# In Search of Earnings Predictability*

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**Abstract**

We use search volume for a firm's products to predict the earnings surprises of that firm. We find that increases (decreases) in the search volume index (SVI) of a firm's most popular product predict positive (negative) revenue surprises and standardized unexpected earnings (SUE). SVI also predicts earnings surprises relative to analyst forecasts and the earnings announcement return. Taken together, the evidence suggests that search volume for a firms' products is a value-relevent leading indicator that the market does not fully incorporate into its expectations of earnings.

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> "... if you can assemble a diverse group of people who possess varying degrees of knowledge and insight, you're better off entrusting it with major decisions rather than leaving them in the hands of one or two people, no matter how smart those people are."
>
> —James Surowiecki, *The Wisdom of Crowds*

# 1 Introduction

Search queries reflect the intentions of those who query. For example, when search volume for a brand of automobile is high, sales for that brand of auto are also high. Therefore, when economic data are released with a lag, search volume may be able to predict the content of these lagged releases. According to Choi and Varian (2009) "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." Choi and Varian (2009) support this claim by providing evidence that search volume can predict subsequent reports of home sales, automotive sales and tourism.

Because search data appear well-suited to predict lagged releases of economic activity, here 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 have four key findings. First, we find that the search volume index (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, this predictability also holds for the earnings per share of the firm: changes in SVI predict standardized unexpected earnings (SUE). Third, when we consider the earnings surprise relative to the consensus analyst forecast (SAFE), we find that changes in SVI predict SAFE especially among firms with high information uncertainty (high forecast dispersion). Finally, we find that SVI changes predict announcement-window returns, even after controlling for contemporaneous revenue and earnings surprises. These findings suggest that the information contained in SVI is value-relevant and incremental to other fundamental information about the firm.

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 two papers closest to our are Truman et al. (2001) and Rajgopal et al. (2000) 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.* 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 (2009) 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 provides evidence that SVI predicts standardized unexpected earnings (SUE). Section 5 considers how SVI predicts earnings surprises from analysts forecasts. Section 6 examines predictability for returns around the earnings announcement. 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.[1] 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 the set of firms which are publicly traded to COMPUSTAT's unique identifier (GVKEY). This results in 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: its 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. Then, we consider how 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.[2]

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

[1] 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.

[2] 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."

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 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.[3] For search terms without enough search volume, Google Trends and Google Insights will return an error message. Because we observe more of these errors in Google Trends, we use Google Insights to download the SVI for each search term.

## 2.2 Other Data

We obtain 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

[3] Da, Engelberg and Gao (2009) 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 (2009) for more details.

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 earnings of Garmin LTD and CEC Entertainment in Figure 2, we see that the SVI for their products closely follows the reported earnings. 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 ingredients of 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 long-term contracts or competitive procurement processes. Thus, the cost structure is relatively stable and easy to forecast. 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.

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

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

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.[4]

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

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

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 GIC sector fixed effects and 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 by .20 (t-stat = 9.86).

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

[4] 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.

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 in making earnings 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 two 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. Controlling for the (non seasonally-adjusted) lagged revenue surprise actually increases the coefficient on $SVI\_Change_{i,q,1}$ from .875 to .919.

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 ($SVI\_Change_{i,q,4}$). Nevertheless, 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 significant (t-stat of 2.43).

# 4 Predicting Earnings Surprises

Earnings announcements convey important incremental information to financial markets. Beaver (1968) 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 weaker. This is not surprising as search volume may be directly related to revenue but not to costs.

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:

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

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 Mendenall (2006). As expected, search volume has a weaker relationship with earnings than it does with sales.

There are several ways to look at these results. First, these results may be related to corporate's decisions on earnings smoothing and choice of accruals. In untabulated results, we have also considered the possibility that $SVI\_Change$ is a proxy for accruals. If accruals exhibit a mean reverting tendency (Sloan, 1996), future earnings surprises are related to past accrual decisions. Although we find a positive coefficient on lagged accruals, in our sample it is neither economically or statistically significant. Again, after including accruals in the regression, the relationship between $SVI\_Change$ and $SUE$ remains qualitatively similar.

Second, these results may also be consistent with the view that earnings numbers – by numerical value itself – do not convey all value-relevant accounting information, especially at the quarterly frequency. Put differently, the value-relevance of non-financial information may be related to earnings numbers but goes beyond the earnings number. We explore this point further in the following sections.

# 5 SVI and Analyst Forecasts

In the previous section we found evidence that $SVI\_Change_{i,q,4}$ predicts earnings surprises as calculated from a simple time-series model. The model, however, does not capture additional information analysts may have beyond last year's earnings per share. In order to measure earnings surprise relative to analysts' forecasts, we define $SAFE_{i,q}$:

$$SAFE_{i,q} = \frac{EPS_{i,q} - Med(AF_{i,q})}{P_{i,q-4}}.$$

where $Med(AF_{i,q})$ is the median analyst forecast taken from I/B/E/S summary files for firm $i$ in quarter $q$.

In Table 5, we report a series of regressions where the standardized analyst forecast error, $SAFE_{i,q}$, is the dependent variable and $SVI\_Change_{i,q,4}$ is the independent variable. Each regression includes the control variables of Table 4. The first column shows a positive, albeit weak relationship between $SAFE$ and $SVI\_Change$ (coefficient of .098 and $t$-stat = 1.89). The fact that $SVI\_Change$ is a stronger predictor of revenue surprise and $SUE$ but a weaker predictor of $SAFE$ is consistent with the notion that, on average, analysts have some information contained in $SVI\_Change$.

However, there is large cross-sectional variation in the information environment of firms. While, on average, analysts may have the information which coincides with the information content of $SVI\_Change$, for a set of firms with opaque or complex information environment, the information content of $SVI\_Change$ may be particularly important. For example, Jiang, Lee and Zhang (2005), and Zhang (2006a, 2006b) suggest that information uncertainty plays an important role in the aggregation of information. High information uncertainty potentially contributes to and exacerbates the biased estimates of fundamental value of a stock, because the feedback on valuation is particularly slow in an environment with high level of information uncertainty. In particular, Zhang (2006b) documents stronger analyst forecast inefficiency - stronger autocorrelations of forecast errors - among set of firms with higher information uncertainty. They use several variables, such as firm age, trading volume, size, and forecast dispersion in delineating the information uncertainty. Since firms in our sample are usually large and mature, some of these proposed proxy variables do not generate economically meaningful cross-sectional dispersions for carrying out statistically powerful tests. Thus, we choose to focus on a simple measure, analyst forecast dispersion, in our empirical analysis.

We follow Diether, Malloy and Scherbina (2002) and use the dispersion of analyst forecasts as a measure of the information uncertainty. When we sort firms based on their meaures of analyst dispersion, we find strong differential performance of $SVI\_Change$ for predicting $SAFE$. The second column of Table 5 repeats the specification of column 1 only among firms below the median analyst forecast dispersion. The third column of Table 5 repeats the specification of column 1 only among firms above the median analyst forecast dispersion. The difference is striking: only among the set of firms with large information uncertainty (high forecast dispersion) do we find a positive and significant effect. In fact, among the set of firms with low forecast dispersion, the coefficient is actually negative ($-.017$) although insignificant (t-stat of $-1.16$).

Taken together, these results suggest that SVI may be a useful forecasting tool for analysts, especially when information about earnings is difficult to acquire. Meanwhile, these results also suggest that sell-side analysts exhibit some ability in incorporating product level information into their earnings forecast, though incorporation of such information is incomplete among the set of firms where the information uncertainty is particularly high.

# 6 SVI and Announcement Returns

Motivated by our previous finding that analysts may not have some information contained in search volume, here we examine whether search volume can predict the market response around earnings announcements. 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 is not found in other places. Beyond aggregate sales and to a lesser extent the sales by geographical segments, 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 value-relevant. Second, a key difference between earnings surprise as measured by analysts or a time-series model and surprise as measured by announcement return is that only the latter is forward-looking. Returns incorporate future information about fundamentals and there is good reason to believe that the information in search contains forward-looking information: customers search for information about products before executing their purchase.

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:

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

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

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

Table 6 reports the results of two regressions which regress $CAR_{i,q}$ on $SVI\_Change_{i,q,4}$. The first column, which contains the standard controls as in Table 5, shows a strong relationship between announcement returns and $SVI\_Change$. In fact, 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 20 basis points over the three-day period (about 17% annualized). Interestingly, $SVI\_Change$ remains a strong predictor of announcement returns even after including the *contemporaneous* earnings surprise (column 2) or *contemporaneous* revenue surprise (column 3).

Table 7 considers the relationship between post-earnings announcement returns and pre-earnings announcement search volume changes. We define the post-earnings announcement period return as

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

where $d(i, q+1)$ is the number of trading days until firm $i$'s quarter $q+1$ earnings announcement. Table 7 regresses $POST\_CAR_{i,q}$ on $SVI\_Change_{i,q,4}$ and our standard controls. Surprisingly, we find $SVI\_Change_{i,q,4}$ even has some predictability for $POST\_CAR_{i,q}$ but that this is weakened when $CAR_{i,q}$ is added to the specification (column 2).

Taken together, the results in Tables 6 and 7 confirm that changes in product-level search volume contain substantial value-relevant information that goes beyond quarterly information released in earnings and revenues.

# 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 predict positive (negative) revenue surprises and standardized unexpected earnings (SUE). Changes in search volume also predict earnings surprise relative to the median analyst forecast, especially among firms with high information uncertainty. Finally, we find strong evidence that innovations in SVI predict announcement-window abnormal returns, even after controlling for the earnings and revenue surprise at the announcement. Taken together our findings suggest that search volume for a firm's products may be a promising leading indicator for revenues and earnings announcements of the firm. 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 initial product launches. Nissan will launch the first mass-produced, all-electric vehicle (the Nissan Leaf) in December 2010 and there is enormous uncertainty about the future demand for this product. Search volume seems well-suited for such a situation. By examining the time series of search volume for the Nissan Leaf leading up to the December launch and by comparing search volume for the Nissan Leaf with search volume for other Nissan products where actual sales are observed, Nissan and its analysts may gather useful information about a very uncertain outcome. Identifying such key situations in which search volume becomes a most useful tool for forecasting fundamentals appears to be a promising avenue for future research.

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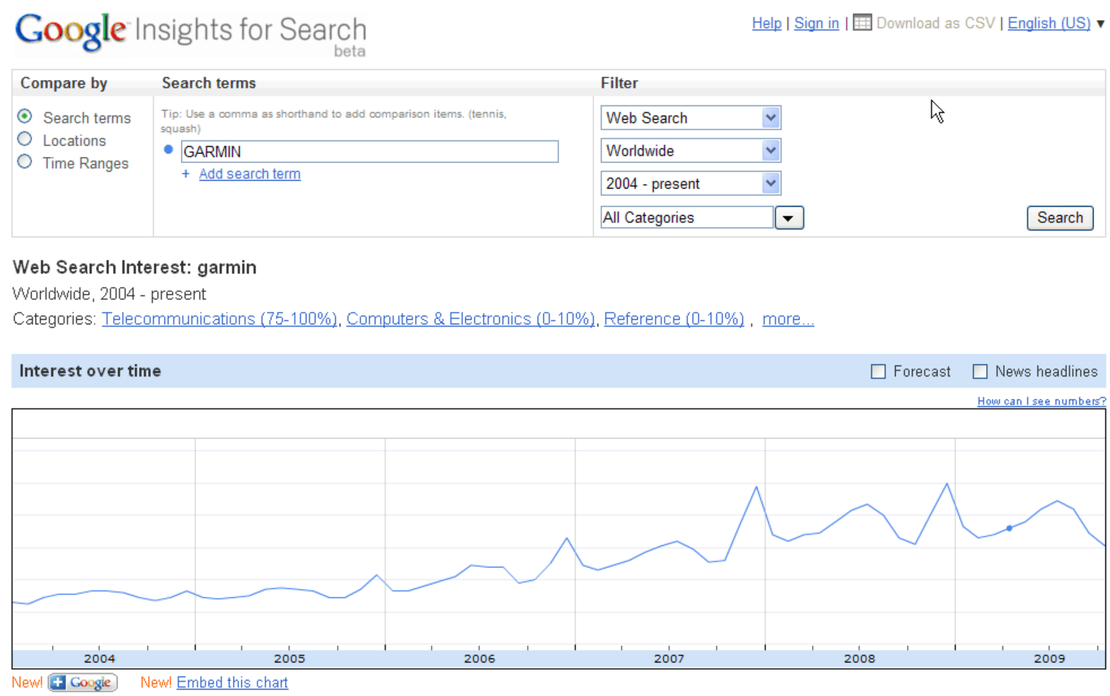
## Figure 1: Search Volume Index (SVI) for "GARMIN" and "CHUCK E CHEESE"

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.



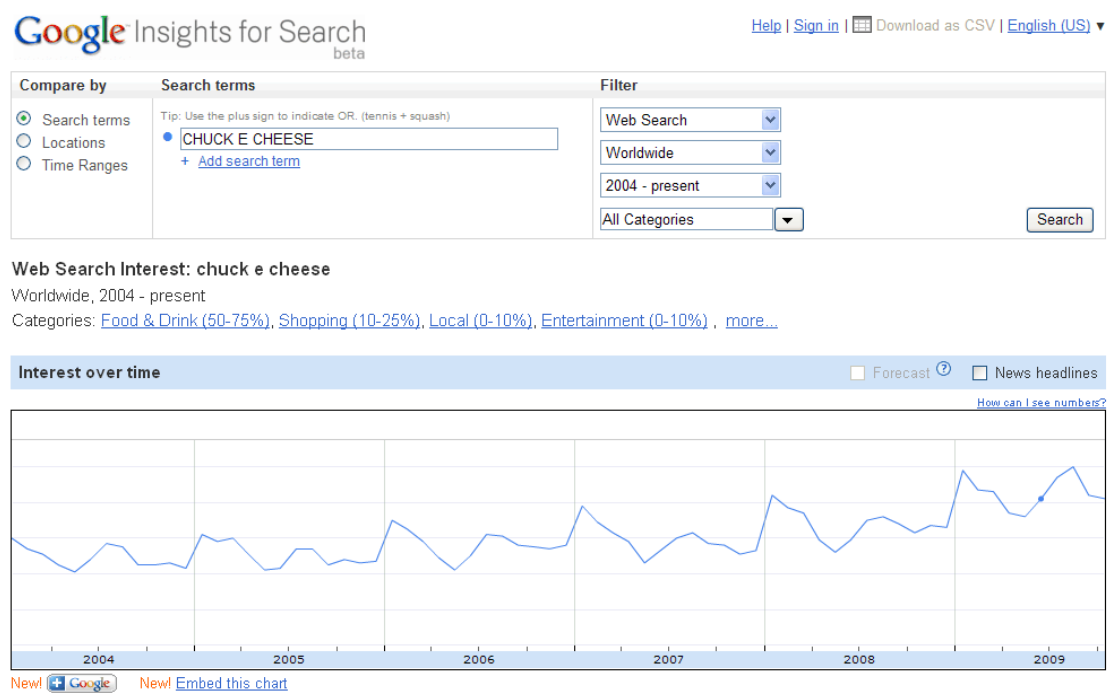
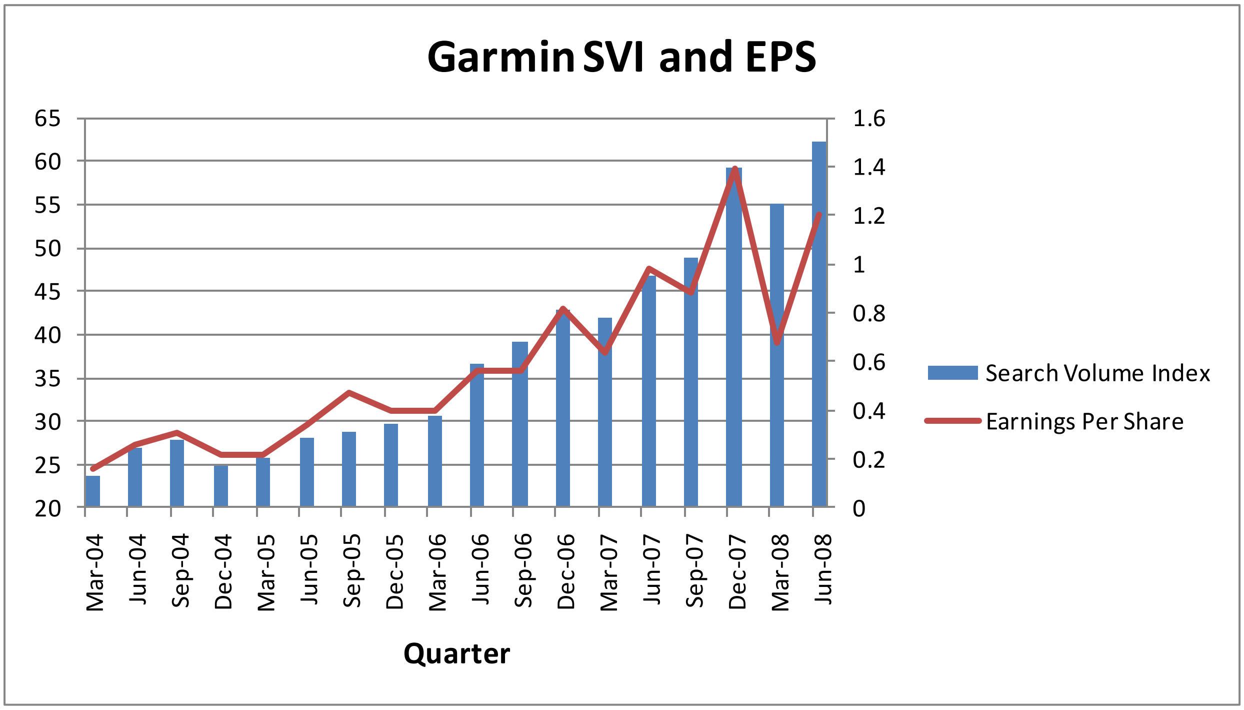
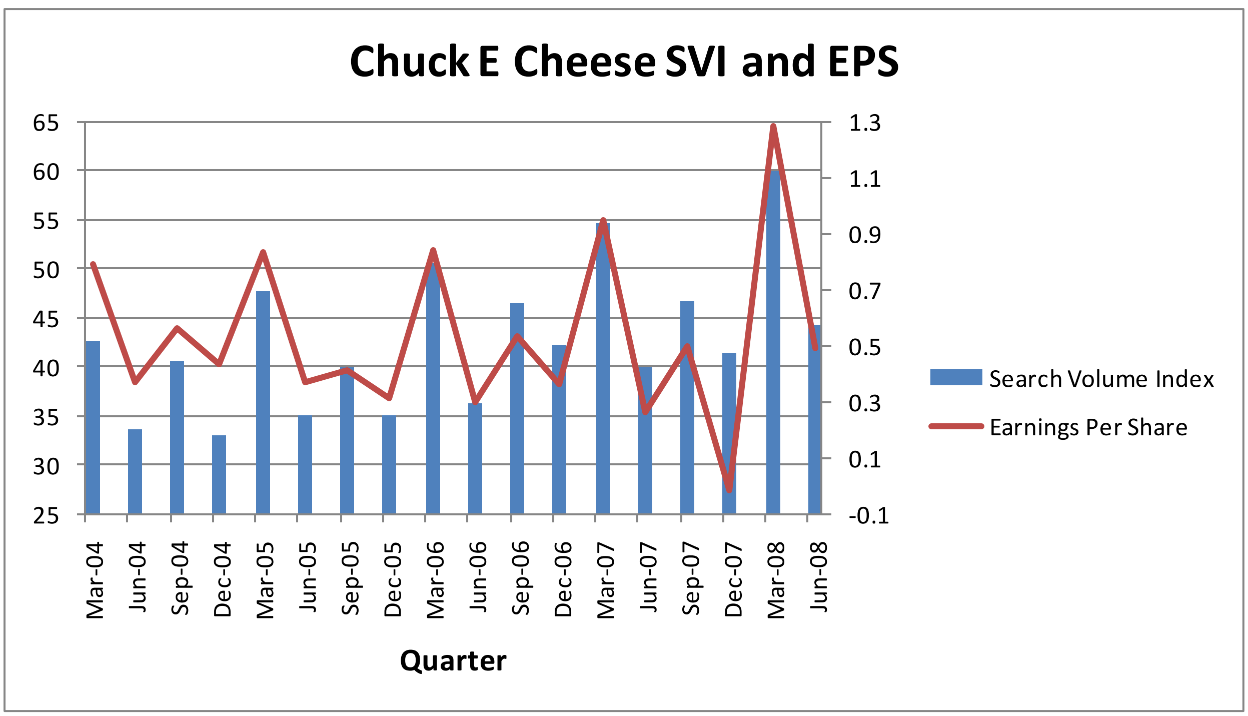



**Figure 2: EPS and SVI for "GARMIN" and "CHUCK E CHEESE"**

The figures plot quarterly search volume index (SVI) and earnings per share (EPS) 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*** | 0.417*** | 0.394*** | 0.402*** | 0.370*** | 0.366*** | 0.357*** | 0.116*** |
| | (0.094) | (0.092) | (0.095) | (0.095) | (0.092) | (0.092) | (0.091) | (0.049) |
| Size | | 0.079*** | 0.075*** | 0.079*** | 0.074*** | 0.074*** | 0.068*** | 0.025*** |
| | | (0.012) | (0.012) | (0.013) | (0.013) | (0.013) | (0.013) | (0.006) |
| Market-to-Book | | | 0.041 | 0.042 | 0.034 | 0.033 | 0.032 | 0.011 |
| | | | (0.030) | (0.031) | (0.026) | (0.026) | (0.025) | (0.009) |
| Turnover | | | | -0.024* | -0.018 | -0.015 | -0.014 | -0.016** |
| | | | | (0.012) | (0.013) | (0.014) | (0.014) | (0.007) |
| Prior Return | | | | | 0.909*** | 0.909*** | 0.884*** | 0.479*** |
| | | | | | (0.101) | (0.101) | (0.100) | (0.065) |
| Institutional Ownership | | | | | | -0.035 | -0.034 | 0.021* |
| | | | | | | (0.032) | (0.032) | (0.011) |
| Firm Guidance: Negative | | | | | | | -0.116* | -0.149*** |
| | | | | | | | (0.069) | (0.039) |
| Firm Guidance: Neutral | | | | | | | 0.181*** | 0.058** |
| | | | | | | | (0.055) | (0.029) |
| Firm Guidance: Positive | | | | | | | 0.302*** | 0.168*** |
| | | | | | | | (0.068) | (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 Time-Series 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 | 1.221** | 0.383* |
| | (0.603) | (0.238) |
| Size | -0.030 | 0.000 |
| | (0.075) | (0.049) |
| Market-to-Book | 0.271*** | 0.207*** |
| | (0.084) | (0.070) |
| Turnover | -0.697*** | -0.479*** |
| | (0.266) | (0.180) |
| Prior Return | 7.632*** | 3.692*** |
| | (2.493) | (0.849) |
| Institutional Ownership | 1.790** | 1.209** |
| | (0.755) | (0.563) |
| Firm Guidance: Negative | 0.020 | -0.169 |
| | (0.256) | (0.130) |
| Firm Guidance: Neutral | 0.087 | -0.109 |
| | (0.258) | (0.202) |
| Firm Guidance: Positive | 0.816** | 0.411** |
| | (0.371) | (0.187) |
| Lag(SUE) | 0.049 | 0.027 |
| | (0.041) | (0.027) |
| Industry Fixed Effects | YES | YES |
| Year Fixed Effects | YES | YES |
| Observations | 7225 | 7231 |
| R-Squared | 0.03282 | 0.04829 |

## Table 5: SVI Change and Analyst Earnings Surprises

The dependent variable the analyst earnings surprise (median analyst forecast minus actual EPS scaled by price) 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. The last two columns divide the sample by analyst dispersion defined as the standard deviation of earnings forecasts scaled by the absolute value of the mean earnings forecast (Diether, Malloy, and Scherbina (2002)). Robust standard errors clustered by firm are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

| | Dependent Variable: Analyst Earnings Surprise | | |
|---|---|---|---|
| | ALL FIRMS | Low Dispersion Firms | High Dispersion Firms |
| SVI Change | 0.098* | -0.017 | 0.134* |
| | (0.052) | (0.015) | (0.081) |
| Size | 0.028** | 0.000 | 0.039* |
| | (0.013) | (0.006) | (0.020) |
| Market-to-Book | 0.010 | -0.008** | 0.042 |
| | (0.014) | (0.004) | (0.027) |
| Turnover | -0.033 | -0.018 | -0.046 |
| | (0.023) | (0.013) | (0.032) |
| Prior Return | 0.411*** | 0.249** | 0.418* |
| | (0.143) | (0.105) | (0.213) |
| Institutional Ownership | 0.167 | -0.079 | 0.226 |
| | (0.129) | (0.060) | (0.175) |
| Firm Guidance: Negative | 0.073*** | -0.005 | 0.134*** |
| | (0.026) | (0.018) | (0.048) |
| Firm Guidance: Neutral | 0.005 | -0.008 | 0.026 |
| | (0.034) | (0.010) | (0.103) |
| Firm Guidance: Positive | 0.105*** | 0.034* | 0.173*** |
| | (0.033) | (0.017) | (0.062) |
| Lag(SUE) | 0.009 | 0.037** | 0.002 |
| | (0.007) | (0.016) | (0.005) |
| Industry Fixed Effects | YES | YES | YES |
| Year Fixed Effects | YES | YES | YES |
| Observations | 6595 | 3330 | 3131 |
| R-Squared | 0.03052 | 0.05533 | 0.0324 |

## Table 6: 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 7: 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 |