><strong>RR[...]</strong></td>
<td>Return ratios estimated as the absolute value of abnormal returns during the pre-announcement period divided by the absolute value of abnormal returns during the earnings announcement period. The ratio is estimated using two pre-announcement windows, $[FQE,-1]$ or $[-6,-1]$.</td>
<td>CRSP</td>
</tr>
<tr>
<td><strong>Size</strong></td>
<td>Market capitalization ($PRCCQ \times CSHOQ$).</td>
<td>CRSP</td>
</tr>
<tr>
<td><strong>Turnover</strong></td>
<td>Average monthly trading volume, scaled by the average number of shares outstanding over the one year period ending on the fiscal quarter end date</td>
<td>CRSP</td>
</tr>
<tr>
<td><strong>UEAF</strong></td>
<td>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.</td>
<td>Compustat</td>
</tr>
<tr>
<td><strong>UETS</strong></td>
<td>Difference between actual earnings and actual earnings for the same quarter in the prior year (seasonal change) as reported in IBES, scaled by stock price at the fiscal end date as reported in CRSP.</td>
<td>Compustat</td>
</tr>
</tbody>
</table>
REFERENCES


FIGURE 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.
In this figure, we plot abnormal Google search volume ($AbSearch$) around earnings announcements for sample firms. The figure is centered around the quarterly earnings announcement date, $t = 0$, and extends 30 trading days before and after that date. $AbSearch$ is defined in Appendix A 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.
This table presents descriptive statistics for information search and control variables. The sample consists of 4,393 quarterly observations for S&P 500 firms over the period 2005 to 2008. Variable definitions are presented in Appendix A. All variables, except returns, are winsorized at the 1st and 99th percentiles.
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 presented in Appendix A. All variables, except returns, are winsorized at the 1st and 99th percentiles. The correlations coefficients that are statistically significant ($p < 0.10$) are in bold face.

| Variables                                | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20  | 21  | 22  | 23  |
|------------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|     |
| **TABLE 2**                              |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| Pearson (Above) and Spearman (Below)     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| **Variables**                            | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20  | 21  | 22  | 23  |     |
| **Variables**                            | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20  | 21  | 22  | 23  |     |
| **Variables**                            | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20  | 21  | 22  | 23  |     |
| **Variables**                            | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20  | 21  | 22  | 23  |     |
| Rank of Size                             | -0.05 | 0.03 | 0.19 | -0.01 | 0.02 | 0.00 | -0.06 | -0.07 | -0.01 | 0.08 | 0.49 | -0.34 | -0.12 | 0.13 | -0.02 | -0.32 | -0.09 | 0.01 | 0.25 | 0.36 | 0.33 | 0.34 |     |
| Rank of Book-to-Market                   | 0.01 | -0.03 | 0.08 | 0.06 | 0.01 | 0.00 | -0.07 | -0.06 | 0.05 | -0.13 | -0.12 | -0.02 | -0.12 | -0.08 | 0.26 | 0.05 | 0.03 | 0.01 | 0.18 | 0.05 | 0.03 | 0.03 |     |
| Earnings Persistence                     | 0.01 | 0.03 | 0.07 | -0.01 | 0.01 | 0.00 | -0.02 | -0.02 | -0.04 | 0.14 | 0.25 | 0.06 | 0.14 | -0.10 | -0.01 | 0.13 | 0.03 | -0.07 | 0.12 | -0.04 | 0.00 | -0.03 |     |
| Earnings Volatility                      | 0.04 | -0.04 | 0.09 | 0.00 | 0.01 | -0.04 | -0.11 | -0.10 | 0.09 | 0.04 | 0.13 | 0.09 | 0.09 | 0.40 | -0.11 | -0.28 | 0.04 | -0.02 | 0.23 | 0.16 | 0.13 | 0.08 |     |
| Turnover                                 | 0.03 | 0.01 | 0.07 | -0.02 | -0.07 | -0.01 | 0.07 | 0.05 | 0.01 | 0.00 | 0.02 | 0.42 | 0.37 | 0.00 | 0.11 | 0.27 | -0.03 | 0.05 | 0.15 | -0.02 | 0.00 | 0.02 |     |
| Rank of # Announcements                  | 0.02 | 0.00 | -0.08 | -0.03 | 0.01 | -0.02 | -0.06 | -0.04 | 0.04 | 0.08 | -0.13 | 0.11 | -0.09 | 0.03 | 0.03 | 0.10 | -0.02 | 0.01 | 0.12 | -0.04 | -0.11 | -0.17 |     |
| Management Forecast                      | 0.05 | 0.03 | 0.02 | 0.02 | -0.01 | 0.00 | -0.06 | -0.05 | -0.03 | 0.01 | -0.04 | -0.02 | 0.01 | 0.01 | -0.06 | -0.01 | -0.04 | 0.01 | 0.03 | 0.03 | 0.00 | -0.01 |     |
| # Analyst Forecasts                      | 0.04 | 0.01 | 0.04 | -0.01 | 0.01 | 0.00 | -0.18 | 0.12 | 0.00 | 0.02 | 0.30 | 0.05 | 0.27 | 0.19 | 0.07 | 0.29 | 0.13 | 0.09 | 0.04 | 0.17 | 0.10 | 0.08 |      |
| # News Articles                           | -0.01 | -0.01 | 0.10 | 0.02 | 0.00 | 0.00 | -0.03 | -0.04 | -0.05 | -0.02 | -0.07 | 0.14 | 0.11 | 0.30 | 0.01 | -0.03 | 0.02 | -0.05 | -0.10 | 0.02 | 0.12 | 0.71 | 0.57 |     |
| Earnings Volatility                      | -0.02 | 0.00 | 0.12 | 0.03 | 0.00 | -0.01 | 0.01 | 0.00 | -0.03 | 0.08 | 0.16 | -0.15 | 0.15 | 0.33 | 0.03 | 0.04 | 0.03 | 0.00 | -0.17 | -0.01 | 0.11 | 0.64 | 0.52 |     |
### TABLE 3
The Association between Information Search and Various Event Dates

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Earnings Announcements</strong></td>
<td>0.119***</td>
<td>0.105***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td><strong>Management Forecast Announcements</strong></td>
<td>0.085***</td>
<td>0.077***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.022)</td>
</tr>
<tr>
<td><strong>Analyst Forecast Announcements</strong></td>
<td>0.039***</td>
<td>0.034***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td><strong>Dividend Announcements</strong></td>
<td>0.024***</td>
<td>0.022***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td><strong>Acquisition Announcements</strong></td>
<td>0.152***</td>
<td>0.147***</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.034)</td>
</tr>
<tr>
<td><strong>Abs(Return)</strong></td>
<td></td>
<td>0.821***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.148)</td>
</tr>
<tr>
<td><strong>Firm Fixed Effects</strong></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>366,827</td>
<td>366,827</td>
</tr>
<tr>
<td><strong>Adj R-square</strong></td>
<td>0.027</td>
<td>0.029</td>
</tr>
</tbody>
</table>

This table presents the results of model (1). Standard errors are presented in parentheses below the coefficient estimates and are clustered by time (calendar quarter) and industry (Fama French 17 classifications). The sample consists of S&P 500 firms from 2005 to 2008. Variables are Appendix A. *, **, *** indicates statistical significance at the $p < 0.10, 0.05, 0.01$ level, respectively. We use one-tailed tests when a direction is predicted.
### TABLE 4
The Association between Information Search and Firm Characteristics

<table>
<thead>
<tr>
<th>Variables</th>
<th>AbSearch[FQE,-1]</th>
<th>AbSearch[-6,-1]</th>
<th>AbSearch[0,+1]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abs(AR[FQE,-1])</td>
<td>0.071***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Abs(AR[-6,-1])</td>
<td></td>
<td>0.185</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.117)</td>
<td></td>
</tr>
<tr>
<td>Abs(AR[0,+1])</td>
<td></td>
<td></td>
<td>0.259***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.062)</td>
</tr>
<tr>
<td>Log (1+Analyst Following)</td>
<td>0.012</td>
<td>0.011</td>
<td>-0.011</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.013)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Institutional Ownership</td>
<td>-0.005</td>
<td>0.034</td>
<td>-0.013</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.045)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Rank of Size</td>
<td>-0.073**</td>
<td>-0.036</td>
<td>-0.057</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.033)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Rank of Book-to-Market</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.060***</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.021)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Earnings Persistence</td>
<td>0.011</td>
<td>0.008</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.014)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Earnings Volatility</td>
<td>0.009</td>
<td>0.012</td>
<td>0.019*</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.011)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Turnover</td>
<td>-0.095***</td>
<td>-0.125***</td>
<td>-0.207***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.042)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Management Forecast</td>
<td>0.035*</td>
<td>0.048*</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.028)</td>
<td>(0.027)</td>
</tr>
<tr>
<td># Analyst Forecasts</td>
<td>0.000</td>
<td>-0.002</td>
<td>-0.004**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Fourth Qtr</td>
<td>0.030***</td>
<td>0.037***</td>
<td>0.031***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Rank of # Announcements</td>
<td>-0.014*</td>
<td>-0.015</td>
<td>-0.025**</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.014)</td>
<td>(0.011)</td>
</tr>
<tr>
<td># News Articles[FQE,-1]</td>
<td>-0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td># News Articles[-6,-1]</td>
<td></td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td># News Articles[0,+1]</td>
<td></td>
<td></td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.005)</td>
</tr>
<tr>
<td>Firm Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>4,393</td>
<td>4,393</td>
<td>4,393</td>
</tr>
<tr>
<td>Adj R-square</td>
<td>0.184</td>
<td>0.171</td>
<td>0.564</td>
</tr>
</tbody>
</table>
This table presents the results of model (2). Standard errors are presented in parentheses below the coefficient estimates and are clustered by time (calendar quarter) and industry (Fama French 17 classifications). The sample consists of S&P 500 firms from 2005 to 2008. Variables are Appendix A. *, **, *** indicates statistical significance at the $p < 0.10, 0.05, 0.01$ level, respectively. We use one-tailed tests when a direction is predicted.
TABLE 5
The Association between Returns Ratios and Information Search

<table>
<thead>
<tr>
<th>Variables</th>
<th>RR[FQE,-1]</th>
<th>RR[-6,-1]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>AbSearch[FQE,-1]</td>
<td>-0.170**</td>
<td>-0.167*</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>AbSearch[-6,-1]</td>
<td></td>
<td>-0.114*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.071)</td>
</tr>
<tr>
<td>Log (1+Analyst Following)</td>
<td>0.114***</td>
<td>0.102***</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Institutional Ownership</td>
<td>0.181*</td>
<td>0.137</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.121)</td>
</tr>
<tr>
<td>Rank of Size</td>
<td>-0.229***</td>
<td>-0.295***</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Rank of Book-to-Market</td>
<td>-0.094**</td>
<td>-0.114**</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Earnings Persistence</td>
<td>0.005</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Earnings Volatility</td>
<td>0.038</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Turnover</td>
<td>-0.544***</td>
<td>-0.513***</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Management Forecast</td>
<td>-0.375***</td>
<td>-0.387***</td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td>(0.132)</td>
</tr>
<tr>
<td># Analyst Forecasts</td>
<td>-0.045***</td>
<td>-0.030***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Fourth Qtr</td>
<td>-0.060</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>Rank of # Announcements</td>
<td>-0.100**</td>
<td>-0.079*</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.047)</td>
</tr>
<tr>
<td># News Articles[FQE,-1]</td>
<td>0.002</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td># News Articles[-6,-1]</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.647***</td>
<td>0.742***</td>
</tr>
<tr>
<td></td>
<td>(0.125)</td>
<td>(0.136)</td>
</tr>
<tr>
<td>N</td>
<td>4,393</td>
<td>4,393</td>
</tr>
<tr>
<td>Adj R-square</td>
<td>0.050</td>
<td>0.026</td>
</tr>
</tbody>
</table>
This table presents the results of model (3). Standard errors are presented in parentheses below the coefficient estimates and are clustered by time (calendar quarter) and industry (Fama French 17 classifications). The sample consists of S&P 500 firms from 2005 to 2008. Variables are Appendix A. *, **, *** indicates statistical significance at the $p < 0.10$, $0.05$, $0.01$ level, respectively. We use one-tailed tests when a direction is predicted.
This table presents the results of model (4). Standard errors are presented in parentheses below the coefficient estimates and are clustered by time (calendar quarter) and industry (Fama French 17 classifications). The sample consists of S&P 500 firms from 2005 to 2008. Variables are Appendix A. *, **, *** indicates statistical significance at the \( p < 0.10, 0.05, 0.01 \) level, respectively. We use one-tailed tests when a direction is predicted.
TABLE 7
The Association between Announcement Returns, the Earnings Surprise, and Information Search

This table presents the results of model (5). Standard errors are presented in parentheses below the coefficient estimates and are clustered by time (calendar quarter) and industry (Fama French 17 classifications). The sample consists of S&P 500 firms from 2005 to 2008. Variables are Appendix A. *, **, *** indicates statistical significance at the $p < 0.10$, 0.05, 0.01 level, respectively. We use one-tailed tests when a direction is predicted.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Analysts (1)</th>
<th>Time-Series (2)</th>
<th>Analysts (3)</th>
<th>Time-Series (4)</th>
<th>Analysts (5)</th>
<th>Time-Series (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$UE$</td>
<td>5.697***</td>
<td>2.593***</td>
<td>4.075**</td>
<td>2.142***</td>
<td>5.914***</td>
<td>2.194***</td>
</tr>
<tr>
<td></td>
<td>(1.809)</td>
<td>(0.569)</td>
<td>(1.776)</td>
<td>(0.518)</td>
<td>(1.424)</td>
<td>(0.514)</td>
</tr>
<tr>
<td>$AbSearch[FQE,-1]$</td>
<td>0.008</td>
<td>0.012</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$UE \times AbSearch[FQE,-1]$</td>
<td>-4.133*</td>
<td>-2.499**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.907)</td>
<td>(1.174)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$AbSearch[-6,-1]$</td>
<td></td>
<td>0.008*</td>
<td>0.009*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$UE \times AbSearch[-6,-1]$</td>
<td>-3.517**</td>
<td>-1.914**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.645)</td>
<td>(1.101)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$AbSearch[0,+1]$</td>
<td></td>
<td></td>
<td>0.003</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$UE \times AbSearch[0,+1]$</td>
<td>-2.462*</td>
<td>-1.169</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(1.788)</td>
<td>(1.379)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>$UE \times Controls$</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>$N$</td>
<td>4,393</td>
<td>4,393</td>
<td>4,393</td>
<td>4,393</td>
<td>4,393</td>
<td>4,393</td>
</tr>
<tr>
<td>Adj R-square</td>
<td>0.070</td>
<td>0.047</td>
<td>0.085</td>
<td>0.058</td>
<td>0.073</td>
<td>0.036</td>
</tr>
</tbody>
</table>

AR[0,+1]

Earnings expectations based on