In Search of Fundamentals*

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Abstract

We use internet search volume for firms' products to predict revenue surprises, earnings surprises and earnings announcement returns. We find that increases (decreases) in the search volume index (SVI) of a firm's most popular product strongly predicts positive (negative) revenue surprises. This predictive power is weaker for standardized unexpected earnings (SUE). SVI has strong predictability for returns around earnings announcements, especially among firms with few products, growth firms and firms that manage their reported earnings. Taken together, the evidence suggests that search volume for a firm's products is a value-relavent leading indicator about a firm's future cashflow that the market does not fully incorporate into prices before the earnings announcement.

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1 Introduction

Civilization's first joint-stock corporation, the Roman *publicani* of the 2nd century BC, often placed bids for public contracts such as tax collecting or temple building. Informed bids required knowledge of local fundamentals and so the *publicani* enlisted a large group of couriers who traveled throughout the Roman territories to aggregate information from local townspeople about supply and demand for these public services (Chancellor (2000)).

Two thousand years later, the aggregation of information about fundamentals is no less important for firms and shareholders. While the emerging marketplace for goods and services during Roman times was The Forum, today it is the Internet. Thus, the technology to aggregate information has changed dramatically. In particular, because consumers now search for goods and services online, internet search volume generated by consumers has the potential to become an innovative way of aggregating information about fundamentals.

The intuition behind the information aggregation role of search volume is simple. Search queries reflect the intentions of those who query. Thus, when aggregate search volume for a particular product is high, demand for that product is likely to be high. Choi and Varian (2009) claim that search volume can "predict the present" because "query data may be correlated with the current level of economic activity in given industries and thus may be helpful in predicting the subsequent data releases." They support their claim with evidence that search volume can predict lagged releases of home sales, automotive sales and tourism. More recently, Goel et al. (2010) show that aggregate search volume can also predict future economic activity: search volume for movies can predict their box-office revenues, search volume for songs can predict placement on the Billboard Hot 100 Chart and search volume for video games can predict first-month sales.

Because search data appear well-suited to predict releases of fundamental information, in this study we consider the predictability of search volume for firm earnings announcements. Firms report earnings information with a lag four times a year. This paper examines whether search volume can predict the content of these announcements. We gather search volume data from Google, which accounted for 72.1 percent of all search queries performed in the United States at the end of sample period.[1] Google makes public the Search Volume Index (SVI) of search terms via its products Google Trends (http://www.google.com/trends) and Google Insights (http://www.google.com/insights/search/). SVI is simply a scaled, time-series of weekly search volume beginning in 2004.

We have four key findings using Google's SVI. First, we find that the SVI of a firm's most popular product is related to the revenue announced by the firm. Increases (decreases) in SVI strongly predict positive (negative) revenue surprises for the firm on its announcement day. This result holds even after including a host of controls that have been shown to predict revenue surprises in previous research.

Second, we find that search volume's predictability for firm earnings is much weaker. This is not surprising: if search volume aggregates demand for particular products then it should be strongly related to firm revenues but not firm costs. For example, search volume will detect a growing interest in the demand for iPhones but it is unlikely to detect an increase in the cost of hardware used to manufacture iPhones. Thus, we expect a stronger relationship between search volume and iPhone sales than search volume and iPhone profits.

Third, we find that search volume predicts returns around earnings announcements. When we regress three-day announcement period abnormal returns on the change in product search volume and controls, we find that firms with large increases (decreases) in product search volume experience high (low) returns around their earnings announcement. This suggests that search volume contains value-relevant information that is not incorporated into prices until the announcement. Moreover, even when we include the current revenue surprise as an independent variable in the regression, search volume still has predictive power for the announcement period returns. In other words, search volume's predictability for announcement returns in *not* solely driven by it's ability to predict current-quarter revenues. Search volume appears to contain information incremental to current-quarter revenues, possibly

[1] Source: Hitwise (http://www.hitwise.com/press-center/hitwiseHS2004/google-searches-feb-09.php)

firms' long-run earnings power.

Fourth, we find the informativeness of search volume varies considerably in the cross-section. Not surprisingly, firms with fewer products are precisely those for which the search volume of the most popular product is most informative. In the extreme, the demand for a firm with one product will be well-captured by the search volume of its most popular product (i.e., its only product). In addition, search volume is most informative among growth firms with low book-to-market ratios whose valuations are particularly sensitive to the growth rate in long-run cash flows. Finally, we find that search volume is particularly informative among firms which are like to engage in earnings management. These are firms for which reported earnings may be less informative of for actual performance, and so a third-party metric like search volume is relatively informative. In summary, search volume has the strongest predictability for earnings announcement returns among firms with few products, firms that manage earnings and growth firms.

Our paper is not the first to suggest a non-GAAP leading economic indicator which can predict earnings-related fundamentals. Tetlock (2009), Demers and Vega (2009), Li (2006, 2008) and Feldman et al. (2009) show that the linguistic content of press stories and 10-Ks have incremental predictability for future earnings. Mayew and Venkatachalam (2009) provide evidence that the negative affect in a manager's voice during the earnings announcement conference call can predict returns shortly after the announcement. Other non-GAAP leading indicators include firm patents (Deng, et al., (1999); Hall et al., (2000); Gu and Lev (2002, 2004)), customer satisfaction (Ittner and Larcker (1998), order backlogs (Rajgopal et al. (2003)), and same-store sales growth rates (Yang, 2007).

The three papers closest to our are Trueman et al. (2000, 2001) and Rajgopal et al. (2003) who find a relationship between web traffic and the profitability of Internet and e-Commerce firms. While search volume and Internet traffic are certainly related, our study has two key advantages. First, we do not limit ourselves to Internet firms. The firms in this study include airlines, restaurants, department stores, drug companies and many others.

The fact that these are not Internet firms is irrelevant: search reflects household demand for a wide variety of products. Second, households may search for a firm's products or product information without ever visiting a firm's website. A household which is interested in purchasing a new Ford product may search for driver reviews online and visit a local Ford dealership for purchase without ever visiting Ford.com or an affiliate dealership. Because search engines are the portal by which households arrive at information, search volume has the potential to measure interest in products without specifying a set of firm-related websites.

Perhaps the most unique aspect of the leading indicator we propose in this paper is its source. Intuitively, there are two natural sources for leading indicators of earnings: firms and customers. Consider, for example, the firm Apple Inc. which sells iPods to millions of customers and then announces the sales at some later date (e.g. the "earnings announcement"). Each customer is partially informed about Apple's sales: they each know of their own purchase and little else. Apple may be fully informed of its sales and, for this reason, the most popular leading indicators originate from the firm (e.g., Feldman et al (2009), Demers and Vega (2009), Deng, et al. (1999); Hall et al. (2000); Gu and Lev (2002, 2004), Mayew and Venkatachalam (2009), Rajgopal et al. (2003); Yang (2007)).

This paper proposes a leading indicator which originates *from the customers*. Consider again the millions of customers who buy iPods. Now suppose these customers search for iPods online in a search engine like Google before executing their purchases. Then by aggregating the search volume for iPods, the search engine can coordinate the information of each customer. In the extreme case where every iPod customer searches for an iPod before making his purchase, search volume will perfectly signal Apple's future announcement of iPod sales.

The customer-based leading indicator we propose has several advantages over a firm-based one. First, search volume data are reported and updated daily, while most leading indicators are released sporadically throughout the year. The real-time nature of search volume not only allows information producers to constantly update but it also allows for event-time analysis for products that have specific release dates. For example, Microsoft released Windows 7 on October 22, 2009. A real-time indicator such as search volume allows information producers to estimate demand around the release date. Second, search volume is produced by a third-party and is therefore less likely to be biased. Most leading indicators are released by firms who may have an incentive to spin or selectively disclose information most favorable to the firm (Dyck and Zingales (2004)). Finally, a customer-based leading indicator *may even be useful to firms.*[2] Along the chain of suppliers and customers, information does not transmit without friction or delay. Thus, even a firm's manager may not necessarily observe all the customer's detailed product level demand information. In summary, the product search volume data have the potential to provide value-relevant information about the firm on a real-time basis.

Some of these advantages have already been recognized in papers which have used search volume to measure household demand for a variety of information. Ginsberg et al. (2008) found that search data for forty-five terms related to influenza predicted flu outbreaks one to two weeks before Centers for Disease Control and Prevention (CDC) reports. The authors conclude that, "harnessing the collective intelligence of millions of users, Google web search logs can provide one of the most timely, broad-reaching influenza monitoring systems available today." More recently, Da, Engelberg and Gao (2010a) examined search volume for stock tickers (e.g., "MSFT" and "AAPL"). They provide evidence that stock-ticker search volume reflects retail demand for shares and has predictability for short-term returns, especially among small stocks.

The rest of the paper is organized as follows. Section 2 describes our data sources and the way in which we construct the SVI for firm products. In Section 3, we use the product-level SVI to predict firm revenue surprises. Section 4 examines its predictability on standardized unexpected earnings (SUE). Section 5 considers how SVI predicts stock returns around and after the earnings announcement and how such predictability varies in the cross-section.

[2] Chen and Plott (2002) discuss an interesting example of how Hewlett-Packard Corporation implemented an Information Aggregation Mechanism (IAM) to better forecast its sales.

Section 6 explores search volume and post-earnings announcement period return. Finally, Section 7 concludes.

2 Data and Sample Construction

2.1 Main Data

Because we wish to estimate household demand for firm products, our first challenge is to obtain a list of products for each firm. We begin by gathering data on firm products from Nielsen Media Research (NMR) which tracks television advertising for firms.[3] NMR provided to us a list of all firms which advertised a product on television during our time period of 2004 - 2008. From this list of 9,764 unique firms, we hand-match to obtain the set of firms which are publicly traded and are covered by Standard and Poor's COMPUSTAT database. This procedure yields a list of 865 firms. For those unmatched firms, nearly all of them are private firms (e.g., the Law Offices of James Sokolove; Empire Today and City Mattress) or non-profit organizations (e.g., Habitat for Humanity; the American Red Cross and the Public Broadcasting Service).

Our sample of 865 firms are associated with 12,259 brand/products in the Nielsen database. Some firms have hundreds of products while others have very few products. For example, Time Warner Inc. has 886 products in the database, ranging from magazines such as *People* to home videos such as seasons of *Friends* and the *West Wing*. On the other hand, Lojack Inc. only advertises one product: the *Lojack Security System*. In fact, there are 337 firms which only advertise one product according to NMR.

To make our data collection process manageable, for each firm we select its most popular product as measured by the number of ads in the Nielsen database.[4] Then, we consider how

[3]Using detailed corporate level advertisement information is relatively new in the accounting literature. Cohen, Mashruwala and Zach (2009) use a database from an anonymous data vendor to track corporate monthly advertisement spending and explore managerial discretion in real earnings management. However, we are not aware of any prior studies using Nielson Media Research's product-level advertisement dataset used in this paper.

[4]As expected, when we restrict our attention to the subsample of firms with below-average number of

these 865 products might be searched in Google. We do this by having two independent research assistants report how they would search for each product. Where there are differences between the reports, we use Google Insights "related search" feature to determine which query is most common.[5]

The resulting database is a list of firms associated with search terms for their most popular product. Table 1 provides a random sample of 75 firms and their associated search term. For example, for Apple Inc. the associated search term is "iPod", for Amgen Inc the associated search term is "Neulasta" and for Home Depot Inc. the associated search term is "Home Depot." For many firms, the search term is simply its common firm name (e.g. Jetblue Airways and "Jetblue") but this is not always the case (e.g. Evercore Partners and "National Enquirer" or Nautilus Inc. and "Bowflex"). The fact that a firm's most popular product may not share the same name as the firm itself underscores the importance of the NMR data in mapping firms to their underlying products.

Next, we input each search term into Google Insights (http://www.google.com/insights/search) and download each query's historical search volume index (SVI). In Google Insights, SVI is calculated as weekly search volume scaled by a constant: the maximum search volume over the search period. For our purposes in this paper, the scaling constant is irrelevant because we will be calculating *changes* in SVI before earnings announcements.[6] For search terms without enough search volume, Google Insights will return an error message.[7] For each firm, we then aggregate these weekly SVIs at quarterly frequency using its fiscal quarter end information. In this aggregation step, we exclude the weekly SVI during the week of the fiscal

products, the predictability results are much stronger.

[5]For each term entered into Google Insights (http://www.google.com/insights/) it returns ten "top searches" related to the term. According to Google, "Top searches refer to search terms with the most significant level of interest. These terms are related to the term you've entered...our system determines relativity by examining searches that have been conducted by a large group of users preceding the search term you've entered, as well as after."

[6]Da, Engelberg and Gao (2010b) compare search volume across terms. In their context, the scaling constant was important so they ran comparative searches which fixed the scaling constant across terms. Intereted readers are referred to Da, Engelberg and Gao (2010b) for more details.

[7]Google also supplies SVI at Google Trends (http://www.google.com/trends). For robustness check, we also apply the SVI obtained from Google Trends, and the results are very similar both qualitatively and quantitatively.

quarter end in order to avoid any potential forward-looking biases.

2.2 Other Data

We obtain sell-side analyst earnings forecasts and reported earnings from the Institutional Brokerage Estimation System (I/B/E/S). Since there is a difference between the earnings reported by the firm according to the generally accepted accounting principles (GAAP) while analysts forecast so-called "Street earnings", which exclude items non-recurring, among many other adjustments. I/B/E/S adjusts the reported earnings to be compatible to the analyst forecasts. Therefore, when we define earnings surprises using I/B/E/S, we define earnings surprises according to I/B/E/S forecasts and I/B/E/S actual earnings. The corporate issued guideline (CIGs) announcements are obtained from Thomson Financial First Call Corporate Issued Guideline database. From Standard and Poor's COMPUSTAT quarterly files, we obtain quarterly earnings announcement dates and quarterly earnings per share values. Other accounting information is obtained from COMPUSTAT annual files.

Table 2 presents some summary statistics (mean, median and standard deviation) for these variables and compares and compares them to the CRSP/COMPUSTAT universe over our sample period (2004 - 2008). On average, firms that advertise on national TV are larger firms with higher turnover and lower Market-to-Book ratios. While our sample of firms are likely to tilt towards larger and growth firms, in terms of revenue surprise or earnings surprises, as well as past return performance, there is no noticeable and economically significant difference. For instance, for our sample of firm, the earnings surprise (measured from the time-series model) is about 0.144 to 0.146, while the COMPUSTAT/CRSP universe is about 0.141 to 0.143. The average analyst earnings forecast surprise in our sample is about 0.045, and the average forecast surprise in the COMPUSTAT/CRSP universe is about 0.041.

2.3 Examples

Figure 1 provides a sample of our data for two firms: Garmin LTD (search term "Garmin") and CEC Entertainment (search term "Chuck E Cheese"). The SVI for "Garmin" indicates a rapid growth in interest for Garmin products, consistent with the rapid growth in GPS navigation products. On the other hand, the SVI for "Chuck E Cheese" indicates very little growth between 2004 and 2007 and some modest growth beginning in 2008. The SVI for "Chuck E Cheese" appears to have more seasonality than the SVI for "Garmin." Turning to the revenues of Garmin LTD and CEC Entertainment in Figure 2, we see that the SVI for their products closely follows the reported revenues. In both cases, the correlation between revenue and search volume is over 90%. Of course, these anecdotes are simply illustrations. In the next section we begin a more rigorous examination of the predictability of SVI for firm fundamentals.

3 Predicting Revenue Surprises

We begin our analysis of the relationship between search volume and firm fundamentals where we expect it to be strongest: sales. Indeed, if households search for a product before their purchase, we should find a strong relationship between search patterns and sales patterns (Choi and Varian (2009)).

Predicting such sales patterns is a worthwhile endeavor. From a practical point of view, revenue or sales forecasts are important for both market participants and firm managers. First, revenue forecasts are often key ingredients for financial statement analysis. Sound investment recommendations and decisions partially depend on sound revenue or sales forecasts. Ultimately, a company's earnings derive from sales less costs. For many modern firms, especially those outside basic materials sector, input prices are relatively sticky because of long-term contracts or a competitive procurement processes. Thus, cost structure is relatively stable and easy to forecast, especially at short horizons (see, for example, Andersen, Banker, and Janakiraman (2003)). However, the demand-side forces, i.e., revenue or sales, are more volatile. Therefore, not surprisingly, sales volatility drives earnings volatility for many firms. Second, revenue forecasts are crucial inputs for firm managers to make internal capital allocation decisions, even though managers are supposed to have better access to product-level sales information. In reality, because the retailers, wholesalers and manufacturers are not perfectly integrated in sharing information, sales information is not readily available to most managers in real time (Chen and Plott (2002)).

According to Lundholm, McVay and Randall (2009), there is "surprisingly little" accounting research on forecasting of sales and revenues. Recent literature (Ertimur, Livant, and Martikainen, 2003; Jegadeesh and Livnat, 2006; Ghosh, Gu, and Jain, 2005) finds revenues and revenue surprises convey incremental information about earnings and market valuation. However, there is little research exploring the relationship between non-financial information and revenue surprises. In other words, it is not clear whether non-financial information in a general setting is able to provide incremental information about revenue surprises. In this section, we provide strong evidence that search volume forecasts revenue surprises.

Following Jegadeesh and Livnat (2006), for each firm in each quarter we define revenue surprise as

$$SUS_{i,q,k} = \frac{REV_{i,q} - REV_{i,q-k}}{\delta\left(REV_i\right)} \tag{1}$$

where REV_i is the quarterly sales (in dollar value) reported by firm i, $REV_{i,q-k}$ is firm i's quarterly sales reported k periods ago and $\delta\left(REV_i\right)$ is the standard deviation of revenue during the past eight quarters. We consider both $k = 1$ and $k = 4$ in our analysis. When $k = 1$, the (naive) expectation of sales is that of the previous quarter; when $k = 4$, revenue surprises are seasonally adjusted.[8]

[8] As a robustness check, for each firm in each quarter we construct its $Sales\_Growth_{i,q:q-1}$ defined as the percentage change in sales between quarter q and quarter $q-1$ for firm i. We also construct $Sales\_Growth_{i,q:q-4}$ to take into account the seasonality in sales. Using these alternative definitions of revenue growth, we obtain very similar results.

For each firm in each quarter we define the change in search volume as:

$$SVI\_Change_{i,q,k} = \log(SVI_{i,q}) - \log(SVI_{i,q-k}) \tag{2}$$

where $SVI_{i,q}$ is the average weekly search volume index for firm i during quarter q.

Table 3 considers a regression of $SUS_{i,q,k}$ on $SVI\_Change_{i,q,k}$ and a series of control variables. The top panel considers last quarter's sales as the expectation ($k = 1$) while the bottom panel considers sales four quarters ago as the expectation ($k = 4$). Each specification includes Global Industry Classification Code (GIC) sector fixed effects and calendar year fixed effects.

The first column of the top panel demonstrates that $SVI\_Change_{i,q,1}$ has strong predictability for $SUS_{i,q,1}$ .A one standard deviation increase in $SVI\_Change_{i,q,1}$ corresponds to an increase in standardized unexpected revenues per share by .233 (= 0.283 × 0.825), which is statistically significant at the one percent level (t-stat = 9.86).[9] The median, mean and standard deviation of the standardized unexpected revenues per share are 0.823, 0.851 and 1.355, respectively, so the economic magnitude of the predictability is quite sizeable. For instance, a one standard deviation increase in $SVI\_Change_{i,q,1}$ corresponds to almost a 1/6 standard deviation change in standardized unexpected revenues per share.

Beginning in column two, the top panel adds a series of control variables including size, market-to-book, turnover, historical return, and institutional ownership. Each has a negligible effect on the variable of interest.

As our leading indicator originates from customers rather than firms, we control for management forecasts in column 7. Management's discretionary disclosure policy affects the analyst choice of whether to cover the firm, which in turn affects a firm's information environment (Lang and Lundholm, 1996). In addition, managers may guide the analysts

[9] Ideally, one would like to put even more economic meaning behind the numeric values of SVI. For example, one question is how many user searches will generating corresponding SVI value. However, as we discuss early, due to the data limitation introduced by the normalization, we can not provide such interpretation.

in making forecasts through the earning cycle (Cotter, Tuna, and Wysocki, 2006). From the First Call Corporate Issued Guideline database, we count the number of management issued guidelines related to quarterly earnings between quarters. Management forecasts also have strong predictability for revenue surprises with coefficients that have the predicted sign: the number of positive (negative) management forecasts has a positive (negative) effect on $SUS_{i,q,1}$. Nevertheless, the coefficient on $SVI\_Change_{i,q,1}$ remains economically and statistically significant (t-stat of 9.98).

The final specification (column 8) adds lagged revenue surprise as an independent variable. The lagged revenue surprise adds substantial predictive power for current revenue surprise, as the R-squared increases from 0.041 to 0.107. However, controlling for the (not seasonally-adjusted) lagged revenue surprise actually increases slightly the coefficient on $SVI\_Change_{i,q,1}$ from .875 to .919 and it remains statistically significant at the 1% significance level.

While the previous results suggest that search volume correlates well with sales, we do not know whether this effect is due to seasonality. For example, a retailer's sales are often high during the holiday season, and so is search volume for its products. The bottom panel asks whether search volume has predictability for sales beyond seasonality. For example, can search volume predict whether a retailer's sales this holiday season will be better than the prior one?

The evidence suggests "yes." The bottom panel of Table 3 regresses seasonally-adjusted revenue surprises ($SUS_{i,q,4}$) on seasonally-adjusted search volume ($SVI\_Change_{i,q,4}$). The coefficient on $SVI\_Change_{i,q,4}$ is large (.487) and statistically significant (t-stat of 5.17). As in the top panel, we add control variables one at a time in each specification. In the last specification, we control for the (seasonally-adjusted) lagged revenue surprise. The coefficient on lagged (seasonally-adjusted) revenue surprise is large and significant, consistent with prior work that finds a strong autocorrelation in revenue surprises (Jegadeesh and Livnat (2006)). The presence of lagged revenue surprise reduces the coefficient on $SVI\_Change_{i,q,4}$

from .357 to .116, but it remains highly significant (t-stat of 2.43).

4 Predicting Earnings Surprises

Earnings announcements convey important incremental information to financial markets. Beaver (1968), Bernard and Thomas (1989, 1990), and Ball and Shivakumar (2008), among others provide evidence that information revealed by quarterly earnings announcements is useful to shareholders. Similarly, Easton, Monahan, and Varsvari (2009) study investors reaction in the bond market to quarterly earnings announcements. Earnings announcements also change the expectations of investors as demonstrated by Lakonishock, Shleifer and Vishny (1994) and Skinner and Sloan (2002). Given the importance and prevalence of earnings announcements, a large body of literature has been developed to study earnings surprises.

In the previous section, we provided evidence that innovations in search volume had predictability for revenue surprises. In this section, we ask whether this predictability extends to earnings surprises. Again, the answer appears to be "yes", although the relationship is much weaker. This is not surprising as search volume may be directly related to revenue but not to costs. In addition, reported earnings are subject to temporary smoothing and other forms of earnings management.

We follow Livnat and Mendenhall (2006) and calculate the random-walk version of standardized unexpected earnings (SUE). Specifically, $SUE_{i,q}$ is the change in earnings per share between quarter q and quarter $q-4$ for firm i scaled by the price per share:

$$SUE_{i,q,4} = \frac{EPS_{i,q} - EPS_{i,q-4}}{P_{i,q-4}}. \tag{3}$$

Table 4 reports the results of two regressions which regress $SUE_{i,q,4}$ on $SVI\_Change_{i,q,4}$. The full set of controls used in column 8 of Table 3 are deployed here except that we replace lagged revenue surprise with lagged SUE in these specifications. In the first column of

Table 4, SUE is calculated without excluding extraordinary items whereas in the second column we exclude extraordinary items as in Livnat and Mendenhall (2006). As expected, search volume has a weaker relation with earnings surprises (without special items) than it does with sales. A one standard deviation increase in $SVI\_Change_{i,q,1}$ corresponds to an increase in standardized unexpected earnings per share by 0.0985 (= 0.283 × 0.348), which is significant at the 10% level. This positive relation disappears completely when we include special items in the earnings calculation (column 1), perhaps because search volume has limited power to predict items which are nonrecurring in nature and more likely to be under the discretion of management.

These results may also be consistent with the view that the earnings numbers themselves do not convey all value-relevant accounting information, especially at the quarterly frequency. In other words, the value-relevance of non-financial information may be related to earnings but contain information incremental information which is relevant for prices. We explore this point further in the following sections by directly examining stock returns around and after the earnings announcement.

5 SVI and Earnings Announcement Period Returns

5.1 SVI and Average Earnings Announcement Period Returns

There are several reasons to believe information contained in search volume is value-relevant and may predict announcement returns. First, the information contained in search volume may not be found other places. Beyond aggregate sales, firms usually do not disclose detailed product level information. However, as illustrated in Boatsman, Behn, and Patz (1993), disaggregate information – such as sales by geographic segments – is also value-relevant. Second, while current-quarter revenues and earnings directly incorporate current-quarter cash flow shocks, returns incorporate future information about fundamentals, and there is good reason to believe that the information in search contains forward-looking valuation-relevant information: customers search for information about products before executing their purchases so search volume may also contain useful information about the long-run cash flows of the firm beyond the current fiscal quarter.

To measure the market response, we take the standard approach and calculate cumulative abnormal returns (CARs) over the three-day window surrounding the earnings announcement. Abnormal return is calculated as the raw daily return from CRSP minus the daily return on size and market-to-book matched portfolio as in Livnat and Mendenhall (2006). All CARs are in basis points. Formally we define the abnormal return for firm i, t days after its quarter q earnings announcement as:

$$CAR_{i,q,t} = R_{i,q,t} - BR_{i,q,t} \tag{4}$$

where $R_{i,q,t}$ is the for firm i, t days after its quarter q earnings announcement and $BR_{i,q,t}$ is the size and book-to-market matched "benchmark portfolio" return for firm i, t days after its quarter q earnings announcement. Then the announcement-window cumulative abnormal return for firm i in quarter q is computed as

$$CAR_{i,q} = \prod_{t=-1}^{1} (1 + R_{i,q,t}) - \prod_{t=-1}^{1} (1 + BR_{i,q,t}). \tag{5}$$

Table 5 reports the results of three regressions which regress $CAR_{i,q}$ on $SVI\_Change_{i,q,4}$. The first column, which contains the standard controls as in Table 4, shows a strong relationship between announcement returns and $SVI\_Change_{i,q,4}$. In fact, it is the only variable in the specification that is significant at the 1% level (t-statistic = 2.64). The economic effects are also large. A one standard deviation increase in SVI_Change corresponds to an increase of about, 27 ($= 0.283 \times 95.086$) basis points over the three-day period (about $27 \times 250/3 = 22.50\%$ annualized). Interestingly, $SVI\_Change_{i,q,4}$ remains a strong predictor of announcement returns even after including the *contemporaneous* earnings surprise (column 2) or *contemporaneous* revenue surprise (column 3).

5.2 SVI and Cross-Sectional Variations in Earnings Announcement Period Returns

So far, we have three main results: search volume has (1) strong predictability for revenue surprises, (2) weak predictability for earnings surprises and (3) strong predictability for announcement returns. Taken together, these findings are consistent with Ertimur et. al. (2003) and Jegadeesh and Livnat (2006) which show that revenue surprises may contain value-relevant information over and above earnings surprise. There are several potential reasons. First, revenue surprises are likely to be more homogeneous than earnings surprises and thus less noisy (and the market tends to react more to a less noisy signal). Second, revenue changes are usually more persistent than earnings changes and most valuation models predict more persistent surprises to have a stronger impact on market prices. In other words, the revenue changes might be more informative about the long-run cash flow fundamentals of the firm which drive valuation. Third, compared to earnings, revenue numbers are less prone to manipulation or "management" and are thus more informative. For these reasons, search volume, which strongly predicts revenue surprises, would also predict abnormal returns during the earnings announcement window even though it has weaker predictability for earnings surprises.

These arguments generate three testable predictions regarding the predictive power of search volume in the cross-section. First, we would expect search volume to have stronger predictive power about the announcement return among firms where it carries a less noisy signal about firm revenue. Second, we would expect search volume to have stronger predictive power among growth firms with low book-to-market ratios whose valuations are particularly sensitive to long-run cash flow growth. Third, we would expect search volume to have stronger predictive power among firms that manage their earnings (so that search volume is relatively informative). We test each of these three predictions in the cross section.

In Table 6, we repeat the CAR regression separately in subsamples of firms sorted based on their number of products (as identified by Nielsen) and their book-to-market ratios (BM).

The first two columns suggest that firms with fewer products are precisely those for which the search volume of the most popular product is most informative. In fact, search volume predicts announcement return in a significant way only among these firms. The result is intuitive and supports our first prediction. In the extreme, the demand for a firm with one product will be well-captured by the search volume of its most popular product (i.e., its only product). The last two columns of Table 6 confirm our second prediction: search volume predicts announcement return only among growth firms. The coefficient on SVI change among growth firms is more than four times larger than the coefficient among value firms, consistent with the notation that a growth firm's valuation is more sensitive to its long-run cash flow growth rate for which search volume provides an informative signal.

In Table 7, we repeat the CAR regression separately in subsamples of firms sorted based on their degrees of earnings management. We consider two measures of earnings management. The first measure, *earnings smoothness* (ES), is computed as the ratio between the standard deviation of the reported earnings (excluding extraordinary items) and the standard deviation of the operating cash flow, while the second measure, *accruals volatility* (AV), is defined as the standard deviation of total accruals measured according to Sloan (1996). A firm that manages its earnings by manipulating its accounting accruals will have higher *accruals volatility* and lower *earnings smoothness*. The results in Table 7 suggest the predictive power of search volume on announcement-window return to be much stronger and only significant among firms with above-median *accruals volatility* and below-median *earnings smoothness*, i.e. firms that are likely to engage in the practice of earnings management. Taken together, the cross-sectional variation of SVI change's predictive power on announcement returns suggests that the value relevance of non-financial information, including customer-generated information such as internet search volume, varies with respect to the underlying firm's information environment.

6 SVI and Post Earnings Announcement Period Returns

Through the paper, we have argued that search volume contains value-relevant information. Here we ask whether the information in search volume information is immediately incorporated into stock prices during the earnings announcement period. Our empirical strategy is to consider the relationship between post-earnings announcement period returns and pre-earnings announcement search volume changes. We define the post-earnings announcement period return as

$$POST\_CAR_{i,q} = \prod_{t=2}^{d(i,q+1)} (1 + R_{i,q,t}) - \prod_{t=2}^{d(i,q+1)} (1 + BR_{i,q,t}) \tag{6}$$

where $d(i, q+1)$ is the number of trading days until firm i's quarter $q+1$ earnings announcement. Table 8 regresses $POST\_CAR_{i,q}$ on $SVI\_Change_{i,q,4}$ and our standard controls. We find $SVI\_Change_{i,q,4}$ has some weak predictability for $POST\_CAR_{i,q}$ but this predictability disappears when $CAR_{i,q}$ is added to the specification (column 2). On balance, Table 8 suggests that the market incorporates most of the pre-earnings announcement period search volume information by the time of the earnings announcement, and there seems to be no statistically discernible delay.

7 Conclusion

Motivated by other empirical findings that search volume is well-suited to predict lagged releases of economic activity (Choi and Varian (2009)), we use the search volume for a firm's key product to predict revenue and earnings surprises for that firm. We find that increases (decreases) in the search volume index (SVI) of a firm's most popular product strongly predict positive (negative) revenue surprises and that predictability for standardized unexpected earnings (SUE) is weaker. We also find strong evidence that changes in SVI predict announcement-window abnormal returns, even after controlling for the earnings and revenue surprise at the announcement. Interestingly, such predictive power is stronger among firms with few products, growth firms and firms that manage earnings. Taken together our findings suggest that search volume for a firm's products may be a promising leading indicator for revenues and announcement returns. Thus, search volume may be a useful tool for information producers such as analysts and fund managers who are charged with forecasting firm fundamentals.

While search volume seems promising as a leading indicator of lagged economic announcements such as earnings announcements, there appears to be no reason why search volume cannot be applied to other situations. For example, search volume may be particularly helpful when little information exists to predict sales, as is the case with new products or products which have undergone substantial regulatory changes. In addition, search volume may also help to answer other important economic questions, such as how the aggregation of information and beliefs affects asset prices (Ottaviani and Sorensen (2010)). We leave these questions for future research.

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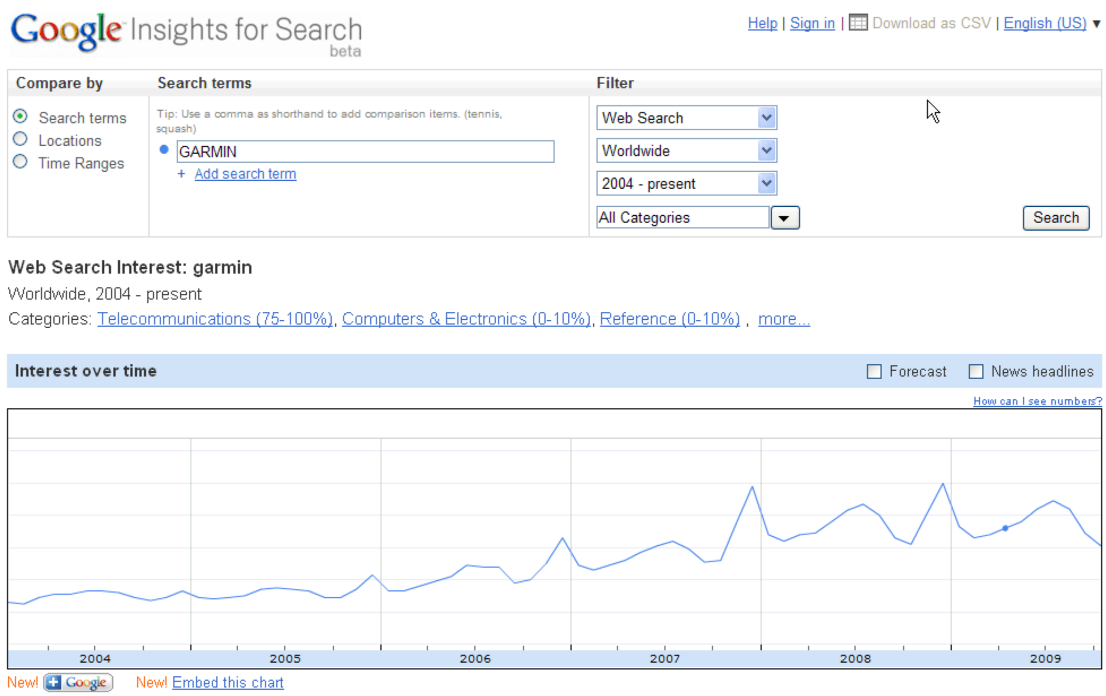
Figure 1: Search Volume Index (SVI) for “GARMIN” and “CHUCK E CHEESE”

The figures are screenshots taken from Google Insights (http://www.google.com/insights/). The top panel plots the search volume index (SVI) for the term “GARMIN” from March 2004 to October 2009. The bottom panel plots the search volume for the term “CHUCK E CHEESE” over the same time period.



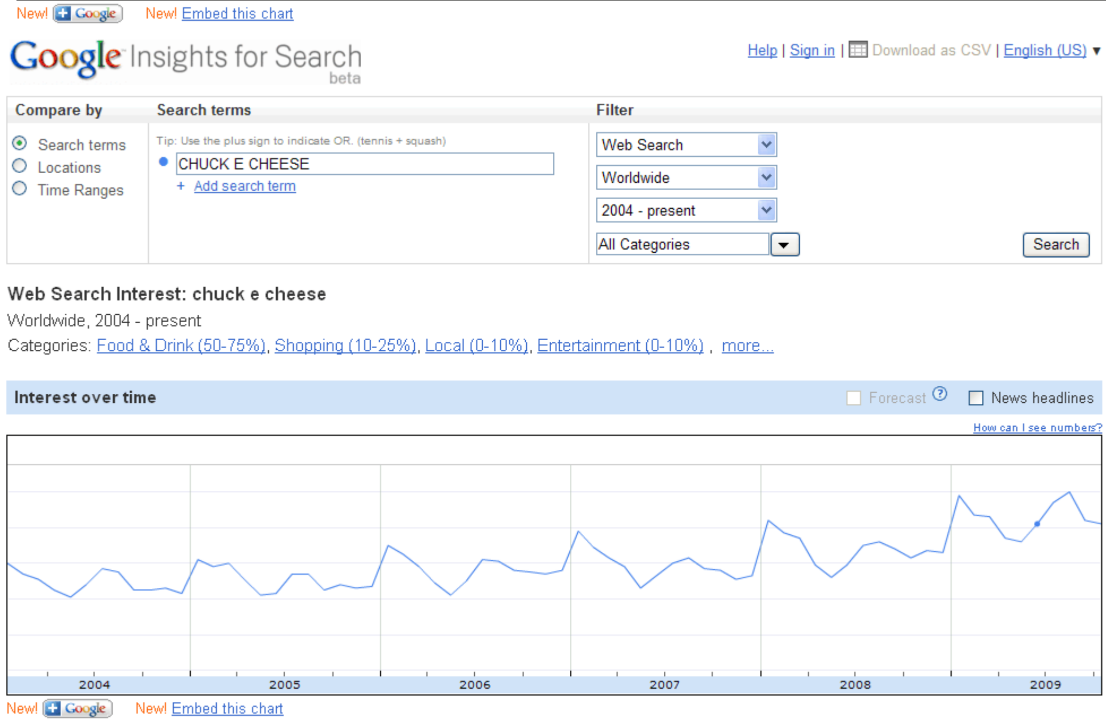
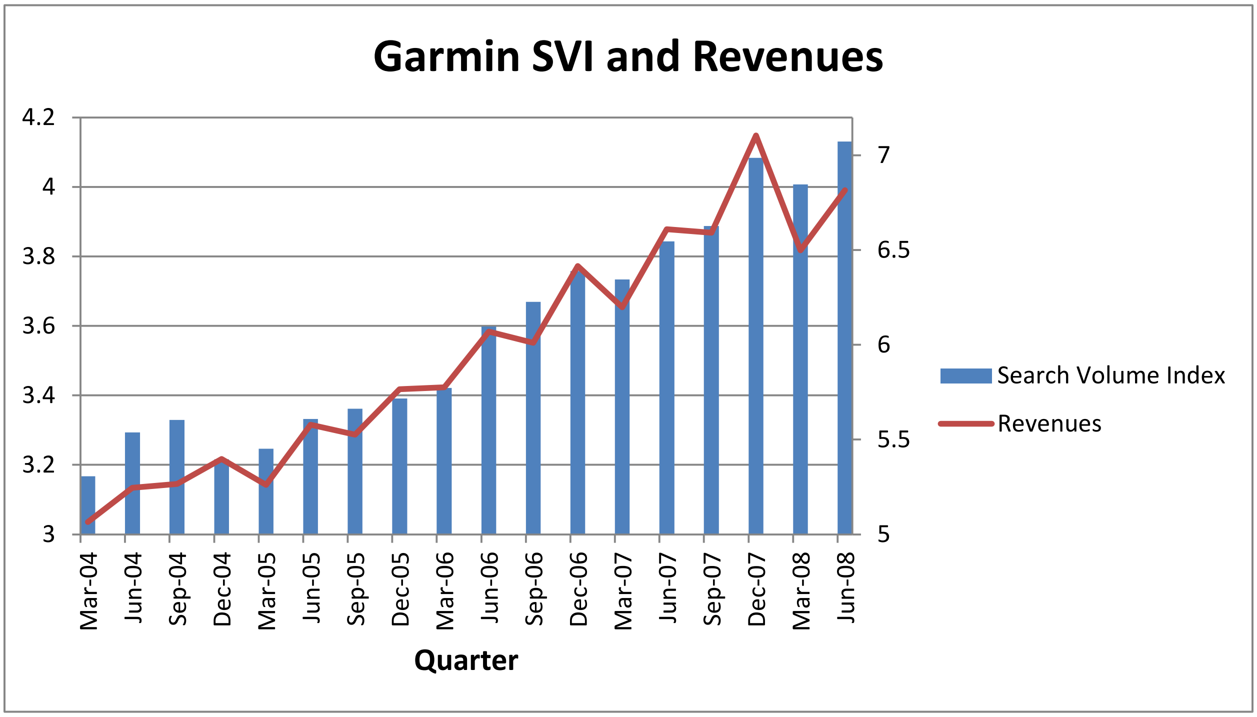


Figure 2: Revenues and SVI for "GARMIN" and "CHUCK E CHEESE"

The figures plot the natural log of the quarterly search volume index (SVI) and the natural log of quarterly revenues for Garmin LTD (search term "GARMIN") and CEC Entertainment Inc (search term "CHUCK E CHEESE").



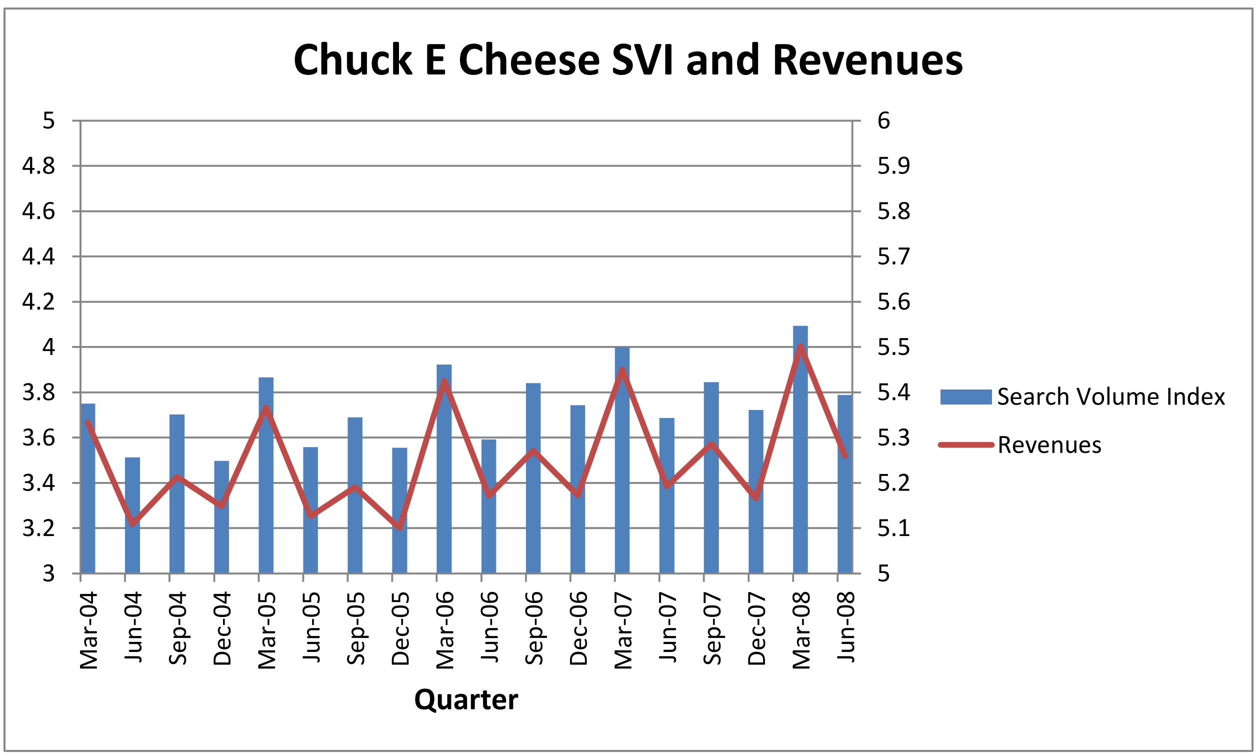


Table 1: Sample of Firms and Search Terms

The table presents a sample of 75 firms and the associated search queries. The query is based on the most popular product as determined by advertising statistics kept by the Nielsen Media Research.

Firm	Search Term	Firm	Search Term	Firm	Search Term
A M R CORP	AMERICAN AIRLINES	HANESBRANDS INC	PLAYTEX	MIDAS INC	MIDAS SHOP
ALLERGAN INC	RESTASIS	HOME DEPOT INC	HOME DEPOT	NAUTILUS INC	BOWFLEX
AMGEN INC	NEULASTA	HONDA MOTOR LTD	HONDA	NETFLIX INC	NETFLIX
APPLE INC	IPOD	I H O P CORP NEW	APPLEBEES	NEWELL RUBBERMAID	SHARPIE
ASHLAND INC	VALVOLINE	IAC INTERACTIVE	MATCH.COM	NUTRISYSTEM INC	NUTRISYSTEM
AUTOZONE INC	AUTOZONE	INTUIT INC	QUICKEN	OHIO ART CO	ETCH A SKETCH
AVAYA INC	AVAYA	INVACARE CORP	INVACARE	PEPSICO INC	GATORADE
BEBE STORES INC	BEBE	IROBOT CORP	ROOMBA	POPULAR INC	ELOAN
BOSTON BEER INC	SAMUEL ADAMS	JARDEN CORP	FOODSAVER	PRICELINE COM INC	PRICELINE.COM
C A INC	CA COMPUTER	JETBLUE AIRWAYS	JETBLUE	PROCTER & GAMBLE CO	FEBREZE
CEC ENTERTAINMENT	CHUCK E CHEESE	KIMBERLY CLARK	KLEENEX	RC2 CORP	BOB THE BUILDER
COCA COLA CO	COKE	KNOT INC	THE KNOT	RESEARCH IN MOTION	BLACKBERRY
CONSECO INC	COLONIAL PENN	KOHLS CORP	KOHLS	RUBY TUESDAY INC	RUBY TUESDAY
DELL INC	DELL	KONAMI CORP	KONAMI	SARA LEE CORP	HILLSHIRE FARMS
DIAMOND FOODS INC	EMERALD NUTS	KRAFT FOODS INC	OREO	SEPRACOR INC	LUNESTA
EARTHLINK INC	PEOPLEPC	KROGER COMPANY	FRED MEYER	SUPERVALU INC	ALBERTSONS
EBAY INC	EBAY	L C A VISION INC	LASIKPLUS	TIVO INC	TIVO
ECOLAB INC	NASCAR AUTOCARE	LEVITT CORP FLA	BOWDEN HOMES	TREE COM INC	LENDINGTREE
ENDOCARE INC	CRYOCARE	LIZ CLAIBORNE INC	LIZ CLAIBORNE	U A L CORP	UNITED AIRLINES
EVERCORE PARTNERS	NATIONAL ENQUIRER	LO JACK CORP	LOJACK	UNITED ONLINE INC	NETZERO
FEDEX CORP	FEDEX	MACYS INC	MACYS	V F CORP	WRANGLER JEANS
GANNETT INC	CAREERBUILDER	MASCO CORP	DELTA FAUCETS	VIVENDI	ACTIVISION
GAP INC	OLD NAVY	MCDONALDS CORP	MCDONALDS	WYETH	ADVIL
GARMIN LTD	GARMIN	MERCK & CO INC	SINGULAIR	YAHOO INC	YAHOO
GENERAL MILLS INC	CHEERIOS	MICROSOFT CORP	MICROSOFT	YUM BRANDS INC	PIZZA HUT

Table 2: Summary Statistics

The following table compares the mean, median and standard deviation of several variables. "Sample" refers to the sample of firms used in this study. Size is the natural logarithm of market capitalization in millions. Market-to-Book is the ratio of market to book value. Turnover is the average turnover during the fiscal quarter. Prior return is the return over the fiscal quarter. The number of positive, neutral and negative firm issued guidelines is the number of management earning forecasts recorded by First Call constituting positive, neutral, or negative surprises. The revenue surprise (not seasonally adjusted) is defined as the difference between quarter (q) and quarter (q-1), divided by the standard deviation of revenue from (q-8) to (q-1). The revenue surprise (seasonally adjusted) is defined as the revenue difference between quarter (q) and quarter (q-4), divided by the standard deviation of revenue from (q-8) to (q-1). Time Series Earnings Surprise is the fiscal quarter's earnings minus the earnings four quarters ago scaled by price; Analyst Earnings Surprise is the fiscal quarter's earnings minus the median analyst forecast scaled by price; is the three day cumulative abnormal return (CAR) surrounding the earnings announcement. CAR – Earnings Window is the cumulative abnormal return (CAR) in basis points for the three days surrounding the earnings announcement while CAR – Subsequent Quarter is the CAR cumulated from two days after an earnings announcement through one day after the next quarterly earnings announcement. All earnings surprise and CAR variables are calculated as in Livnat and Mendenhall (2006).

	Sample			CRSP/COMPUSTAT Universe		
Variable	Mean	Median	St. Deviation	Mean	Median	St. Deviation
Size (natural log) in millions	8.277	8.207	2.258	5.307	5.506	2.896
Market-to-Book	1.605	1.195	2.072	2.815	0.923	10.254
Turnover	1.946	1.476	1.856	1.701	1.050	3.555
Prior Return	0.022	0.018	0.178	0.024	0.010	0.247
Firm Guidance: Negative	0.076	0	0.265	0.005	0	0.076
Firm Guidance: Neutral	0.132	0	0.338	0.007	0	0.103
Firm Guidance: Positive	0.056	0	0.230	0.002	0	0.053
Revenue Surprise (seasonally-adjusted)	0.299	0.218	1.336	0.311	0.184	1.353
Revenue Surprise (not seasonally-adjusted)	0.856	0.827	1.363	0.805	0.765	1.625
Time-Series Earnings Surprise	-0.009	0.146	2.266	0.062	0.141	2.917
Time-Series Earnings Surprise (w/o special items)	0.001	0.144	2.020	0.066	0.143	2.666
Analyst Earnings Surprise	0.003	0.045	0.958	-0.040	0.041	1.292
CAR - Earnings Window (in basis points)	28.518	13.231	699.583	3.328	0.474	774.957
CAR - Subsequent Quarter (in basis points)	-47.125	-2.164	1619.610	-36.748	-0.385	1909.350

Table 3: SVI Change and Revenue Surprises

In the top panel, the dependent variable is the revenue difference between quarter (q) and quarter (q-1), divided by the standard deviation of revenue from (q-8) to (q-1). In the bottom panel it is the revenue difference between quarter (q) and quarter (q-4), divided by the standard deviation of revenue from (q-8) to (q-1). SVI Change is the change in search volume for a firm's most popular product. In the top panel, this change is calculated as the log difference in average weekly SVI between the announcement quarter and the prior quarter. In the bottom panel, this change is calculated as the log difference in average weekly SVI between the fiscal quarter and four quarters prior. Search volume is taken from Google Insights. Size is the natural logarithm of market capitalization. Market-to-Book is the ratio of market to book value. Turnover is the average turnover during the fiscal quarter. Prior return is the return over the fiscal quarter. Institutional ownership is the fraction of shares owned by institutions. The number of positive, neutral and negative corporate issued guidelines is the number of management earning forecasts recorded by First Call constituting positive, neutral, or negative surprises. If the management forecast does not constitute either a positive or negative surprise, it is coded as neutral. Lag(Revenue Surprise) is the prior quarter revenue surprise. GIC Sector and Year fixed effects are included in each specification. Robust standard errors clustered by firm are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Revenue Surprise							
SVI Change	0.825***	0.823***	0.875***	0.878***	0.873***	0.875***	0.875***	0.919***
	(0.084)	(0.085)	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.082)
Size		0.023***	0.023***	0.025***	0.023***	0.023***	0.020***	0.026***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Market-to-Book			0.006	0.006	0.003	0.003	0.001	0.003
			(0.007)	(0.007)	(0.005)	(0.005)	(0.004)	(0.006)
Turnover				-0.015***	-0.013**	-0.012**	-0.012**	-0.011*
				(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Prior Return					0.410***	0.407***	0.364***	0.536***
					(0.085)	(0.085)	(0.084)	(0.083)
Institutional Ownership						-0.014	-0.013	-0.015*
						(0.010)	(0.010)	(0.009)
Firm Guidance: Negative							-0.191***	-0.172***
							(0.045)	(0.046)
Firm Guidance: Neutral							0.066*	0.077**
							(0.034)	(0.035)
Firm Guidance: Positive							0.273***	0.291***
							(0.052)	(0.054)
Lag(Revenue Surprise)								-0.260***
								(0.013)
Industry Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	11727	11408	10699	10692	10692	10667	10667	10642
R-Squared	0.02794	0.02975	0.03327	0.03363	0.03637	0.03674	0.04097	0.1068

	Dependent Variable: Revenue Surprise (Seasonally Adjusted)							
SVI Change	0.487*** (0.094)	0.417*** (0.092)	0.394*** (0.095)	0.402*** (0.095)	0.370*** (0.092)	0.366*** (0.092)	0.357*** (0.091)	0.116*** (0.049)
Size		0.079*** (0.012)	0.075*** (0.012)	0.079*** (0.013)	0.074*** (0.013)	0.074*** (0.013)	0.068*** (0.013)	0.025*** (0.006)
Market-to-Book			0.041 (0.030)	0.042 (0.031)	0.034 (0.026)	0.033 (0.026)	0.032 (0.025)	0.011 (0.009)
Turnover				-0.024* (0.012)	-0.018 (0.013)	-0.015 (0.014)	-0.014 (0.014)	-0.016** (0.007)
Prior Return					0.909*** (0.101)	0.909*** (0.101)	0.884*** (0.100)	0.479*** (0.065)
Institutional Ownership						-0.035 (0.032)	-0.034 (0.032)	0.021* (0.011)
Firm Guidance: Negative							-0.116* (0.069)	-0.149*** (0.039)
Firm Guidance: Neutral							0.181*** (0.055)	0.058** (0.029)
Firm Guidance: Positive							0.302*** (0.068)	0.168*** (0.042)
Lag(Revenue Surprise)								0.614*** (0.012)
Industry Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	9516	9437	8857	8857	8837	8837	8837	8802
R-Squared	0.04639	0.06342	0.06803	0.08062	0.08086	0.08086	0.08574	0.4236

Table 4: SVI Change and Earnings Surprises

The dependent variable is the seasonally-adjusted standardized earnings surprise with (first column) and without (second column) special items as calculated in Livnat and Mendenhall (2006). Change in SVI is the change in average search volume index calculated as the log difference in average weekly SVI between the fiscal quarter and four quarters prior. Search volume is taken from Google Insights (http://www.google.com/insights/search/). Size is the natural logarithm of market capitalization. Market-to-Book is the ratio of market to book value. Turnover is the average turnover during the fiscal quarter. Prior return is the return over the fiscal quarter. Institutional ownership is the fraction of shares owned by institutions. *** The number of positive, neutral and negative corporate issued guidelines is the number of management earning forecasts recorded by First Call constituting positive, neutral, or negative surprises. Lag(SUE) is the prior quarter earnings surprise. GIC Sector and Year fixed effects are included in each specification. Robust standard errors clustered by firm are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable:	
	SUE	SUE - no special items
SVI Change	-0.047	0.348*
	(0.108)	(0.228)
Size	-0.004	-0.006
	(0.013)	(0.047)
Market-to-Book	0.070***	0.166**
	(0.019)	(0.069)
Turnover	-0.111***	-0.431**
	(0.027)	(0.174)
Prior Return	1.680***	3.152***
	(0.219)	(0.795)
Institutional Ownership	0.203	1.105**
	(0.132)	(0.539)
Firm Guidance: Negative	-0.244***	-0.159
	(0.058)	(0.124)
Firm Guidance: Neutral	-0.008	-0.094
	(0.054)	(0.199)
Firm Guidance: Positive	0.117	0.390**
	(0.088)	(0.172)
Lag(SUE)	0.297***	0.437***
	(0.029)	(0.093)
Industry Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Observations	7225	7231
R-Squared	0.1361	0.07402

Table 5: SVI Change and Announcement Returns

The dependent variable is the three day cumulative abnormal return (CAR) surrounding the earnings announcement. Abnormal return is calculated as the raw daily return from CRSP minus the daily return on size and market-to-book matched portfolio as in Livnat and Mendenhall (2006). All CARs are in basis points. Change in SVI is the change in average search volume index calculated as the log difference in average weekly SVI between the fiscal quarter and four quarters prior. Size is the natural logarithm of market capitalization. Market-to-Book is the ratio of market to book value. Turnover is the average turnover during the fiscal quarter. Prior return is the return over the fiscal quarter. Institutional ownership is the fraction of shares owned by institutions. The number of positive, neutral and negative corporate issued guidelines is the number of management earning forecasts recorded by First Call constituting positive, neutral, or negative surprises. Current SUE is the current quarter earnings surprise, Lag(SUE) is the prior quarter earnings surprise and Current Revenue Surprise is the current quarter revenue surprise. GIC Sector and Year fixed effects are included in each specification. Robust standard errors clustered by firm are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Announcement Return		
SVI Change	95.086***	102.041***	78.377**
	(36.017)	(36.617)	(34.864)
Size	1.762	2.155	-1.870
	(4.637)	(4.647)	(4.551)
Market-to-Book	-6.642	-4.855*	-6.278*
	(9.820)	(2.825)	(3.298)
Turnover	-8.481	-4.666	-9.427
	(8.310)	(8.000)	(7.896)
Prior Return	-94.012	-143.205**	-143.368**
	(69.756)	(71.201)	(70.946)
Institutional Ownership	91.723*	75.246	93.379**
	(46.869)	(46.453)	(46.252)
Firm Guidance: Negative	-11.951	-8.077	-10.165
	(27.925)	(27.440)	(27.484)
Firm Guidance: Neutral	-24.052	-28.790	-39.804
	(25.627)	(25.539)	(25.476)
Firm Guidance: Positive	-6.114	-9.727	-23.319
	(35.828)	(35.809)	(35.375)
Lag(SUE)	-1.339		
	(0.990)		
Current SUE		25.934***	
		(4.982)	
Current Revenue Surprise			57.891***
			(7.107)
Industry Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	7244	7349	7345
R-Squared	0.004551	0.01062	0.01459

Table 6: SVI Change and Accounting Earnings Informativeness

We repeat the last column regression in Table 5 in several subsamples. In columns 1 and 2, we consider the subsample of firms with below median (above median) number of brands according to Nielsen Media Research. In columns 3 and 4, we consider the subsample of firms with below median (above median) book-to-market ratios according to COMPUSTAT. Robust standard errors clustered by firm are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Announcement Returns			
	# of Brands = Few	# of Brands = many	Growth Firms	Value Firms
SVI Change	88.688**	83.636	211.733***	52.044
	(44.158)	(53.871)	(69.588)	(65.605)
Current Revenue Surprise	63.735***	53.649***	64.050***	73.157***
	(10.460)	(9.537)	(13.683)	(13.353)
Size	-4.206	-9.139	-16.695**	11.428
	(6.823)	(6.762)	(8.307)	(9.117)
Book-to-Market	-4.080*	-17.364	-7.388**	11.711
	(2.400)	(13.719)	(3.547)	(51.900)
Turnover	-13.617	2.372	-34.455***	20.172
	(9.192)	(14.290)	(11.476)	(17.220)
Past 3-Month Return	-183.526*	-69.575	-203.128	-160.069
	(93.483)	(109.505)	(128.305)	(120.279)
Institutional Ownership	104.630*	62.904	185.507**	4.522
	(59.648)	(80.877)	(87.881)	(93.201)
Firm Guidance: Negative	-7.749	-12.978	-68.561	-10.444
	(39.470)	(39.216)	(51.082)	(51.446)
Firm Guidance: Neutral	-21.455	-45.973	-104.749***	-23.763
	(41.864)	(31.259)	(40.203)	(56.696)
Firm Guidance: Positive	41.574	-71.208*	-12.857	-98.818
	(60.545)	(39.699)	(50.296)	(76.719)
Industry Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Observations	3716	3614	2413	2076
Clusters	329	297	435	423
R-Squared	0.0193	0.0148	0.03032	0.03049

Table 7: SVI Change and Earnings Management

We repeat the last column regression in Table 5 in several subsamples. In columns 1 and 2, we consider the subsample of firms with below median (above median) earnings smoothness. The earnings smoothness (ES) is computed as the ratio between the standard deviation of the reported earnings (excluding the extraordinary item) and the standard deviation of the operating cash flow. In columns 3 and 4, we consider the subsample of firms with below median (above median) standard deviation of the total accruals. Robust standard errors clustered by firm are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively. Robust standard errors clustered by firm are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Announcement Return			
	Earnings Smoothness = Low	Earnings Smoothness = High	Volatile Accruals = Low	Volatile Accruals = High
SVI Change	99.484**	48.823	7.975	100.105**
	(46.315)	(50.969)	(57.682)	(46.986)
Current Revenue Surprise	60.899***	54.136***	78.303***	77.306***
	(9.406)	(11.046)	(11.464)	(11.883)
Size	-7.642	-4.586	-10.108	-9.575
	(5.135)	(6.887)	(7.032)	(7.756)
Book-to-Market	-6.411**	-5.936	9.799	-6.605**
	(3.214)	(14.990)	(15.712)	(3.332)
Turnover	13.031	-26.659**	7.045	-30.286***
	(9.585)	(12.568)	(11.943)	(10.900)
Past 3-Month Return	-269.876***	-1.365	-391.430***	-36.248
	(89.775)	(109.312)	(91.433)	(110.103)
Institutional Ownership	46.504	157.915**	95.430	192.501***
	(63.618)	(70.432)	(71.605)	(73.010)
Firm Guidance: Negative	-30.840	4.862	-36.939	13.796
	(35.373)	(43.768)	(38.918)	(44.646)
Firm Guidance: Neutral	-55.709*	-24.366	-35.919	-79.437*
	(31.843)	(42.634)	(33.877)	(43.472)
Firm Guidance: Positive	-51.039	1.322	-15.976	-13.405
	(43.865)	(61.704)	(45.376)	(61.068)
Industry Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Observations	4055	3152	3198	3067
Clusters	325	264	464	451
R-Squared	0.02077	0.01557	0.02629	0.02711

Table 8: SVI Change and Post-Announcement Returns

The dependent variable is the CAR cumulated from two days after an earnings announcement through one day after the next quarterly earnings announcement as in Livnat and Mendenhall (2006). All CARs are in basis points. Change in SVI is the change in average search volume index calculated as the log difference in average weekly SVI between the fiscal quarter and four quarters prior. Size is the natural logarithm of market capitalization. Market-to-Book is the ratio of market to book value. Turnover is the average turnover during the fiscal quarter. Prior return is the return over the fiscal quarter. Institutional ownership is the fraction of shares owned by institutions. The number of positive, neutral and negative corporate issued guidelines is the number of management earning forecasts recorded by First Call constituting positive, neutral, or negative surprises. Lag(SUE) is the prior quarter earnings surprise and Announcement Return is the three-day CAR defined in the prior table. GIC Sector and Year fixed effects are included in each specification. Robust standard errors clustered by firm are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Post-Earnings Return	
SVI Change	130.302*	122.899
	(76.762)	(75.587)
Size	-1.106	-1.071
	(11.630)	(11.519)
Market-to-Book	23.579	24.100
	(22.360)	(22.018)
Turnover	-45.866*	-45.212*
	(23.638)	(23.359)
Prior Return	144.315	151.283
	(148.121)	(147.196)
Institutional Ownership	-178.303	-185.832*
	(114.030)	(112.641)
Firm Guidance: Negative	-46.223	-45.297
	(66.693)	(66.293)
Firm Guidance: Neutral	5.090	6.812
	(51.004)	(50.601)
Firm Guidance: Positive	19.507	19.896
	(99.903)	(99.345)
Lag(SUE)	1.556	1.659
	(3.158)	(3.165)
Announcement Return		0.076**
		(0.033)
Industry Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Observations	7234	7234
R-Squared	0.01723	0.01833