Informed versus Uninformed Investors: Internet Searches, Options Trading, and Post-Earnings Announcement Drift

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Abstract

This paper examines the relationship between informed and uninformed investors through their trading and information search activities prior to earnings announcements. We use option market trading to represent informed investor interest and internet search volume for firm earnings information to represent uninformed investor interest. To study the informational effects and interactions of internet searches and option market trading, we examine their ability to predict post-earnings announcement drift (PEAD). Our results indicate that both options trading and internet searches predict PEAD, but when combined, options trading subsumes the information in internet search volume and renders it insignificant. Our findings suggest that the proxy for informed investors captures future returns better than the proxy for uninformed investors and that uninformed investors continue to be at an informational disadvantage around earnings announcements despite the increasing availability of information through the internet.

Keywords: Information Asymmetries; Post Earnings Announcement Drift; Internet Searches; Google Search Volume Index; Options Trading
JEL Classification: G10; G14; G19

I. Introduction

Financial market participants are often characterized into different investor types with varying degrees of sophistication and diverse methods of acquiring and acting upon information. This paper studies the relationship between informed and uninformed investors through their activities during periods of potentially high information asymmetries when the possession of information may have significant value.

Existing literature on information searches and market participation suggests that public investors are reluctant to trade securities when they believe that they have less information than more sophisticated investors. Easley and O'Hara (2004) examine this co-existence of informed and uninformed investors and conclude that uninformed investors demand a higher expected return when informed investors gain an informational advantage over uninformed investors, resulting in lower stock prices. Understanding that the coexistence of informed and uninformed investors and the level of information possessed by each can affect stock prices, we set out to explore this relationship. Identifying informed versus uninformed investors' actions through information searches, or by actions taken resulting from those searches, is difficult. The time periods we examine, earnings announcements, are simpler to identify and justify since these are time periods where possessing information can be valuable, as earnings surprises can result in extreme stock returns both the day of and the days following the earning announcement. Bernard and Thomas (1990), Battalio and Mendenhall (2005), and Ke and Ramalingegowda (2005) find that the abnormal returns following earnings announcement surprises are partially driven by the slow reaction of uninformed investors. This results in a strong incentive to acquire and act on earnings information.

To acquire earnings information, Da, Engleberg, and Gao (2011) argue that institutional investors, who are referred to as informed investors here, use information platforms such as

Reuters and Bloomberg, which are not available to uninformed investors. However, we are unable to observe informed investor information searches over these institutional platforms. As an alternative, numerous studies on informed investors use option market trading volume as a proxy for informed trading activities. These studies, which include Mayhew, Sarin, and Shastri (1995), Easley, O'Hara, and Srinivas (1998), Chakravarty, Gulen, and Mayhew (2004), Cao, Chen, and Griffin (2005), Pan and Poteshman (2006), Ni, Pan, and Poteshman (2008), Roll, Schwartz, and Subrahmanyam (2009, 2010), Johnson and So (2012), Hu (2014), and others, find evidence supporting the notion that option market trading is proportionately dominated by informed traders. Therefore, we use option market activity to measure informed investor interest in firms during earnings announcement time periods.

To measure the interest in and search for information by uninformed investors we use internet search activity for firm earnings information around earnings announcements. Da, Engleberg, and Gao (2011) find that higher levels of internet searches, as measured by Google search volume index (GoogleSVI), are correlated with higher stock trading volume. They also find evidence that GoogleSVI predominantly measures uninformed investor internet searches based on an analysis of stock order information. Drake, Roulstone, and Thornock (2012) and Fricke, Fung, and Goktan (2014) additionally find that uninformed investors reduce information asymmetries through their internet searches, resulting in increased stock trading volumes before earnings announcements and reduced price drift following earnings announcements.

Informed and uninformed investors use different types of information acquisition processes, which have implications on market efficiency. Our first hypothesis is that there is no correlation between the trading activities of informed option traders and information acquisition activities of uniformed investors prior to earnings announcements. We argue that while informed investor activity is based on possessing non-market wide information, uninformed investor activities are based on information readily available to all market participants. Our second hypothesis is that the information acquisition activities should make the markets more efficient – e.g., reduce post-earnings announcement drift (PEAD). We test our second hypothesis by examining whether informed investor trading activities reduce PEAD and whether informed investor trading activities have higher information content than uninformed investor activities – i.e., whether option market trading volume contains more information about PEAD than GoogleSVI.

To test the hypotheses above, our experimental design features 653 quarterly firm-earnings announcement observations from 2004 to 2010. We collect GoogleSVI and options trading volume levels surrounding each earnings announcement and compute stock returns over various event windows related to the earnings announcement. Then to shed light on the information effects of internet searches and option market trading, we examine the ability of internet searches and option market trading to predict firm earnings and PEAD.

Our main findings are summarized as follows. First, we find that option trading volume of informed investors is not significantly correlated to the internet searches of uninformed investors prior to the earnings announcement. Second, we find that both option trading volumes and internet searches are not correlated with subsequent earnings surprises as measured by the percentage difference between the actual and expected earnings. Third, after earnings announcements, we find that higher levels of both options trading volume and internet searches reduce PEAD. When combined into single regression, however, options trading volume subsumes the information in internet search volume and renders it insignificant.

In terms of contributions, this study is among the first to highlight the nexus between options trading and internet searches. We provide new findings on the empirical relations between internet searches and option market trading during the informational event of earnings announcements. In contrast to Fricke, Fung, and Goktan (2014) which focuses on internet searches, this study focuses on the interactions of internet searches and informed option trading in predicting PEAD. While Fricke, Fung, and Goktan (2014) find that internet search volumes are associated with higher degrees of firm-level information uncertainty and reduce PEAD, this study clarifies the informational role of internet search volumes and presents new evidence that uninformed investors continue to be at an informational disadvantage around earnings announcements despite the increasing availability of information through the internet. We address the omitted variable issue and show that informed option trading subsumes the relevant information in internet search volume related to PEAD.

Our findings fill a gap in the literature comparing and examining the possible interactions between informed investor trading in the options market and uninformed investor information searches and their ultimate trading in stock markets. By controlling for both uninformed and informed investors' information acquisition activities, our findings synthesize the existing literature related to uninformed investors' information activities (e.g., Da, Engleberg, and Gao (2011) and Drake, Roulstone, and Thornock (2012)) and literature supporting the informed trading role of option market investors (e.g., Mayhew, Sarin, and Shastri (1995), Easley, O'Hara, and Srinivas (1998), Chakravarty, Gulen, and Mayhew (2004), Cao, Chen, and Griffin (2005), Pan and Poteshman (2006), Ni, Pan, and Poteshman (2008), Roll, Schwartz, and Subrahmanyam (2009, 2010), Johnson and So (2012), Hu (2014), Du and Fung (2018), and Du, Fung, and Loveland (2018)). In essence, our findings imply three things: (i) the information obtained in internet searches is already known to informed investors, (ii) option traders tend be more informed traders, and (iii) uninformed traders can successfully find information through internet searches. However, this new information is still a subset of what informed investors know. These findings provide new insight on the co-existence and interactions of informed and uninformed investors in the cross-market setting.

The rest of the paper is organized as follows. Section II discusses the literature and hypotheses. Section III presents the methodology and data. Section IV discusses the results. Section V concludes.

II. Related Literature and Hypotheses

The use of option market trading volume as a proxy for informed trading activities is supported by the existing literature. Mayhew, Sarin, and Shastri (1995) find that informed trading predominantly occurs in the option markets, and Easley, O'Hara, and Srinivas (1998) find that trading activities in option markets are the actions of sophisticated traders. Easley, O'Hara, and Srinivas (1998) and Chakravarty, Gulen, and Mayhew (2004) find evidence that options trading contains information about future stock prices, supporting an informational role for options whereby stock price discovery occurs in the option markets.[1] Cao, Chen, and Griffin (2005) find evidence of informed trading in option markets during the informational event of corporate takeovers. Pan and Poteshman (2006) argue that option trading volume

[1] In contrast, Muravyev, Pearson, and Broussard (2013) find that price discovery occurs in the stock market rather than in the option market.

predicts future stock prices due to non-public information possessed by option traders rather than market inefficiency.

Ni, Pan, and Poteshman (2008) find evidence of informed trading in the option market by showing that the demand for volatility can predict future stock volatility. They also find that volatility demand has a positive price impact on stock prices that increases as information asymmetry intensifies on the days leading up to earnings announcements. In a similar vein, Roll, Schwartz, and Subrahmanyam (2010) observe higher option trading volumes (relative to stock trading volumes) around earnings announcements and that the pre-announcement option trading volumes can predict post-announcement absolute stock returns.[2] Johnson and So (2012) show that option trading volume (relative to stock trading volume) reflects private information and predicts stock returns. More recently, Hu (2014) examines the interaction between stock and option markets via option hedging activities and finds that options order flow contains an important informative component about future stock price movement that is not found in stock market trading activities. Du and Fung (2018) examines the directional information effects from the options market trades to underlying asset valuations. They find that information asymmetries in the banking industry setting accentuate the informational role of option trades, especially negatively informed trades.

Furthermore, informational role of options market are supported during different information events and announcements. Jin, Livnat, and Zhang (2012) find evidence of information advantage of option traders relative to equity traders during earnings announcements and other corporate information events. Atilgan (2014) finds that option volatility spreads have stronger predictability of stock returns during earnings announcements. Chan, Ge, and Lin (2015) find evidence of informed options trading during the events of merger and acquisitions. Gharghori, Maberly, and Nguyen (2017) find that option measures can predict both stock volatility levels and changes after stock split announcements. Zhang (2018) finds evidence that informed options trading predicts dividend change announcement returns. Du, Fung, and Loveland (2018) find that options market provides an important source of informed trading during Federal Open Market Committee (FOMC) announcements.

Overall, the predominance of informed trading in option markets appears well supported.[3] Yet the comparison between informed traders in option markets and uninformed traders in other financial markets remains an under-studied area in the literature, despite the importance of their co-existence (Easley and O'Hara (2004)). As a contribution to the existing literature, our study is among the first to examine the empirical relations between internet searches and option market trading during the informational event of earnings announcements. While the existing studies discussed above focuses on the ability of option trading data to predict stock returns, our study provides a different insight into the information content of options trading before corporate announcements, especially in the presence of information acquisition activities of uninformed investors.

We use internet searches as a proxy for the effort of uninformed investors' attempts to gain information. Da, Engleberg, and Gao (2011) find evidence that higher internet search volumes for stock ticker symbols are subsequently associated with higher trading volumes

[2] Roll, Schwartz and Subrahmanyam (2009) find that options trading is associated with higher firm valuation as informed trading increases firm information efficiency.
[3] In contrast, Stephan and Whaley (1990), Chan, Chung, and Johnson (1993), and O'Connor (1999) do not find support for the informational role of option markets as they find that stock markets lead option markets.

and stock returns.[4] After studying the stock orders associated with the increased trading volumes, they find that it is non-institutional investors who are driving the internet search and increased trading and returns association.

Drake, Roulstone, and Thornock (2012) argue that prior to earnings announcements, uninformed investors reduce information asymmetries through internet searches, resulting in increased stock trading volumes before as opposed to after earnings announcements. In addition, Fricke, Fung, and Goktan (2014) find that internet search volumes are higher for firms with higher levels of information asymmetries and that higher internet search volumes reduce PEAD.

In this study, we provide a unique setting in which informed and uninformed investors' information-related activities (proxied by option market trading and internet searches, respectively) may interact to predict firm earnings and PEAD. We propose the following hypothesis in testing the relationship between internet searches and option market trading:

H1. Trading activities of informed option traders and information acquisition activities of uniformed investors are uncorrelated during earnings announcements.

According to Hypothesis 1 (H1) above, informed investors' trading activities are based on possessing non-market wide information; in contrast, uninformed investors' search activities are based on overall firm information uncertainty. As such, these activities are not necessarily correlated

Our experimental design focuses on earnings announcements to examine informed options trading (e.g., Ni, Pan, and Poteshman (2008), Roll, Schwartz, and Subrahmanyam (2010), Jin et al. (2012), and Atilgan (2014)). In contrast to the existing studies, we provide a joint examination of the informational effects of both internet searches and option market trading on firm earnings information and PEAD. The PEAD anomaly is partially driven by the slow reaction of uninformed investors who have less information than informed investors (Bernard and Thomas (1990), Battalio and Mendenhall (2005), and Ke and Ramalingegowda (2005)). Thus, 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. Francis, Lafond, Olsson, and Schipper (2007) and Vega (2006) find that PEAD is also positively related to the level of private information available for a firm. Garfinkel and Sokobin (2006) and Anderson, Harris, and So (2007) find that PEAD is positively related to a firm's divergence of investor opinion, and Fricke, Fung, and Goktan (2014) find that PEAD is negatively correlated with the level of internet earnings information searches prior to the earnings announcement. Based on the above insights, we test the following hypothesis:

H2. Stock option trading volume provides more information about PEAD than GoogleSVI.

According to Hypothesis 2 (H2) above, stock option trading volume should provide more information about PEAD than GoogleSVI, because informed investor trading activities have higher information content than uninformed investor activities.

[4] Da et al. (2011) propose GoogleSVI 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.

III. Methodology and Data

A. Internet Search Volume, Option Trading Volume, and Analyst Forecasts

Our data features 653 quarterly firm-earnings announcement observations from 2004, the year Google search volume data first became available, to 2010, the year our data collection ended. Google, Inc. collects user search term and frequency information, aggregates the data on a weekly basis, and then makes it available at Google Trends (http://www.google.com/trends). The available data, GoogleSVI, represents the number of unique searches for a given search term. The search volume data, however, are only available in the "relative scaling" or "fixed scaling" formats. "Relative scaling" deflates search volume by average volume over a specified time period. "Fixed scaling" deflates volume by average volume since a fixed point in time (generally 2004 when Google begins storing search data). We use "fixed scaling" data since it ensures a consistent base across firm-period observations.

To construct our dataset of internet searches we use a methodology similar to Fricke, Fung, and Goktan (2014), which collects GoogleSVI data using the search term "*firm name* earnings" where *firm name* is a S&P 500 index listed company. S&P 500 firms are used to provide a consistent dataset and also to ensure the largest and most popular stocks are used to meet Google's minimum search level requirements. Of all available firms from 2004 to 2010, twenty-seven have weekly GoogleSVI data.

The weekly search data is then merged with total weekly call and put option trading volume which is collected from OptionMetrics for each stock and all strike price and maturity date combinations. Per Figure 1, each firm earnings announcement day is matched to the GoogleSVI and options trading volume weekly data, whereby time t = 0 is the week of the earnings announcement, occurring between Monday and Sunday of that week. Times $t = -1$, $t = -2$, and $t = -3$ represent the one-, two-, and three-week periods prior to the earnings announcement week.

Refer Figure 1

Analyst earnings forecast data is collected from I/B/E/S (Institutional Brokers' Estimate System), abnormal event returns data is collected around each earnings announcement from CRSP, and financial information is collected for each firm from COMPUSTAT. The sample ultimately includes 27 firms and 653 quarterly firm-earnings announcement observations.

B. Earnings Announcement Surprise Control Variables

We use several proxies for potential divergence of investor opinion including stock return volatility, bid-ask spread, daily turnover (*DTO*), standardized unexplained trading volume, and analyst forecast dispersion. Stock return volatility (*Volatility*) is the standard deviation of the previous 180 trading days' returns. Bid-ask spread (*BASpread*) for firm *i* is the difference between the bid and ask prices deflated by the mean of the bid and ask prices as calculated in equation (1) and in Chung and Zhang (2009) and Glushkov (2010).

$$BASpread_{i,t} = (Ask_{i,t} - Bid_{i,t}) / \{(Ask_{i,t} + Bid_{i,t}) / 2\} \qquad (1)$$

Daily turnover (*DTO*), shown in equation (2), is the daily firm trading volume deflated by shares outstanding (*Vol*/*Shs*) and adjusted for market trading volume and the median market adjusted firm trading volume over the past 180 trading days.

$$DTO_{i,t} = (Vol/Shs)_{i,t} - (Vol/Shs)_{mkt,t} - \text{Median}_{t,t\text{-}180}\{(Vol/Shs)_i - (Vol/Shs)_{mkt}\} \quad (2)$$

Standardized unexplained volume (*SUV*), shown in equation (3), is the residual from daily trading volume regressed on daily returns, separated between positive return days and negative return days (equation (4)), similar to Garfinkel (2009) and Glushkov (2010). Finally, the residual volume is then deflated by the regression residual's standard deviation.

$$SUV_{i,t} = \{Vol_{i,t} - \text{E}(Vol_{i,t})\} \,/\, S_{residuals} \quad (3)$$

$$\text{E}(Vol_{i,t}) = a_i + b_1|R_{i,t}|^+ + b_2|R_{i,t}|^- \quad (4)$$

Analyst earnings forecast dispersion (*DISP*) is calculated from I/B/E/S data by deflating the standard deviation of forecasts by the absolute value of the mean analyst forecast for each firm-earnings announcement observation similar to Glushkov (2010) and shown below in equation (5).

$$DISP_{i,t} = S_{forecasts,i,t} \,/\, \text{E}(forecasts)_{i,t} \quad (5)$$

C. Earnings Announcement Returns

Stock returns over various event windows related to earnings announcements are first calculated using daily abnormal returns relative to the market model in equation (6).

$$AR_{i,t} = R_{i,t} - (R_{f,t} + \hat{\beta}_{i,t}(R_{m,t} - R_{f,t})) \quad (6)$$

The abnormal return for stock *i* on day *t* ($AR_{i,t}$) is calculated as the difference between the actual return ($R_{i,t}$) and the market model estimated return which is computed as the risk-free rate ($R_{f,t}$) plus the estimated slope parameter for stock *i*, $\beta_{i,t}$, multiplied by the return of the market ($R_{m,t}$) minus the risk-free rate. Beta hat ($\hat{\beta}_i$) is the ordinary least squares estimate of beta (β_i) obtained from regressing $R_{i,t}$ on $R_{m,t}$ using 255 days (approximately one year of trading days) of history up to 46 days preceding the event day. The CRSP value-weighted market index is used for the market return.

The cumulative abnormal return (*CAR*) for stock *i* over an event window (*d*1, *d*2) is defined in equation (7).

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

D. Summary statistics

Table 1 shows statistics of key variables from our dataset of 653 firm-earnings announcement observations. GoogleSVI varies considerably from a minimum value of 0 to a maximum value of 55 at the t–1 lag and 38 at the t–2 lag. Mean values are less than one with standard deviations from 3.605 to 1.942. Weekly call option trading volume (*CallVolume*) generally rises in the few weeks before an earnings announcement with mean values of 166,722 at the t–1 lag and 152,983 at the t–2 lag. There is also considerable variation in volume as levels rise from under 10,000 to between 2 and 6 million with standard deviations in the several hundreds of thousands. Weekly put option trading volume (*PutVolume*) is lower than call option volume, but also increases up to the announcement and displays considerable variation. Table 1 then lists control variables for earnings announcements that proxy for divergence of investor opinion and firm-level uncertainties.

Refer Table 1

The correlation matrix in Table 2 shows that GoogleSVI has positive correlations with both call and put volumes. Put volume has the higher correlation of 0.237, which is statistically significant at the 0.01 level in unreported results. In addition, GoogleSVI has positive correlations with proxies for firm-level information asymmetries such as daily stock turnover (*DTO*), stock volatility (*Volatility*), bid-ask spread (*BASpread*), and analyst forecast dispersion (*DISP*). Volatility has the highest correlation of 0.218 which is statistically significant at the 0.01 level.

Refer Table 2

IV. Empirical Results

A. Internet search volume

Our study examines how internet search volume, as measured by GoogleSVI, is related to option trading volume and firm-level information asymmetries. As informed traders begin trading on their information through options, this test will determine if uninformed traders are potentially aware of the information asymmetries and attempt to reduce them via internet searches. Table 3 shows regression results modeling GoogleSVI.

$$\begin{aligned} GoogleSVI_{i,t} = b_0 &+ b_1(Call{+}PutVolume)_{i,t-1} + b_2DTO_{i,t} + b_3SUV_{i,t} \\ &+ b_4Volatility_{i,t} + b_4BASpread_{i,t} + b_5DISP_{i,t} + b_6MV_{i,t} \\ &+ b_7NAnalys_{i,t} + Residual_{i,t} \end{aligned} \tag{8}$$

Total call and put volume (*Call+PutVolume*) in equation (8) represents the combined call and put option trading volume. This combined volume is used to predict GoogleSVI rather than call or put option volume alone due to the directional nature of the options. In Table 3, controls for various proxies of firm-level information asymmetries, including firm size and number of analysts providing forecasts, are also shown. Models (1) and (2) in Table 3 test the ability of combined call and put volume to predict GoogleSVI. Neither the one- nor two-week lagged call and put volumes significantly drive GoogleSVI. This might mean that while uninformed investors are searching for information, informed investors are already acting on their own private information.

In addition, stock volatility and bid-ask spread significantly predict GoogleSVI. The R-squared values of the models in Table 3 show that combined call and put volume lags of 0.022 and 0.027 is in the range of predictive power of the bid-ask spread (0.027) and roughly half the predictive power of stock volatility (0.048). These findings possibly lend weak support to the idea that uninformed investors search for more information when they are at an informational disadvantage.

Refer Table 3

B. Earnings announcement surprise

Table 4 shows results from regressions of earnings announcement surprise measured as the absolute value of abnormal returns over the trading day following the announcement per equation (9).

$$\begin{aligned} \left| CAR_i(0, 1) \right| = b_0 &+ b_1GoogleSVI_{i,t} + b_2(Call{+}PutVolume)_{i,t-1} + b_3DTO_{i,t} \\ &+ b_3SUV_{i,t} + b_4Volatility_{i,t} + b_5BASpread_{i,t} + b_6DISP_{i,t} \end{aligned} \tag{9}$$

$$+ b_7 MV_{i,t} + b_8 NAnalys_{i,t} + Residual_{i,t}$$

Both GoogleSVI and total call and put trading volume are examined to determine their ability to predict earnings surprises during earnings announcements. Results in Table 4 indicate that GoogleSVI has statistically significant power in predicting earnings surprises, as measured by abnormal returns, but not in predicting surprises, as measured by the difference in actual versus forecasted earnings. Total call and put volume, however, does not appear to be a significant predictor of either measure of earnings surprise.

These findings support the idea that GoogleSVI, with no power to predict earnings surprises as measured by earnings surprise (UES), are not a proxy for informed investor search activity. However, the ability of GoogleSVI to predict announcement day abnormal returns (CAR(0,1)) supports the findings of Da, Engleberg, and Gao (2011), who argue that GoogleSVI is predominantly a measure of non-institutional investors' searches and thus a measure of uninformed investor attention. The inability of total call and put volume to predict earnings surprises is supported by Corn and Rathinasamy (2013). Corn and Rathinasamy (2013) find that while options trading is related to stock prices it does not appear to be related to the actual level of earnings surprise. Furthermore, these results support the notion that internet searches and options trading may contain independent sources of information.

Refer Table 4

C. Post-earnings announcement returns

Table 5 shows the results of regressing post earnings announcement returns on GoogleSVI, call option trading volume, put option trading volume, and the set of firm information asymmetry control variables as shown in equation (10).

$$\begin{aligned} CAR_i(1, j) = b_0 &+ b_1 GoogleSVI_{i,t} + b_2 GoogleSVI_{i,t} {*} CAR_i(0, 1) + CAR_i(0, 1) \\ &+ b_3 CallVolume_{i,t-1} + b_4 PutVolume_{i,t-1} + b_3 DTO_{i,t} + b_4 SUV_{i,t} \\ &+ b_5 Volatility_{i,t} + b_6 BASpread_{i,t} + b_7 DISP_{i,t} + b_8 MV_{i,t} \\ &+ b_9 NAnalys_{i,t} + Residual_{i,t} \end{aligned} \qquad (10)$$

Results in Table 5 are primarily related to the coefficient of the interaction term between GoogleSVI and CAR(0,1) and to the coefficients on CallVolume and PutVolume. Models (1) and (2), (3) and (4), and (5) and (6) run regressions of equation (9) over time horizons of 20, 40, and 60 days after the earnings announcement, respectively. Only models (2), (4), and (6) include the CallVolume and PutVolume variables.

While GoogleSVI is negatively related to post earnings returns on average, the more telling statistic is the interaction term between GoogleSVI and announcement surprise (CAR(0,1)). Given a positive surprise, the statistically significant, negative coefficient in model (1) means that higher internet search volumes tend to reduce PEAD over 20 days following the announcement. In terms of economic significance, a standard deviation change in GoogleSVI has a negative effect on CAR(1,20) with a magnitude of –0.011, which is equivalent to –10.50% of the standard deviation of CAR(1,20) reported in Table 1.[5] Similarly, a standard

[5] The economic significance of GoogleSVI is computed as the coefficient of GoogleSVI of –0.003 (in model (1) of Table 5), multiplied by the standard deviation of GoogleSVI of 3.605 (reported in Table 1). The same method of calculation applies to other results of economic significance reported in this paper.

deviation change in GoogleSVI has a negative effect on CAR(1,40) with an economic magnitude of –0.025 (which is –19.87% of the standard deviation of CAR(1,40)) and a negative effect on CAR(1,60) with an economic magnitude of –0.025 (which is –15.11% of the standard deviation of CAR(1,40)). These results imply that increased information searching by uninformed investors can decrease information asymmetries and lead to more efficient stock prices.

In model (2), CallVolume and PutVolume are included in the regression and change the results from model (1). The interaction term between GoogleSVI and earnings surprise becomes insignificant, which suggests the possibility that the information in GoogleSVI related to earnings announcement surprises is not orthogonal to the information in option trading volumes. The finding that the GoogleSVI predictor variable remains significant implies that GoogleSVI is related to future returns. The component of GoogleSVI related to earnings information, however, provides no information beyond what is already in option trading volumes.

In Table 5, the GoogleSVI and earnings surprise interaction term becomes insignificant at the longer time horizons of 40 and 60 days, while PutVolume maintains its significance and CallVolume becomes more significant. The results in models (2), (4), and (6) show that in terms of economic significance, a standard deviation change in PutVolume is associated with negative economic effects of –0.017 on CAR(1,20), –0.027 on CAR(1,40), and –0.029 on CAR(1,60); these economic effects are equivalent to a –16.59%, –21.33%, and –17.10% change in the standard deviation of CAR(1,20), CAR(1,40), and CAR(1,60), respectively. In contrast, a one standard deviation change in CallVolume is associated with positive economic effects of 0.003 on CAR(1,20), 0.008 on CAR(1,40), and 0.010 on CAR(1,60), which are equivalent to a +3.152%, +6.135%, and +6.221% change in the standard deviation of CAR(1,20), CAR(1,40), and CAR(1,60), respectively. In comparison with the economic effects of PutVolume, the differential economic effects of CallVolume are significantly smaller. This finding is consistent with the insight of Pan and Poteshman (2006), Cremers and Weinbaum (2010), and Du and Fung (2018) that positive and negative information trades (proxied by call option volume and put option volume respectively in our case) contain differential, directional information. Also, option trading variables increase the predictability of post-earnings announcement returns. In Table 5, the comparison between models (1) and (2) (similarly, the comparison between model (3) and (4) and comparison between model (5) and (6)) reveals that the R-squared values increase by around 1.5% to 2.3% when PutVolume and CallVolume are added to the regression of post-earnings announcement returns. Overall, these findings lend support to the hypothesis that option traders tend to be more informed traders and that uninformed traders may find information through internet searches. This new information obtained by uninformed investors, however, is also known to informed investors during the post-earnings announcement period. These findings are consistent with Hypothesis 2. They reveal that informed investor trading activities have higher information content than uninformed investor activities, particularly in the context of post-earnings announcement drift – i.e., that stock option trading volume provides more information about PEAD than GoogleSVI.

Refer Table 5

In summary, our findings highlight the nexus between informed investor options trading and uninformed investor internet searches. We find that during earnings announcements, informed trading activities, proxied by option trading volume, are not a significant predictor of uninformed investor activities, proxied by internet search volume. However, the component of uninformed investor internet searches that is related to earnings surprises and mitigates PEAD loses its predictive power when informed investor option trading is taken into account. This may be due to the notion that internet search volumes contain knowledge of information searches that becomes a subset of informed investors' information set after earnings announcements. Internet information searches may also contain information about investor attention. The component related to uninformed investor attention still predicts returns post earnings announcement even after options trading is taken into account.

5. Concluding Remarks

This study is among the first to hypothesize and investigate the interaction of informed and uninformed traders through their trading and information search activities prior to the informational event of earnings announcements. We find evidence that prior to earnings announcements option trading volume of informed investors is not significantly related to the internet searches of uninformed investors. This suggests that informed and uninformed investors represent different types of information acquisition activities and uninformed investors are not entirely aware of informed investors' activities. We also find that option trading volumes and internet searches are not correlated with subsequent earnings surprises as measured by the percentage difference between the actual and expected earnings.

Finally, both options trading volumes and internet searches reduce PEAD, suggesting that both informed and uninformed investors help reduce information asymmetries. This finding suggests PEAD is lessened by the differential information acquisition activities of informed and uninformed investors, but more so by informed traders than by uninformed traders. When combined into single regression, however, options trading volume captures the relevant information in internet search volume related to PEAD. In other words, the informational impact of uninformed traders is subsumed by the impact of informed option market traders after earnings announcements.

While the existing literature focuses on the ability of option trading data to predict stock returns, our results provide a different insight into the information content of options trading before corporate announcements, especially in the presence of information acquisition activities of uninformed investors.

Our results highlight the different informational roles of options trading activities, internet searches, and their intricate interactions. For financial market investors, internet search activities can be interpreted as uninformed investors' attention and informational activities during informational events (such as earnings announcements). Interestingly, these informational activities, reflected by internet searches, can contain information content of post announcement returns for financial market investors. In contrast, options trading activities during earnings announcements can be viewed as an independent source of informational effect, which is not necessarily related to uninformed investor's information search activities. Despite the increasing availability of information through the internet, the information role of options market remains important for the financial markets. Overall, our results provide broader insights and implications on policies and issues related to the informational activities by different financial market participants: i.e., informational activities in the financial markets are not limited to informed investors but uninformed investors can also decrease information asymmetries and lead to more efficient stock prices. These insights are also useful for designing financial market policies that attempt to enhance informational activities during corporate announcements as well as understanding the heterogeneity of informational roles among different financial market participants.

Future research might further distinguish the type of information contained in internet searches and study how this information reduces information asymmetries during earnings and non-earnings related events. Additionally, future research might further examine the strategic interactions and relative impacts of uninformed and informed investors over time and across different firms or industries.

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Figure 1: Timeline of Internet Searches, Options trading, and Earnings Announcements

Figure 1 presents the timeline of internet searches, option trading, and earnings announcements. In our sample, firm earnings announcement day is matched to the GoogleSVI and options trading volume weekly data whereby time t = 0 is the week of the earnings announcement, occurring between Monday and Sunday of that week. Times t = -1, t = -2, and t = -3 represent the one-, two-, and three-week periods prior to the earnings announcement week.

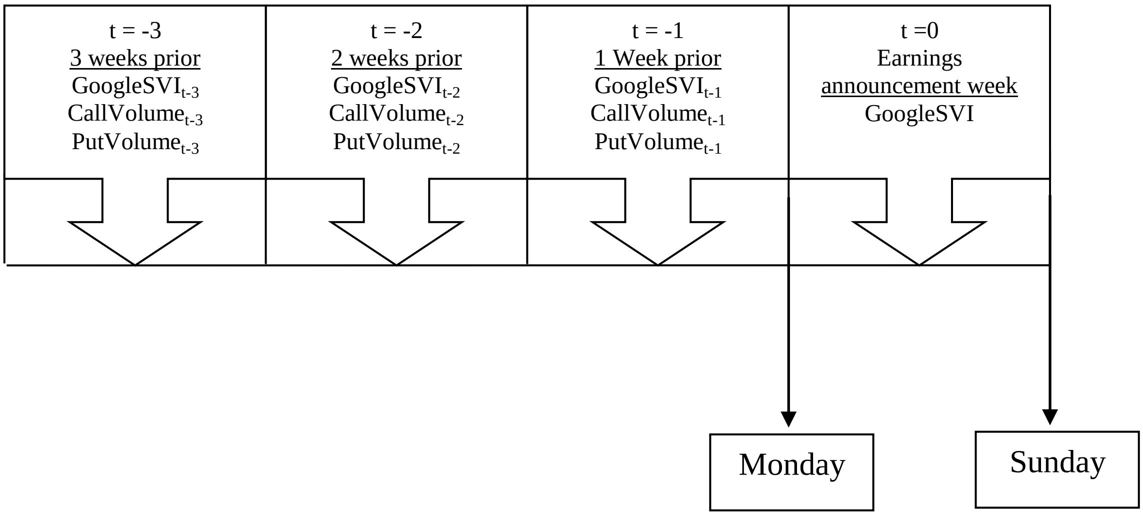

Table 1: Summary statistics

The sample consists of 653 quarterly firm earnings announcement observations. GoogleSVI is the Google search volume index in the 1, 2, and 3 lagged weeks before the earnings announcement. CallVolume (PutVolume) is the total weekly call (put) option trading volume in the lagged weeks before 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 minus 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.

Variable	N	Mean	Std. Dev.	Min	Max
$GoogleSVI_{t-1}$	653	0.581	3.605	0.000	55.000
$GoogleSVI_{t-2}$	653	0.143	1.942	0.000	38.000
$GoogleSVI_{t-3}$	653	0.192	2.658	0.000	61.500
$CallVolume_{t-1}$	653	166,722	229,696	5,216	2,442,292
$CallVolume_{t-2}$	653	152,983	324,636	2,301	6,185,098
$CallVolume_{t-3}$	653	146,627	242,389	1,592	3,298,186
$PutVolume_{t-1}$	653	117,629	156,263	386	1,777,772
$PutVolume_{t-2}$	653	96,578	133,467	1,106	1,240,146
$PutVolume_{t-3}$	653	91,536	126,407	1,076	1,105,036
DTO	653	0.010	0.015	-0.058	0.095
SUV	653	2.382	3.223	-1.954	61.597
Volatility	653	0.022	0.016	0.005	0.165
BASpread	653	0.039	0.031	0.007	0.287
DISP	653	0.165	0.423	0.000	3.172
MV	653	0.081	0.065	0.004	0.315
NAnalys	653	15.109	6.381	2.000	39.000
UES	653	0.001	0.008	-0.040	0.048
CAR(0,1)	653	0.003	0.068	-0.345	0.299
CAR(1,20)	653	0.001	0.103	-0.330	0.707
CAR(1,40)	653	-0.005	0.127	-0.426	0.561
CAR(1,60)	653	-0.007	0.167	-0.554	1.131

Table 2: Correlation Matrix

The sample consists of 653 firm earnings announcements. See Table 1 for variable definitions. Pearson correlation coefficients are listed.

	Google SVI_{t-1}	Call Volume $_{t-2}$	Put Volume $_{t-2}$	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														
Call $Volume_{t-2}$	0.111	1.000													
Put $Volume_{t-2}$	0.237	0.509	1.000												
DTO	0.123	0.049	0.125	1.000											
SUV	-0.024	-0.032	-0.014	0.420	1.000										
Volatility	0.218	0.115	0.350	0.330	-0.059	1.000									
BASpread	0.164	0.047	0.255	0.509	0.173	0.627	1.000								
DISP	0.180	0.064	0.193	0.290	0.048	0.526	0.449	1.000							
LogMV	0.020	0.219	0.277	-0.244	-0.018	-0.305	-0.249	-0.147	1.000						
LogNAnalys	0.023	0.201	0.270	-0.005	-0.058	0.107	0.025	0.033	0.298	1.000					
UES	-0.045	0.050	0.023	0.193	0.055	-0.138	-0.104	-0.137	0.030	0.012	1.000				
CAR(0,1)	-0.038	-0.019	0.062	-0.087	-0.121	0.002	-0.109	-0.119	-0.006	0.015	0.130	1.000			
CAR(1,20)	-0.087	-0.060	-0.077	0.037	0.019	0.121	0.100	0.016	-0.129	-0.010	0.002	0.447	1.000		
CAR(1,40)	-0.161	-0.065	-0.111	0.020	0.021	0.153	0.153	0.040	-0.180	-0.023	-0.059	0.418	0.818	1.000	
CAR(1,60)	-0.144	-0.038	-0.055	0.060	0.035	0.183	0.187	0.063	-0.162	-0.044	-0.041	0.361	0.681	0.870	1.000

Table 3: GoogleSVI Regressions

The sample consists of 653 quarterly firm earnings announcement observations. GoogleSVI $_{t-1}$ is the Google search volume index. Call + Put Volume is the total combined weekly option volume. 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.

Dependent Variable: GoogleSVI $_{t-1}$	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Call + Put	0.143							
Volume $_{t-1}$	(0.102)							
Call + Put		0.146						0.009
Volume $_{t-2}$		(0.111)						(0.009)
DTO			30.012					19.175
			(19.161)					(23.842)
SUV				-0.027				-0.059
				(0.019)				(0.063)
Volatility					45.532*			33.868
					(27.157)			(35.692)
BASpread						19.169*		1.655
						(10.124)		(9.249)
DISP							1.535	0.657
							(1.258)	(1.550)
LogMV								0.348
								(0.286)
LogNAnalys								-0.436
								(0.374)
Constant	0.175	0.217	0.295	0.644	-0.494	-0.168	0.328	-5.646
	(0.190)	(0.189)	(0.180)	(0.244)**	(0.492)	(0.284)	(0.235)	(5.032)
N	653	653	653	653	653	653	653	653
R-squared	0.022	0.027	0.015	0.001	0.048	0.027	0.032	0.078

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

Table 4: Earnings Announcement Returns and Surprise Regressions

The sample consists of 653 quarterly firm earnings announcement observations. GoogleSVI is the Google search volume index. Call + Put Volume is the total combined weekly option volume. 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 minus the median forecast scaled by stock price in percent.

Dependent Variable:	Model (1) |CAR(0,1)|	Model (2) |CAR(0,1)|	Model (3) |UES|	Model (4) |UES|
$GoogleSVI_{t-1}$	-0.0005**	-0.0006**	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Call + Put $Volume_{t-1}$	0.001		0.0002	
	(0.001)		(0.0008)	
Call + Put $Volume_{t-2}$		0.0005		0.0004
		(0.0006)		(0.0006)
DTO	0.135	0.172	0.181*	0.179*
	(0.219)	(0.226)	(0.089)	(0.089)
SUV	0.002***	0.002***	-0.0002	-0.0002
	(0.001)	(0.001)	(0.0002)	(0.0002)
Volatility	0.355	0.400*	0.073**	0.069**
	(0.228)	(0.228)	(0.028)	(0.029)
BASpread	0.445***	0.443***	0.027**	0.027**
	(0.155)	(0.155)	(0.011)	(0.011)
DISP	0.001	0.002	0.003*	0.003*
	(0.003)	(0.003)	(0.002)	(0.002)
LogMV	-0.005	-0.004	-0.0004	-0.001
	(0.004)	(0.004)	(0.001)	(0.001)
LogNAnalys	-0.0001	0.001	-0.001	-0.001
	(0.005)	(0.005)	(0.001)	(0.001)
Constant	0.103	0.078	0.009	0.011
	(0.085)	(0.075)	(0.017)	(0.017)
Observations	653	653	653	653
R-squared	0.247	0.243	0.382	0.383

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

Table 5: Post Earnings Announcement Returns Regressions

The sample consists of 653 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. CallVolume (PutVolume) is call (put) option trading volume in millions. See Table 1 for other variable definitions.

Dependent Variable:	Model (1) CAR(1,20)	Model (2) CAR(1,20)	Model (3) CAR(1,40)	Model (4) CAR(1,40)	Model (5) CAR(1,60)	Model (6) CAR(1,60)
$GoogleSVI_{t-1}$	-0.003***	-0.002**	-0.007***	-0.005***	-0.007***	-0.002**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
$GoogleSVI_{t-1}$ * CAR(0,1)	-0.018***	-0.007	-0.011	0.007	0.018	-0.010
	(0.006)	(0.006)	(0.010)	(0.009)	(0.013)	(0.007)
CAR(0,1)	0.720***	0.723***	0.829***	0.852***	0.936***	0.718***
	(0.137)	(0.137)	(0.116)	(0.117)	(0.120)	(0.139)
$CallVolume_{t-2}$		0.010		0.024**		0.032***
		(0.008)		(0.011)		(0.010)
$PutVolume_{t-2}$		-0.128**		-0.203***		-0.214***
		(0.046)		(0.055)		(0.048)
DTO	-0.332	-0.265	-0.980	-0.892	-0.781	-0.701
	(0.487)	(0.476)	(0.688)	(0.683)	(0.763)	(0.768)
SUV	0.002**	0.002**	0.003**	0.003**	0.004*	0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Volatility	0.425	0.746	0.546	1.025	1.026	1.507
	(0.661)	(0.674)	(0.693)	(0.685)	(1.181)	(1.165)
BASpread	0.410	0.450	0.809**	0.877**	1.039*	1.114*
	(0.452)	(0.443)	(0.377)	(0.371)	(0.577)	(0.577)
DISP	-0.002	-0.001	0.002	0.004	0.004	-0.005
	(0.017)	(0.017)	(0.023)	(0.024)	(.035)	(0.037)
LogMV	-0.010**	-0.004	-0.019***	-0.009	-0.016**	-0.007
	(0.004)	(0.004)	(0.006)	(0.007)	(0.008)	(0.008)
LogNAnalys	0.001	0.005	0.002	-0.007	-0.013	-0.008
	(0.008)	(0.007)	(0.011)	(0.010)	(0.014)	(0.013)
Constant	0.147	0.026	0.286**	0.109	0.255*	0.080
	(0.076)	(0.066)	(0.114)	(0.122)	(0.136)	(0.147)
Observations	653	653	653	653	653	653
R-squared	0.246	0.261	0.273	0.296	0.230	0.245

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

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