Google Search, Information Uncertainty, and Post-Earnings Announcement Drift

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Financial market investors use Internet searches for information acquisition about corporate announcements. This study examines the relation between Internet search volume for firm earnings information and post-earnings announcement drift (PEAD). Our first finding is that Google search volume index (SVI), a measure of Internet search volume, is associated with higher information uncertainty of firms with impending earnings announcements. Secondly, we find evidence that Google SVI does not predict analyst forecast based earnings surprises, but does predict stock market reaction to earnings surprises. These results support the argument that Google SVI reflects information searches by public or uniformed investors. We also find that higher Google SVI appears to reduce PEAD by improving the flow of information and reducing information asymmetries to uninformed investors, thus increasing market efficiency. Google SVI mitigates PEAD up to 40 days after the announcement. Overall, our findings suggest that uninformed investors can reduce the post-earnings announcement returns anomaly and information asymmetries through Internet searches.

INTRODUCTION

The post-earnings announcement returns anomaly, often referred to as post-earnings announcement drift (PEAD), is the finding that stock prices often exhibit a delayed reaction to unexpected earnings news. This anomaly is partially driven by the slow reaction of uninformed investors who are disadvantaged in terms of their ability to access information that informed investors possess (Bernard and Thomas (1990), Battalio and Mendenhall (2005), Ke and Ramalingegowda (2005)).

In a perfectly efficient market in which all investors have access to the same information set, news is impounded into stock prices immediately and PEAD would not be observed. This means that any innovation in the financial markets that makes information available to a greater set of investors in a timelier manner should make the markets more efficient and reduce PEAD. Today, Google search might serve such a purpose, especially for uninformed investors, which could significantly increase the efficiency of financial markets overall.

If the volume of Google searches is a proxy for the effort of uninformed investors' attempt to gain information (Da, Engleberg, and Gao (2011)) and if these searches are successful in reducing information asymmetries (Drake, Roulstone, and Thornock (2012)), then Google search should improve the flow of information to uninformed investors and thus increase market efficiency and reduce PEAD.

To test our hypotheses, we use Google search volume before company earnings announcements as a proxy for the uninformed investors' quest for earnings information. This setting provides a unique opportunity to analyze whether the level of information searches reduces PEAD following periods of potentially high divergence of opinion among different groups of investors in the financial markets.

In contrast with prior studies, we measure Google searches using company earnings information search volume, rather than stock ticker symbol search volume. The novelty of our approach is that search results for a company such as Apple must contain the text "Apple earnings" which more precisely captures the search volume around earnings announcement periods. We also demonstrate that the alternative approach used by other studies such as Da, Engleberg, and Gao (2011) is potentially more noisy and less capable of isolating the investors' quest for earnings related information. The cost, however, of our more refined search criteria is a reduced sample size.

Our empirical analyses feature the following steps and findings. First, we test whether some of the key proxies of divergence of investor opinion and firm-level uncertainties, including daily turnover, stock volatility, and bid-ask spread have a significant relation with Google search volume index (Google SVI). As firm information asymmetries increase, we hypothesize that investors seek more information through increased Internet searches. So for a firm heading into an earnings announcement, higher firm information asymmetries will increase Google SVI. If investors use Google search to gain information, we expect pre-earnings announcement Google SVI to be higher for firms with higher information asymmetries. Our results show that Google search volume is correlated with proxies of firm-level uncertainty such as bid-ask spread and volatility. However, Google search volume is not significantly related to other proxies such as the dispersion of analysts' forecasts and earnings surprise, which suggests that Google SVI is not a significant proxy for the divergence of opinion of sophisticated investors. This result supports previous findings (Da, Engleberg, and (2011)) that Google search is mainly a proxy for the uninformed investors' quest for information. Overall, our results are consistent with the insight that larger information and value uncertainty have a significant impact on search for information by investors. They are also consistent with Barber and Odean (2008), who find that individual investors focus on stocks with extreme returns or, in our case, larger volatility.

Secondly, we examine the effect of Google SVI on PEAD, a relation that is important to the study of information uncertainty and stock returns but is not examined by existing internet search literature. We find that Google SVI has no significant relationship with analyst earnings surprise, but we do find that Google SVI has a significant relationship with announcement abnormal returns (CAR(0,1). These findings are consistent with the idea that Google information searches are not driven by sophisticated market participants (such as analysts), but rather by uninformed investors' in their attempts to gain information.

Third, we find that higher Google search volume is associated with lower (higher) returns following positive (negative) earnings surprises. This finding effectively mitigates PEAD over twenty and forty day horizons. This finding is also consistent with an improved flow of information to investors and increased market efficiency.

Our unique contributions to the literature include the use of an alternative Google key word search focused on company earnings, as opposed to general stock information, and the finding that Google Search Volume Index (SVI) is not only related to investor attention, as Da, Engleberg and Gao (2011) argue, but also firm-level information asymmetries, which is consistent Dzielinski (2011) who finds that Internet search volume is related to economic uncertainty.

Last, we provide evidence that PEAD is mitigated by Google SVI, suggesting that investors' information acquisition through Internet search can reduce information asymmetries, which adds to the results from Drake, Roulstone, and Thornock (2012) who study earnings announcements.

The paper is organized as follows. Section 2 presents the related prior literature and the hypothesis development. Section 3 presents the data and methodology. Section 4 discusses the empirical results and robustness checks. Section 5 concludes.

LITERATURE REVIEW & HYPOTHESES

A recent strand of literature studies how web search volume is related to financial markets. Da, Engleberg and Gao (2011) find increased Google search volume, as measured by the weekly Google SVI, is correlated with higher trading volumes and stock returns. They argue that Google SVI is predominantly a measure of non-institutional investor searches based on an analysis of stock order information. In addition, they argue that institutional investors use alternative search services such as Reuters and Bloomberg. They also find evidence that Google SVI is related to investor attention. Investor attention is the idea that individual investors limit their investment decisions to a subset of available stocks that grab their attention the most through media coverage, extreme returns, or high trading volume (Barber and Odean (2008)). Da, Engleberg, and Gao (2011) propose Google SVI as an alternative measure of investor attention since they find that the increased trading volume accompanied by higher search volumes is mainly attributed to individual investors and is highly correlated with media coverage.[1]

Drake, Roulstone, and Thornock (2012) find evidence that high Google SVI starting two weeks before an earnings announcement tends to shift price changes and trading volume from the announcement day to before the announcement. They argue that if Google information searches reduce uncertainty, then investors' new information resulting from the searches will preempt the information in the announcement. These findings are related to those of Chae (2005), who finds that uninformed investors will not want to trade with informed investors before an earnings announcement (see also Milgrom and Stokey (1982) and Black (1986)). Since discerning the presence of informed traders is difficult, uninformed traders simply limit trading when information asymmetries are high, like around earnings announcements. This explains the existence of lower trading volumes before earnings announcement of firms with high information asymmetries, and also explains the higher trading volumes after the announcement. If, however, uninformed investors reduce information asymmetries through Google searches, then trading volumes should increase before the announcement.

Existing literature on information searches and market participation suggests that public investors who are disadvantaged in terms of the information they possess, relative to sophisticated investors, are reluctant to enter the financial markets. Thus, they participate in the financial market more as they reduce their information deficiency. Based on the existing literature that shows the positive relation between the uninformed investors' quest for information and market uncertainty, we develop our first empirical hypothesis as follows:

> *H1. The volume of uninformed investors' information acquisition through Google search, as proxied by Google SVI, is correlated with proxies for firm-level uncertainty.*

This study also examines the relationship between financial market investors' search for firm earnings information before earnings announcements and post-earnings announcement drift (PEAD). The empirical literature on PEAD finds that firms with positive earnings surprises tend to perform better than firms with negative earnings surprises. This result suggests that investors underreact to the information content in earnings announcements, resulting in a predictable continuation of stock returns. Research by Ball and Brown (1968), Bernard and Thomas (1989), Bernard et al. (1997), and others, identify and document this anomaly. More recent studies relate the presence of PEAD to the information environment surrounding a firm. Francis et al. (2004) and Vega (2005) find that PEAD is positively related to the level of private information available for a firm. In addition, Garfinkel and Sokobin (2006) and Anderson, Harris, and So (2007) find evidence that PEAD is positively related to a firm's divergence of investor opinion.

The relationship between firm information and stock valuation can be interpreted through a firm's cost of capital or expected returns (Varian (1985); Kraus and Smith (1989)). When the level of information is low, investors expect a greater return to compensate for the added risk. This higher expected return reduces the value of the stock.

Easley and O'Hara (2004) provide an alternative explanation built on the co-existence of informed and uninformed investors in the market. As a result of access to more information, some investors gain an informational advantage over uninformed investors. Aware of their disadvantage, uninformed investors demand a higher expected return, resulting in lower stock prices.

Furthermore, O'Hara (2003) and Rees and Thomas (2010) argue that divergence of investor opinion is an additional source of risk that is priced into stock valuation. Confronted with high divergence of investor opinion, investors have an incentive to incur the costs of an information search and again demand a higher expected return.

Relating Google SVI to information uncertainty, Dzielinski (2011) finds evidence that Internet search volume is related to economic uncertainty and stock returns when analyzing the Google SVI for the word "economy" before, during, and after the financial crisis of 2008.

According to evidence in prior literature, Google search is expected to reduce the information asymmetry by enabling the flow of information to uninformed investors. Since reduction in information asymmetry is shown to have an effect on stock returns, we develop our second hypothesis as follows:

H2. The volume of investors' information acquisition through Google search, as proxied by Google SVI, reduces PEAD.

DATA

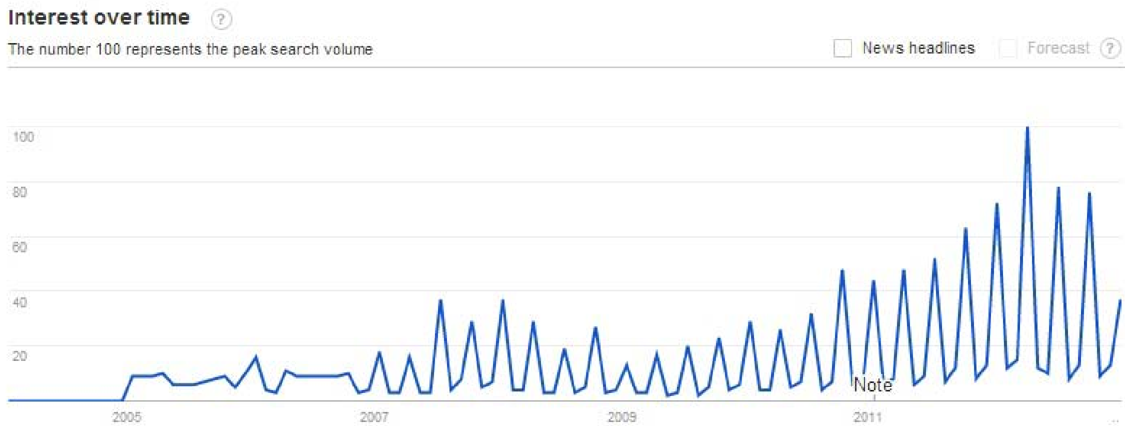
Google SVI

Since the beginning of 2004 Google Trends (http://www.google.com/trends) has collected information on search terms and search volume on a weekly basis. The normalized data shows the volume of searches made for a specific search term relative to the average number of searches for that term over time. The search volume is normalized or scaled to ease the comparison of values across different periods. There are two scaling options; "relative scaling" and "fixed scaling". The "relative scaling" option scales the data to the average traffic amount during the entire time period you chose to examine. The "fixed scaling" option scales the graph from the average traffic amount during a fixed point in time (generally when Google begins tracking the search data for the term). We use the "fixed scaling" data because it ensures that the "scalar" is unchanged.

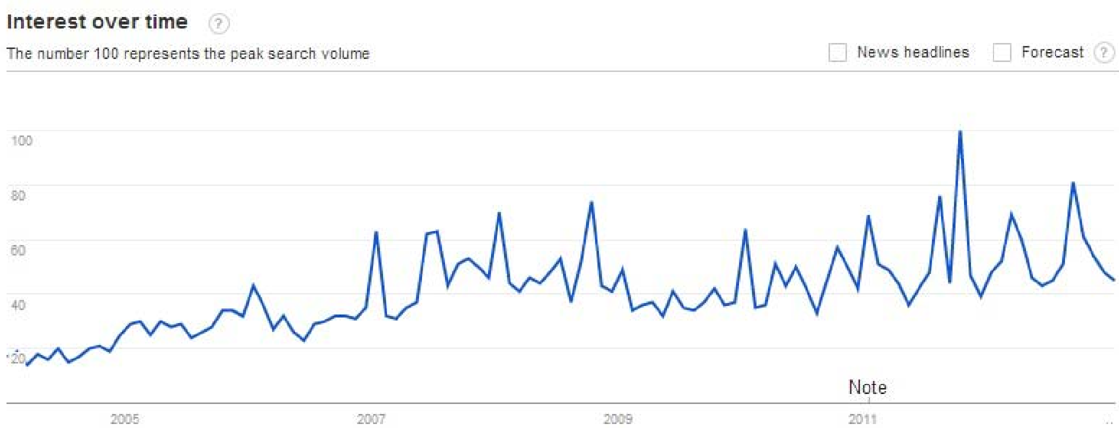
Given our research focus on Google search statistics around earnings announcements, we construct a sample of firms by starting with the firms identified in the S&P 500 index. The reason for limiting our sample to this index is due to the fact that Google only provides data for searches that exceed a certain threshold, and only the largest, most popular stocks have available search data.

In contrast to prior studies, we do not require the company name or ticker symbol to be searched for, but instead we require the term "earnings" to be searched together with the company name. For example, we gather the data on the search results for "Apple earnings" rather than "Apple". We realize that this approach has its advantages and disadvantages. The advantage, as one can see in Figure 1, Panel A, is that our search results for "Apple earnings" precisely capture the search volume around earnings announcement periods. There are 4 upward ticks per year in search volume exactly around the period of earnings announcements. As can be seen in Figure 1, Panels B and C, if we were to search only for the term "Apple" or the ticker symbol "AAPL", Google SVI would be very noisy, and it would be more difficult to argue that the data gathered truly represents the investors' quest for information around earnings announcement periods.

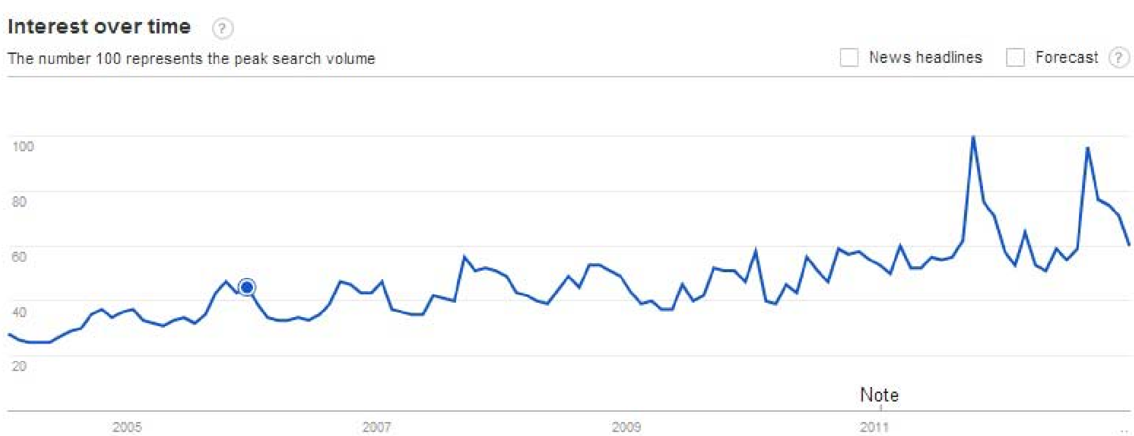
FIGURE 1
PANEL A: GOOGLE SVI FOR "APPLE EARNINGS"



PANEL B: GOOGLE SVI FOR APPLE TICKER SYMBOL "AAPL"



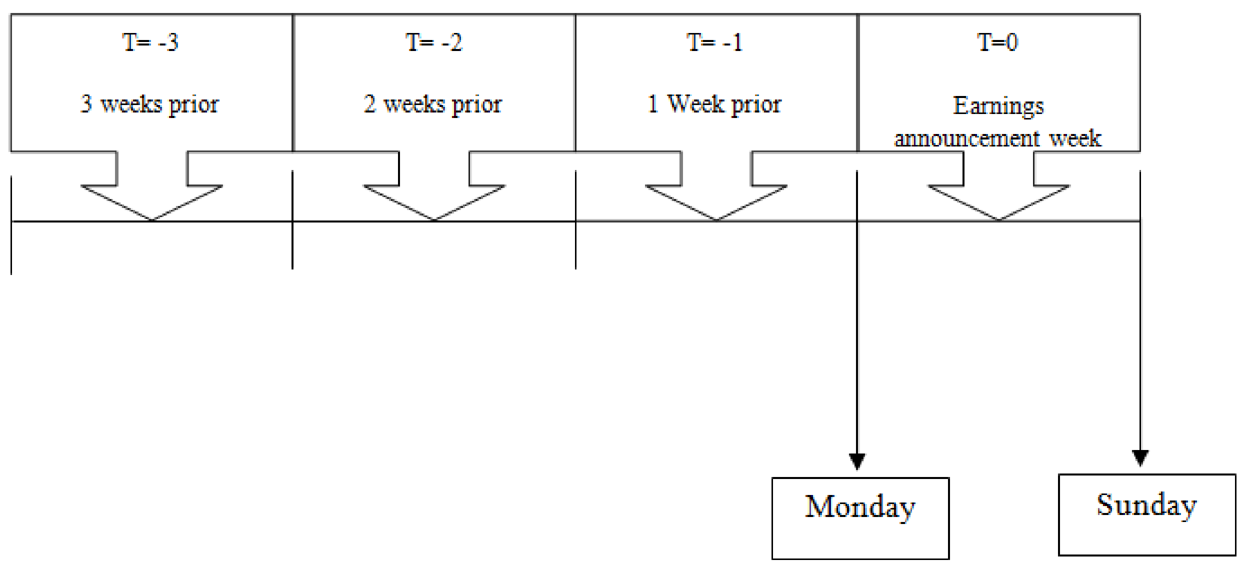
PANEL C: GOOGLE SVI FOR "APPLE"



The disadvantage of our method is that search statistics are only available for companies that have enough searches for the specific term “X earnings” where X is the name of the company. Google does not provide statistics for searched terms that are not commonly used. The term “Apple” is naturally searched more frequently than the term “Apple earnings”. Thus, we sacrifice the number of observations for a greater precision of data that more efficiently captures the needs of our research.

Out of the 500 companies within the S&P 500 index, we are able to gather Google search data on 27 for which Google provides the search statistics between the years of 2004 and 2010. We then match our Google search data with IBES (Institutional Brokers’ Estimate System) data to gather information on earnings expectations and analyst forecasts. As detailed in Figure 2, we match the earnings announcement day to the Google SVI reported weekly data by defining GoogleSVIt=0 as the search volume during a week of an earnings announcement, which could happen at any time between Monday and Sunday of that week. The Google SVI data itself is for Google searches from Monday through Sunday of a given week. We also define GoogleSVIt=-1, GoogleSVIt=-2, GoogleSVIt=-3 as the Google search volumes over one, two, and three week periods prior to the earnings announcement week, respectively. These lagged values of search volume are used to measure the volume of Internet searches leading up to the announcement week. Finally, we collect data from CRSP in order to calculate abnormal returns around earnings announcements and data from Compustat for firm financial information. Our final sample includes 27 firms and 708 total quarterly firm earnings announcements.

FIGURE 2



Proxies for Divergence of Investor Opinion and Firm Information Uncertainty

We use several proxies for divergence of investor opinion based on trading volume, stock return volatility, bid-ask spread, and analyst forecast dispersion. Unexplained trading volume, or Daily Turnover (DTO), is the daily trading volume of the firm, first adjusted for market trading volume and then adjusted for the firm’s median market adjusted trading volume over the previous 180 trading days.

$$DTO = \{(Vol/Shs)_{i,t} - (Vol/Shs)_{mkt,t}\} - \text{Median}_{t,t\text{-}180}\{(Vol/Shs)_i - (Vol/Shs)_{mkt}\} \quad (1)$$

Standardized unexplained volume (SUV) is calculated as the residual from a rolling regression of daily trading volume on the absolute value of daily returns separated between positive and negative return days as used by Garfinkel (2009) and Glushkov (2010). The residual is then standardized by deflating by the standard deviation of regression residuals.

$$SUV_{i,t} = \{Vol_{i,t} - \mathrm{E}(Vol_{i,t})\} \;/\; S_{residuals} \tag{2}$$

$$\mathrm{E}(Vol_{i,t}) = a_i + b_1|R_{i,t}|^{+} + b_2|R_{i,t}|^{-} \tag{3}$$

Stock return volatility (Volatility) is calculated as the standard deviation of returns over the previous 180 trading days. The bid-ask spread (BASpread) is calculated as the difference between bid and ask prices deflated by the midpoint of the bid and ask prices using CRSP data following Chung and Zhang (2009) and Glushkov (2010).

$$BASpread_i = (Ask_i - Bid_i) \;/\; \{(Ask_i + Bid_i) / 2\} \tag{4}$$

To measure analyst forecast dispersion, we collect data from IBES' detailed forecasts database for each firm and reporting period combination. We first exclude analyst forecasts that have not been updated over the 105 days prior to the announcement date, similar to Glushkov (2010), to reduce forecast staleness. We then calculate forecast standard deviation and deflate it by the absolute value of the mean analyst forecast (DISP).

Abnormal Returns and Post-Earnings Announcement Drift

We use the market model to estimate abnormal returns:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{5}$$

R_{it} is the rate of return of stock i on day t; R_{mt} is the rate of return of a market index on day t; α_i is intercept; β_i is slope parameter measuring the systematic risk of a stock i; ε_{it} is a random error term with an expected value of zero.

The abnormal return (AR) for stock i on day t (AR_{it}) is calculated as the difference between the actual return and the estimated return computed as follows:

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}) \tag{6}$$

Alpha hat and beta hat ($\hat{\alpha}_i$ and $\hat{\beta}_i$) are ordinary least squares estimates of alpha and beta (α_i and β_i) obtained from regressing R_{it} on R_{mt} over an estimation period. We use the estimation period of 255 days (about one year of trading days) ending on the 46th day preceding the event day. The CRSP value-weighted market index is used to derive the Ordinary Least Squares estimates of parameters for the market model. The cumulative abnormal return (CAR) for stock i over the event window ($d1$, $d2$) is:

$$CAR_i(d1, d2) = \sum_{t=d1}^{d2} AR_{it} \tag{7}$$

Descriptive Statistics

Table 1 displays descriptive statistics of key variables from the sample of 708 firm earnings announcements. Web search volume, shown as Google SVI, has a minimum value of 0 and a maximum value of 70 which represents peak volumes around earnings announcements. Also included in Table 1 are proxies of divergence of investor opinion and firm-level uncertainties.

TABLE 1
SUMMARY STATISTICS

Variable	N	Mean	Std. Dev.	Min	Max
$GoogleSVI_{t-1}$	708	0.605	3.880	0.000	55.000
$GoogleSVI_{t-2}$	708	0.198	2.566	0.000	47.000
$GoogleSVI_{t-3}$	708	0.276	3.675	0.000	70.500
DTO	708	0.011	0.031	-0.058	0.697
SUV	708	2.314	3.140	-2.573	61.597
Volatility	708	0.022	0.019	0.005	0.176
BASpread	708	0.040	0.034	0.007	0.287
DISP	708	0.193	0.489	0.000	3.565
MV	708	0.217	0.560	0.003	3.250
Nanalys	708	14.807	6.325	2.000	39.000
UES	708	0.001	0.012	-0.067	0.051
CAR(0,1)	708	0.002	0.068	-0.345	0.299
CAR(1,20)	708	0.002	0.111	-0.359	0.986
CAR(1,40)	708	-0.005	0.142	-0.746	1.270
CAR(1,60)	708	-0.008	0.187	-1.195	1.482

The sample consists of 708 quarterly firm earnings announcement observations. GoogleSVI is the Google search volume index lagged 1, 2, and 3 weeks before the week of the earnings announcement. Daily Turnover (DTO) is the daily trading volume of the firm divided by number, adjusted for market trading volume and then adjusted for the firm's median market adjusted trading volume over the previous 180 trading days. Standardized unexplained volume (SUV) is calculated as the residual from a rolling regression of daily trading volume on the absolute value of daily returns. Stock return volatility (Volatility) is calculated as the standard deviation of returns over the previous 180 trading days. The bid-ask spread (BASpread) is calculated as the difference between bid and ask prices deflated by the midpoint of the bid and ask prices. Analyst forecast dispersion (DISP) is forecast standard deviation deflated by the absolute value of the mean analyst forecast. MV is firm market value measured in $Trillions. NAnalys is the number of analysts providing forecasts for a firm. UES is the unexpected earnings surprise measured as the actual earnings less the median forecast scaled by stock price. CAR(0,1) is the one day cumulative abnormal return after the earnings announcement. CAR(1,60) is the cumulative abnormal return from the trading day after the earnings announcement to 60 trading days later.

Table 2 displays a correlation matrix among key variables. The results in Table 2 reveal that Google SVI has a positive correlation with the key proxies of divergence of investor opinion and firm-level uncertainties, including daily turnover (DTO), stock volatility (Volatility), bid-ask spread (BASpread), and analyst forecast dispersion (DISP). Of these variables, volatility has the highest correlation with Google SVI at 0.269 (statistically significant p value of less than 0.01 in unreported results) for both the first and second lag. Google SVI, however, has low (insignificant in unreported results) correlations with standardized unexplained volume (SUV) and the number of analysts (NAnalys). Overall, the high correlation between Google SVI and volatility shows some initial support for hypothesis H1.

Furthermore, Table 2 shows that Google SVI appears to have negative correlations with unexpected earnings surprise (UES) and measures of cumulative abnormal returns directly after the earnings announcement (CAR(0, 1)) and the days after the earnings announcement up to 60 trading days later (CAR(1, 60)). These results, however, are simple correlations and do not take into account how the effect of Google SVI on PEAD might be influenced by other factors.

In the PEAD literature, UES is often used to measure the magnitude of an earnings announcement surprise. Literature, including Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989), Ball, Kothari, and Watts (1993), and Bushan (1994), however, find that PEAD is very low or insignificant for large firms using UES as the measure of earnings surprise.[2]

This poses a potential problem in our empirical testing of PEAD, since our sample is comprised of large, well known firms. In Table 2, we find correlations all below 0.10 (insignificant in unreported results) between UES and PEAD over 20, 40, and 60 day horizons (CAR(1,20), CAR(1,40), CAR(1,60)).

As an alternative to measuring earnings surprise using UES, research including Skinner and Sloan (2002) and Hirshleifer, Lim, and Teoh (2009) use earnings announcement day returns. Following these studies, we find that announcement day returns, CAR(0,1), have significant positive correlations with post earnings announcement returns (between 0.447 and 0.354 in Table 2). Given the lack of support from previous literature for finding PEAD in large firms using UES and our preliminary, positive results using announcement day returns, our study of PEAD will focus on using announcement day returns as opposed to UES.

Table 2 also displays relatively high correlations between some of the proxies for divergence of investor opinion. For example, volatility and bid-ask spread have a correlation of 0.696, and volatility and analyst forecast dispersion (DISP) have a correlation of 0.504.

TABLE 2
CORRELATION MATRIX

	Google SVI_{t-1}	Google SVI_{t-2}	Google SVI_{t-3}	DTO	SUV	Volatility	BA Spread	DISP	Log MV	Log NAnalys	UES	CAR (0,1)	CAR (1,20)	CAR (1,40)	CAR (1,60)
Google SVI_{t-1}	1.000														
Google SVI_{t-2}	0.743	1.000													
Google SVI_{t-3}	0.318	0.493	1.000												
DTO	0.096	0.099	0.069	1.000											
SUV	-0.018	-0.014	-0.003	0.201	1.000										
Volatility	0.269	0.269	0.167	0.340	-0.061	1.000									
BASpread	0.184	0.173	0.081	0.409	0.145	0.696	1.000								
DISP	0.179	0.068	0.051	0.225	0.026	0.504	0.439	1.000							

LogMV	-0.007	-0.003	0.002	-0.203	-0.054	-0.238	-0.203	-0.046	1.000						
LogNAnalys	-0.009	-0.044	-0.106	-0.125	-0.044	0.026	-0.037	0.007	0.182	1.000					
UES	-0.127	-0.110	-0.158	0.146	0.053	-0.245	-0.209	-0.100	-0.029	0.043	1.000				
CAR(0,1)	-0.011	0.020	0.025	0.051	-0.099	-0.013	-0.081	-0.115	-0.048	0.002	0.094	1.000			
CAR(1,20)	-0.079	-0.022	-0.018	0.171	0.029	0.115	0.162	0.016	-0.126	-0.046	-0.089	0.447	1.000		
CAR(1,40)	-0.181	-0.125	-0.100	0.141	0.035	0.087	0.180	0.019	-0.157	-0.055	-0.088	0.410	0.833	1.000	
CAR(1,60)	-0.167	-0.121	-0.094	0.100	0.053	0.087	0.192	0.029	-0.140	-0.055	-0.069	0.354	0.705	0.884	1.000

Sample consists of 708 firm earnings announcements. See Table 1 for variable definitions. Pearson correlation coefficients listed with p values in parentheses.

EMPIRICAL RESULTS

Google Search Volume Index

Our empirical study examines how Google SVI is related to investor attention and firm-level information asymmetries. As firm-level information asymmetries increase, we expect that investors will seek more information and Google SVI will increase. Table 3 displays regressions modeling Google SVI.

$$GoogleSVI_{it} = b_0 + b_1DTO_{it} + b_2SUV_{it} + b_3Volatility_{it} + b_4BASpread_{it} + b_5DISP_{it} + b_6MV_{it} + b_7NAnalys_{it} + Residual_{it} \quad (8)$$

In comparison to studies that relate SVI to investor attention, we argue that given a firm with high investor attention, Google SVI will increase even more if that firm also has high information asymmetries. So for a firm heading into an earnings announcement, higher firm information asymmetries will increase the Google SVI.

In Table 3, we examine whether or not Google SVI is driven by different proxies of divergence of investor opinion and firm-level uncertainties, including daily turnover, standardized unexplained volume, stock volatility, bid-ask spread, and analyst forecast dispersion. In addition, we examine the impact of firm market value and the number of analysts providing forecasts on Google SVI.

Models (1) to (5) in Table 3 reveal that some of the key proxies of divergence of investor opinion and firm-level uncertainties, including daily turnover, stock volatility, and bid-ask spread have a significant relation with Google SVI. Of these, Model (3), which tests volatility, has the highest R-squared value. Together with our results in Table 1, these findings support our hypothesis H1 that the volume of investors' information acquisition through Google search is correlated with proxies for firm-level uncertainty.

Furthermore, Model (5) in Table 3 shows that Google SVI is not significantly related to the dispersion of analysts' forecasts, which suggests that Google search volume is not a significant proxy for the divergence of opinion of these sophisticated investors. This result supports previous findings (Da, Engleberg, and (2011)) that Google search is mainly a proxy for the uninformed investors' quest for information.

When controlling for all of the proxies of divergence of investor opinion and uncertainty together in the same regression, Model (8), none of the variables remain significant, potentially due to the high correlations between volatility and the other variables. Volatility does appear to be the most important variable, based on the modest 0.006 point increase in R-squared from Model (5) to Model (8).

Our results lead to the following insights. Higher volatility in Model (5) may reflect higher information uncertainty and larger differences in investor opinions. Given higher volatility, it becomes more difficult for investors to infer information from trading activities, resulting in a more active search for information by investors. As such, our results are consistent with the insight that higher information uncertainties impact investors' search for information. In addition, our results are consistent with those of Barber and Odean (2008) who find that individual investors focus on stocks with extreme returns (or larger volatility in our case).

TABLE 3
GOOGLE SVI REGRESSIONS

Dependent Variable: $GoogleSVI_{t-1}$	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
DTO	12.027**							1.216
	(5.499)							(5.865)
SUV		-0.022						0.000
		(0.017)						(0.040)
Volatility			55.862**					55.573
			(21.91)					(32.768)
BASpread				20.860**				-2.081
				(8.589)				(9.516)
DISP					1.417			0.416
					(0.984)			(1.117)
LogMV						-0.022		-0.194
						(0.087)		(0.177)
LogNAnalys							-0.085	-0.251
							(0.394)	(0.267)
Constant	0.473**	0.655***	-0.649	-0.237	0.331	0.994	0.834	-3.489
	(0.189)	(0.225)	(0.418)	(0.252)	(0.215)	(1.596)	(1.088)	(3.255)
N	708	708	708	708	708	708	708	708
R-squared	0.009	0.000	0.073	0.034	0.032	0.000	0.000	0.079

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The sample consists of 708 quarterly firm earnings announcement observations. GoogleSVI $_{t-1}$ is the Google search volume index. Daily Turnover (DTO) is the daily trading volume of the firm divided by number, adjusted for market trading volume and then adjusted for the firm's median market adjusted trading volume over the previous 180 trading days. Standardized unexplained volume (SUV) is calculated as the residual from a rolling regression of daily trading volume on the absolute value of daily returns. Stock return volatility (Volatility) is calculated as the standard deviation of returns over the previous 180 trading days. The bid-ask spread (BASpread) is calculated as the difference between bid and ask prices deflated by the midpoint of the bid and ask prices. Analyst forecast dispersion (DISP) is forecast standard deviation deflated by the absolute value of the mean analyst forecast. LogMV is the log of firm market value measured in $Trillions. LogNAnalys is the log of 1 plus number of analysts providing forecasts for a firm.

Earnings Surprise and Google SVI

Table 4 displays results from regressions explaining earnings surprise as measured by both the absolute value of the abnormal return over one trading day following the announcement (Equation (9)) and the absolute value of the earnings surprise. We use absolute value because measures of high information uncertainty leading up to an earnings announcement convey a higher likelihood of surprise and not necessarily the direction of the surprise.

$$\left| CAR_i(0, 1) \right| = b_0 + b_1 GoogleSVI_{it} + b_2 DTO_{it} + b_3 SUV_{it} + b_4 Volatility_{it} + b_5 BASpread_{it} + b_6 DISP_{it} + b_7 MV_{it} + b_8 NAnalys_{it} + Residual_{it} \tag{9}$$

Table 4 examines the predictability of earnings surprises using Google SVI. If Google SVI can predict future earnings surprises as measured by UES, which is based on analyst expectations, then Google SVI may reflect information acquisition and dissemination by informed investors. In contrast, if Google SVI does not predict future earnings surprises based on analyst expectations, but does predict surprises based on stock market reaction or announcement day returns, then this would support the idea that Google SVI reflects information searches by public or uniformed investors.

Results in Table 4 support the latter argument and show that Google SVI has no significant relationship with earnings surprise, as measured by earnings surprise (UES). However, Google SVI does have a significant relationship with announcement day abnormal returns (CAR(0,1)). These findings suggest that Google SVI is not likely driven by informed investor searches, but rather by uninformed investor searches, which is consistent with Da, Engleberg, and Gao (2011) who argue that Google SVI is predominantly a measure of non-institutional investors' searches. While they base their argument on an analysis of stock order information, we arrive at this finding using an alternative test methodology.

TABLE 4
EARNINGS ANNOUNCEMENT SURPRISE AND RETURN REGRESSIONS

Dependent Variable:	Model (1) |CAR(0,1)|	Model (2) |UES|
$GoogleSVI_{t-1}$	-0.084**	0.011
	(0.040)	(0.010)
DTO	14.512***	6.496**
	(3.558)	(2.855)
SUV	0.214***	-0.015*
	(0.067)	(0.008)
Volatility	44.014**	15.663***
	(20.196)	(4.881)
BASpread	43.265***	6.674***
	(13.279)	(2.314)
DISP	0.444	0.425**
	(0.300)	(2.059)
LogMV	-0.222	0.010
	(0.197)	(0.057)
LogNAnalys	0.255	-0.335*
	(0.489)	(0.173)
Constant	4.714	0.394
	(4.556)	(1.284)
Observations	708	708
R-squared	0.298	0.470

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The sample consists of 708 quarterly firm earnings announcement observations. GoogleSVI is the Google search volume index. Daily Turnover (DTO) is the daily trading volume of the firm divided by number, adjusted for market trading volume and then adjusted for the firm's median market adjusted trading volume over the previous 180 trading days. Standardized unexplained volume (SUV) is calculated as the residual from a rolling regression of daily trading volume on the absolute value of daily returns. Stock return volatility (Volatility) is calculated as the standard deviation of returns over the previous 180 trading days. The bid-ask spread (BASpread) is calculated as the difference between bid and ask prices deflated by the midpoint of the bid and ask prices. Analyst forecast dispersion (DISP) is forecast standard deviation deflated by the absolute value of the mean analyst forecast. LogMV is the log of firm market value measured in $Trillions. LogNAnalys is the log of 1 plus the number of analysts providing forecasts for a firm. |CAR(0,1)| is the absolute value of the one day cumulative abnormal return after the earning announcement in percent. |UES| is the absolute value of the unexpected earnings surprise measured as the actual earnings less the median forecast scaled by stock price in percent.

Earnings Announcement Drift and Google SVI

Table 5 examines the predictability of PEAD by Google SVI, which provides an important empirical test of whether information searches by uninformed investors are successful in reducing information asymmetries. As stated in our hypothesis H2, Google search should improve the flow of information to uninformed investors, and thus increase market efficiency and reduce PEAD.

As indicated by the positive regression coefficients of announcement day returns (CAR(0,1)) in predicting PEAD over 20, 40, and 60 day horizons ($CAR_i(1,20)$, $CAR_i(1,40)$, and $CAR_i(1,60)$) in Table 5, PEAD occurs in the same direction as announcement day returns. Thus following a positive surprise, higher Google SVI should reduce positive PEAD. Following a negative surprise, higher Google SVI should limit the negative PEAD. If information gathering does reduce information asymmetry, then PEAD, no matter the direction, should be mitigated by higher Google SVI. To support our hypothesis H2, the coefficient of the interaction term between Google SVI and CAR(0,1), (b1) in Equation (10) should be negative.

$$\begin{aligned} CAR_i(1, j) = {} & b_0 + b_1 Google\ SVI_{it} + b_2 Google\ SVI_{it}{*}CAR_i(0, 1) + b_3 DTO_{it} \\ & + b_4 SUV_{it} + b_5 Volatility_{it} + b_6 BASpread_i + b_7 DISP_{it} + b_8 MV_{it} \\ & + b_9 NAnalys_{it} + Residual_{it} \end{aligned} \tag{10}$$

Models (1), (2), and (3) of Table 5 show the effect of Google SVI on earnings announcement drift over different event windows of j = 20, 40, and 60 days. Model (1) presents the impact of Google SVI on PEAD over the (+1, +20) window. These results suggest that Google SVI, measured 1 week before the earnings announcement week, has a negative and significant impact on PEAD over the (+1, +20) window based on the significantly negative regression coefficient of the interaction term between Google SVI and CAR(0,1). In addition, this finding suggests that given a positive market reaction to an earnings announcement, higher Google SVI will lead to lower returns over the next 20 days, which supports our hypothesis that Google searches increase market efficiency.

Model (2) shows that Google SVI mitigates the impact of a market reaction to earnings news over the 40 day window as well. Over the 60 day window shown in Model (3) Google SVI no longer appears to mitigate returns. Together, the findings over 20 and forty day horizons support Hypothesis 2 which states that higher Google SVI can reduce information asymmetries.

These findings build on the results of Drake, Roulstone, and Thornock (2012), who find that Google information searches preempt some of the information content of announcements.

Finally, our findings in Table 5 reveal that Google SVI is not only a proxy for investor attention, but is also related to investor information acquisition during times of information asymmetry. Da, Engleberg, and Gao (2011) propose Google SVI as an alternative measure of investor attention since they find that the increased trading volume accompanied by higher search volumes is mainly attributed to individual investors. Our empirical findings are among the first to document the relation between Google SVI and firm-level information uncertainty around earnings announcements. We find evidence that higher Google SVI can reduce information asymmetry by mitigating the post earnings announcement returns, suggesting the effort of the uninformed investors' attempts to gain information are successful.

Our results are also consistent with those of Dzielinski (2011), who finds that Internet search volume is related to economic uncertainty. While Drake, Roulstone, and Thornock (2012) show that higher Google SVI's tend to preempt the information content of announcements and that Google SVI increases pre-announcement, our findings shed new light on understanding the impact of Google SVI on post-announcement price changes and mitigation of information asymmetry. Most interestingly, we find that such impact is influenced by information uncertainty in impending earnings announcements.

TABLE 5
POST EARNINGS ANNOUNCEMENT RETURNS REGRESSIONS

Dependent Variable:	Model (1) CAR(1,20)	Model (2) CAR(1,40)	Model (3) CAR(1,60)
$GoogleSVI_{t-1}$	-0.003***	-0.008***	-0.010***
	(0.001)	(0.001)	(0.002)
$GoogleSVI_{t-1}$ * CAR(0,1)	-0.018***	-0.027**	-0.015
	(0.006)	(0.011)	(0.022)
CAR(0,1)	0.755***	0.904***	1.048***
	(0.127)	(0.119)	(0.125)
DTO	0.235*	0.114	-0.168
	(0.126)	(0.236)	(0.218)
SUV	0.001	0.001	0.002
	(0.001)	(0.001)	(0.002)
Volatility	0.041	-0.388	-0.663
	(0.688)	(0.964)	(1.579)
BASpread	0.605	1.091**	1.579**
	(0.460)	(0.441)	(0.655)
DISP	-0.004	0.001	0.005
	(0.011)	(0.014)	(0.023)
LogMV	-0.004*	-0.009**	-0.011*
	(0.002)	(0.004)	(0.006)
LogNAnalys	-0.007	-0.010	-0.015
	(0.008)	(0.010)	(0.015)
Constant	0.062	0.155**	0.186*
	(0.039)	(0.064)	(0.104)
Observations	708	708	708
R-squared	0.264	0.278	0.229

Robust, clustered standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The sample consists of 708 quarterly firm earnings announcement observations. CAR(1,t) is the cumulative abnormal return from the trading day after the earnings announcement to “t” trading days later. CAR(0,1) is the cumulative abnormal return on the day of the earning announcement. See Table 1 for other variable definitions.

CONCLUDING REMARKS

This study investigates whether greater access to information by uninformed investors can reduce firm-level information asymmetries and increase market efficiency. Specifically, we examine how the pre-earnings announcement volume of Internet searches, as measured by Google SVI, is related to firm-level information uncertainty and post-earnings announcement drift.

Our study reveals that Internet searches improve the flow of information to uninformed investors, and thus increase market efficiency. Prior to earnings announcements, Google SVI is associated with higher degrees of firm-level information uncertainty, namely volatility. Also, higher levels of Google SVI significantly reduce earnings surprises as measured by the market reaction. Most importantly, higher levels of Google SVI mitigate the abnormal returns associated with PEAD.

Lastly, our findings shed new light on our understanding of the ability of uninformed investors to reduce information asymmetries through Internet searches and, ultimately, post-earnings announcement returns. These findings support the notion that any innovation in the financial markets which makes information available to a greater set of investors in a timelier manner can significantly increase the efficiency of financial markets overall.

ENDNOTES

1. Da, Engleberg, and Gao (2011) argue that institutional investors predominantly use Reuters, Bloomberg, or other professional information sources. In addition, they find that increased SVI is related to higher returns and trading volume over the next two weeks and return reversals over the following year.
2. Foster, Olsen, and Shevlin (1984) find that the absolute value of PEAD is inversely proportional to firm size, meaning large firms have lower levels of PEAD. In a sample of primarily large firms, Ball, Kothari, and Watts (1993) fail to detect PEAD, and Bernard and Thomas (1989) find PEAD to be significantly smaller in large firms compares to medium and small firms. Bushan (1994) finds that PEAD effect is subsumed by transaction costs, which explains why larger, more liquid firms do not exhibit high levels of PEAD.

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