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FORECASTING VOLUME AND PRICE IMPACT OF EARNINGS SURPRISES USING GOOGLE INSIGHTS

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ABSTRACT

This paper examines the predictability of price and volume movements using Google Insights on equities exhibiting earnings surprise and the association with pre-announcement information searching. The motivation for this paper is to answer two primary research questions. First of all, using more recent stocks earnings surprise, is Google search data a good indicator of investor interest prior to the earnings announcement? Second does the Google data add to the predictability of post earnings volume and pricing direction? Data on earnings surprise were taken from Yahoo Finance and Google search volume data were taken from the Google trends website. While the results found in the analyses above are not highly convincing regarding Google trends data and price movement from earnings surprise, the results on the volume models yielded promising (i.e. significant) results. Moreover, Mean Absolute Error was reduced by approximately 8% when incorporating the Google trends data on volume predictions.

JEL: G17

KEYWORDS: Predictability, Volume Movements, Earnings Surprise, Google

INTRODUCTION

Financial research suggests that the impact of earnings surprise on firms quoted price is a function of investor's expectation of the surprise, as well as their reaction to the surprise itself (c.f. Atiase and Bamber, 1994 and Barberis, Shleifer and Vishny, 1998). This implies that pre-earnings expectations will absorb some of the price movements associated with the actual earnings surprise. An unanticipated announcement on the other hand can have both immediate and persistent effects on the market clearing price. The ability to predict (1) the earnings surprise and (2) the price and volume impact on the particular asset has been the focus of considerable research (see for example Barberis, Shleifer and Vishny, 1998). Among the many studies examining this phenomenon researchers have employed event studies, single factor and multi factor models. (c.f., Fama (1991) and Fama and French (1996), Mackinlay (1997)). This paper examines the predictability of price and volume movements using Google Insights on equities exhibiting earnings surprise and the association with pre-announcement information searching.

LITERATURE REVIEW

Considerable work has been done on stock earnings surprise and abnormal returns. For example, Fama (1998) found that finance literature identified many long-term return anomalies that were inconsistent the efficient market hypothesis (EMH). These anomalies are found to exist both pre and post earnings announcement, as well as during merger activity (Wansley, Lane and Yang, 1983). As financial markets have grown, both domestically and internationally, investors and researchers have continued to focus on identifying anomalies in order to earn excess short-term returns (DellaVigna and Pollet, 2009). This particular line of inquiry has influenced (and been influenced by) research that seeks to identify and measure information demand of investors around earnings announcements. Vlastakis and Markellos (2012) studied volatility and information demand. They found that information demand at the market level is positively related to historical and implied measures of volatility. Furthermore they find that information demand increases during periods of higher returns. This is consistent with the idea that trading volume and subsequent price movements react to quarterly earnings announcements (Bamber, 1987).

Drake, Roulstone and Thornock (2012) examined information demand of investors around earnings surprise using Google search index data. They find that the information build up around the event begins approximately two weeks prior to the earnings announcement and continues beyond the earnings announcement. They also find that part of the earnings surprise is already incorporated into the price of the stock prior to earnings; therefore, the price impact of the surprise is diffused around the announcement. The specific motivation in this paper was to assess both the nature and timing of investor information demand (and the pricing impacts) during earnings season. The authors employ a number of regression models that attempt to predict search volume and abnormal returns during varying time windows. The concept of information demand and investor information seeking has been of interest over the last 40 years. As information becomes more accessible, additional data sources available to the public have begun being used. These sources include Facebook, Twitter and Google.

Google trends shows the search volume of a particular topic over a particular point in time. Google describes Google Trends on their website, and define the numbers on the graph as reflecting how many searches have been done for a particular term, relative to the total number of searches done on Google over time. They don't represent absolute search volume numbers, because the data is normalized and presented on a scale from 0-100. Each point on the graph is divided by the highest point, or 100. When we don't have enough data, 0 is shown (https://support.google.com/trends/answer/4365533?hl=en)." Choi and Varian (2009) conducted a broad series of analyses in the paper "Predicting the Present with Google Trends." In this paper the authors employ a seasonal autoregressive model to predict automobile sales, home sales and travel. In doing so they found that using Google search data improved predictive power over an autoregressive model with a single lag parameter. Other research using these data have also been developed given the unique characteristics of Google's data. For example, additional research has been conducted in finance and economics, as well as, epidemiological studies (c.f., Pelat et. al. (2009), Preis et. al. (2013)).

The availability and accessibility of Google search data to researchers has provided an interesting and innovative direction for different types of research. With respect to financial research, and information seeking specifically, Google search data can be seen interpreted as information seeking by individuals and, in the case of this particular analysis, investors. Bushee, Core, Guay and Hamm (2010) recently addressed this topic whereby they examine the impact of the business press on reducing information asymmetry. Their findings indicate that when the media provides information about the potential for surprise, it reduces the price and volume impact for a particular asset. This is a similar result that was found by Drake et al (2012) where they concluded that the Google trends data is a form of information seeking by investors, which reduces pre-announcement information asymmetry.

The motivation for this paper is then to combine the focuses of the three aforementioned papers. There will be two primary research questions. First of all, using more recent stocks earnings surprise, is Google a good indicator of investor interest prior to the earnings announcement? Second does the Google data add to the predictability of post earnings volume and pricing direction? If robust results are found for these questions then the question regarding information asymmetry reduction will provide validation for the Bushee et al (2010) paper.

DATA AND METHODOLOGY

Data on earnings surprises were taken from yahoo finance (http://biz.yahoo.com/z/extreme.html). Here you can search for earnings dates and whether or not there was an earnings surprise associated with a particular equity. In this paper companies were selected over a three day period in August 2012. This period was selected in order to capture a one year time horizon in which the companies analyzed did not have a prior earnings surprise in the prior one year. This article was initially written in September, 2013 and the earnings season from August 2013 was the most relevant. For each day five equities were selected; two with positive earnings surprises (earnings per share (EPS) above analysts' consensus estimates), two with negative earnings surprises (earnings per share (EPS) below analysts' consensus estimates and one that met earnings expectations (i.e. no surprise). Assets with earnings dates in August 2013 were selected. They were further segmented into those with positive, negative and no earnings surprise in order to select from among those groups. Thereafter, assets were selected randomly from within each earnings direction group, irrespective of industry, company size, market capitalization, etc. Furthermore, firm performance (i.e. book to market, P/E ratio, cash flow to price, etc.) was not considered in this study, although the direction and magnitude of surprise can be indicative of current firm performance (Drake et al, 2012). Finally, weekly data were captured for the preceding 52 weeks closing prices and volumes leading up to the earnings announcement in which the surprise occurred. The only caveat to the selection of the assets was that they must not have had any other earnings surprises in the prior 12-month period.

Google interest data were taken from the Google trends website (http://www.google.com/trends/). Google trends data allows users to search a particular keyword over a particular time interval. The interest data are then standardized in order to index relative search volume (not absolute search volume) over time. Term searches are unstructured in the Google trends environment. One can search any term and identify whether or not search volume occurred over the specified time interval. Similarly, when searching for company information, entering the entire company name will generate interest data that are not exclusively search entries that were information gathering as a result of earnings expectations. In order to control for this potential contemporaneous interest result, search terms were only entered as ticker symbols (c.f. Drake, Roulstone and Thornock (2012)). Table 1 shows the companies that were used in the analysis, ticker symbols, surprise type, surprise magnitude, analyst consensus expectation for EPS and actual reported EPS.

Table 1: Companies Used in Analysis and Summary Statistics of Earnings Surprise

Company Name	Symbol	Surprise Date	Earnings Surprise Direction	Surprise %	Reported EPS	Consensus EPS
Medtronic	MDT	8/20/2013	Met	0.0%	0.88	0.88
Best Buy	BBY	8/20/2013	Upside	166.7%	0.32	0.12
Home Depot	HD	8/20/2013	Upside	2.5%	1.24	1.21
Dicks Sporting Goods	DKS	8/20/2013	Downside	-4.1%	0.71	0.74
JC Penney's	JCP	8/20/2013	Downside	-107.6%	-2.2	-1.06
Smuckers	SJM	8/21/2013	Upside	3.3%	1.24	1.20
Lowes	LOW	8/21/2013	Upside	11.4%	0.88	0.79
Hewlett Packard	HP	8/21/2013	Met	0.0%	0.86	0.86
Eaton Vance	EV	8/21/2013	Downside	-3.7%	0.52	0.54
Staples	SPLS	8/21/2013	Downside	-11.1%	0.16	0.18
Prospect	PSEC	8/22/2013	Upside	26.7%	0.38	0.30
Pandora	P	8/22/2013	Upside	100%	0.04	0.02
Gap	GPS	8/22/2013	Met	0.0%	0.64	0.64
Abercrombie	ANF	8/22/2013	Downside	-42.9%	0.16	0.28
Sears Holdings	SHLD	8/22/2013	Downside	-54.6%	-1.70	-1.10

Table 1: Shows companies used in the analysis, ticker symbols, earnings dates and earnings results during August 2013.

In table 1, a surprise type of "Met" indicates EPS expectation was realized in the actual reporting, "Downside" indicates EPS was below expectation and "Upside" indicates EPS expectations were above expectation. Companies were selected that had met expectations as a reference group. This is consistent with some research in the event study literature (c.f., Lee, 2007). Although this is not an event study methodology, the ability to determine a baseline of predictability using companies that had met earnings expectations was utilized as a means of comparison. Table 2 shows the summary statistics for each of the equities used in the analysis, including their surprise, mean, median and range of closing prices, traded volume and Google interest.

METHODOLOGY

The methodology being employed is similar to that in the Choi and Varian (2009) paper. In this paper Choi and Varian employ a basic autoregressive model to estimate various macroeconomic factors mentioned previously. Their results indicate that the when adding Google trends data to the autoregressive model, overall prediction error is reduced significantly.

Table 2: Company, Surprise Direction and Weekly Price, Volume and Google Interest

Company (Ticker)	Surprise	Observations	Mean Weekly Close	Mean Weekly Volume	Mean Weekly Interest
ANF	Negative	52	$45.23	2,358,440	79
BBY	Positive	52	$20.80	8,553,342	60
DKS	Negative	52	$49.81	1,418,013	62
EV	Negative	52	$35.96	866,242	73
GPS	No Surprise	52	$37.15	4,594,827	48
HD	Positive	52	$68.96	7,381,806	53
HPQ	No Surprise	52	$19.43	24,451,706	39
JCP	Negative	52	$19.00	12,752,879	34
LOW	Positive	52	$37.63	9,604,185	81
P	Positive	52	$13.01	5,960,602	56
PSEC	Positive	52	$11.05	3,058,562	42
SHLD	Negative	52	$49.15	1,008,440	48
SJM	Positive	52	$95.25	594,335	64
SPLS	Negative	52	$13.36	11,143,367	44

Table 2: Shows the direction of the earnings surprise, the number of observations evaluated and the weekly mean closing price, volume traded and Google interest.

A similar autoregressive model will be built in this analysis as well, using both prior week's closing prices and volume traded. The model will be used, to forecast pricing and volume, before and after Google trends data are entered as predictors in the model. Secondarily, it will examine the impact of the surprise on the direction of the volume and price movements. For example, pre and post earnings movement exists has been examined extensively in the literature and is referred to as "earnings announcement drift" (c.f. Bernard and Thomas, 1989). Investors will take positions in assets prior to (and post) earnings announcements in order to capitalize on the added volatility (c.f. Sadka, 2006). In the model we will examine the impact of Google search volume as a predictor of volume and closing price in the following week. The hypothesized results will be as follows:

Hypothesis 1-Google trends data will help identify an increase in volume traded for both positive and negative surprise stocks.

Hypothesis 2-Google trends data will help predict the direction of the price change for positive and negative surprise shocks.

*Overall prediction error in both volume and closing price will be reduced as measured by mean absolute error (MAE) by adding Google trends search data. This expected result is consistent with the Choi and Varian (20*09) outcome.

The model specification for the baseline approach will be,

$$volume_t = \beta_0 + \beta_1(volume_{t-1}) + \epsilon_t \tag{1}$$
$$close_t = \beta_0 + \beta_1(close_{t-1}) + \epsilon_t \tag{2}$$

Where, subscript t and t-1 denote current and prior week cumulative values for volume and ending values for price, respectively ϵ_t represents the error term in both models.

Once the baseline coefficients and errors are calculated, the Google interest data will also be included and the following models will be estimated,

$$volume_t = \beta_0 + \beta_1 \log(volume_{t-1}) + X_i + \epsilon_t \tag{3}$$
$$close_t = \beta_0 + \beta_1(close_{t-1}) + X_i + \epsilon_t \tag{4}$$

Where, variables defined previously are the same and the X_i refers to the Google interest data indexed over the prior year. From here the revised parameter estimates will be examined and MAE will be calculated for the models with Google trends data. The results will be compared to the hypotheses listed above. It is expected that the results for volume should always be positive on the Google coefficient. An expectation of a surprise will lead to more volume traded irrespective of whether or not they are sold or bought. Where surprises (positive or negative) exist the coefficient should be significant. Price expectations on the other hand should be directional. Therefore, a stock with positive earnings surprise should be identified by a positive Google interest coefficient and a negative earnings surprise should be identified by a negative coefficient on the Google interest variable.

RESULTS

The results of the various Google interest data were most revealing on volume predictions for stocks with the highest volume and/or stocks with the largest surprises (irrespective of surprise direction). For example, JCP, SHLD and SPLS had significant volume and close coefficients on the Google interest variable. In these assets, both JCP and SPLS have significantly higher median weekly volume, relative to the average of the volume for the entire sample (12.7MM and 11.1MM shares compared with 6.6MM shares for all). SHLD is an anomaly due to below average volume (1MM shares); it has significant Google interest coefficients on both volume and price, although likely due to large funds eliminating remaining positions and/or small and medium sized traders capitalizing on volatility due to the firm's financial distress. This movement in SHLD is more than likely a result of the considerable negative news that has been reported recently. The downward spiral to bankruptcy has been observed in other firms where financial distress has been long term and with significant magnitude (c.f. Gilbert and Menon, 1990). The remainder of the results are quite fragmented (i.e. significant coefficients on Google interest and closing price for no surprise stocks). Additionally, there are a number of assets with sufficient volume and large enough earnings surprise to generate significance that did not. All coefficients on volume and price can be seen in sections 1 and 2 of the appendix. In addition, plots of the predictions (both with and without Google interest) are compared to the actual volumes and closing prices in sections 3 and 4 of the appendix. Generally, the predictions with interest are much closer to predictions without interest particularly in stocks where the Google trends data were significant on both price and volume. This brings us to our third hypothesis, which is whether or not including Google trends data into the model would reduce the mean absolute error (MAE). The MAE is defined as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{5}$$

Where, $\hat{y}_i$ represents the forecast of y_i and y_i represents the actual result. Tables for the MAE on all assets are listed in Table 1 below. Overall, the MAE is reduced from 29.6% to 27.3% for volume and effectively unchanged for closing prices. In order to assess whether or not there was a statistically significant difference in these two values a paired samples t-test was run and the results are listed in Table 3 below.

Table 3: Comparison of Mean Absolute Error (Weekly Volume and Close) by Company

	Volume Error No Interest	Volume Error w/ Interest	Close Error No Interest	Close Error w/ Interest
ANF	30.8%	32.0%	4.1%	4.0%
BBY	44.8%	43.6%	5.1%	5.1%
DKS	25.6%	27.1%	2.2%	2.1%
EV	28.7%	28.7%	2.9%	3.0%
GPS	27.7%	25.5%	2.5%	2.5%
HD	19.0%	19.1%	2.0%	2.1%
HPQ	34.2%	19.7%	4.0%	4.0%
JCP	34.2%	26.6%	6.1%	6.3%
LOW	22.2%	22.1%	2.2%	2.2%
P	33.5%	30.5%	5.9%	5.8%
PSEC	27.2%	29.1%	1.6%	1.6%
SHLD	33.9%	26.4%	5.1%	5.1%
SJM	19.0%	19.2%	1.4%	1.5%
SPLS	34.2%	31.9%	2.5%	2.5%
MEAN	29.64%	27.25%	3.40%	3.42%
Median	29.75%	26.86%	2.72%	2.76%
Minimum	18.96%	19.07%	1.44%	1.46%
Maximum	44.82%	43.64%	6.09%	6.33%

Table 3-Mean Absolute Error for each firms price and volume forecasts with and without Google interest. In the table above "No Interest" is without including Google data and "w/Interest" is with Google data. The final four rows of data are descriptive statistics for each models error.

Table 4 below shows the results of the t-test for the MAE difference in predictive power between models with and without Google interest included.

Table 4: Paired Samples T-Test's for Mean Absolute Error Before and After Including Google Trends in Model

Statistics	Volume Error No Interest	Volume Error w/ Interest	Close Error No Interest	Close Error w/ Interest
Mean	0.2963	0.2725	0.0342	0.034
Variance	0.0048	0.0042	0.0002	0.0003
Observations	14	14	14	14
Pearson Correlation	0.7741		0.9989	
Hypothesized Mean Difference	0		0	
Df	13		13	
t Stat	1.96		1.288	
P(T<=t) one-tail	0.0358		0.11	
t Critical one-tail	1.77		1.771	
P(T<=t) two-tail	0.0717		0.22	
t Critical two-tail	2.16		2.16	

Table 4-Paired two sample t-test comparing differences in group means between models with and without Google trends data. Statistically significant difference exists in MAE on volume prediction differences (lower MAE with Google trends data than without). Difference in MAE on close prediction differences is not statistically significant.

The mean MAE for closing price indicated no meaningful difference between the models (3.42% to 3.40%). The paired samples t-test found that the difference between these two groups was not statistically significant. The difference on volume on the other hand was found to be statistically significant at the 5% level (p-value .035 and t-statistic 1.96). When re-examining the coefficients (appendix sections 1 and 2) it is clear that 9 of the 14 firms examined had statistically significant parameter estimates on the Google trends data variable in the volume models compared to 4 of 14 for the closing price models.

CONCLUDING COMMENTS

This paper attempted to apply the methodology from Choi and Varian (2009) to stock earnings surprise. Predicting volume and pricing using Google trends data appears to provide some lift in prediction accuracy of forecasts. The focus of this paper was to examine the efficacy of Google insights data as predictors in a model. Because the data are an index of the time period of interest we do not truly see absolute search volume, but only relative minimum and maximum values over our specified time interval. The results found an increased predictive power, via a lower MAE, for the volume forecast. Results on price prediction were not as promising. For example, the asset selection process in this paper was very subjective. Assets were selected based on an arbitrary time period (the most recent earnings season) and were then filtered according to the non-existence of earnings surprise in the prior year. A more robust selection process on a larger number of assets may yield more insightful results. Furthermore, only a one year time horizon was examined using weekly data. The frequency of the data and/or the time horizon may also have been limiting factors in generating significant (and consistent) results. The fact that MAE reduction did occur with statistical significance is promising and should provide a good starting point for examination in future research.

APPENDIX

Appendix 1: Volume Data

Company and Model Used	Intercept	Lag of Volume	Google Interest
ANF (w/o Google Interest)	2,103,453.13***	0.12	
ANF (w/ Google Interest)	-3,195,523.26	0.12	67303.03
BBY (w/o Google Interest)	5,031,934.41***	0.41***	
BBY (w/ Google Interest)	8,826.72	0.4***	85955.1**
DKS (w/o Google Interest)	1,246,790.78***	0.13	
DKS (w/ Google Interest)	-1,174,675.54**	0.12	38968.31***
EV (w/o Google Interest)	512,310.58***	0.41***	
EV (w/ Google Interest)	44,1947.98	0.42***	883.29
GPS (w/o Google Interest)	2,609,322.32***	0.43***	
GPS (w/ Google Interest)	426,065.06	0.41***	47980.93**
HD (w/o Google Interest)	5,870,569.89***	0.21	
HD (w/ Google Interest)	5,344,977.36***	0.18	13601.76
HPQ (w/o Google Interest)	17,743,397.61**	0.28*	
HPQ (w/ Google Interest)	-3,693,140.62	0.08	674538.98***
JCP (w/o Google Interest)	4,430,108***	0.68***	
JCP (w/ Google Interest)	-155,759.68	0.15*	323134.12***
LOW (w/o Google Interest)	558,349.27***	0.42***	
LOW (w/ Google Interest)	464,9445.24	0.41***	11998.26
P (w/o Google Interest)	3,469,315.71***	0.41***	
P (w/ Google Interest)	-3,386,505.07*	0.33***	130810.55***
PSEC (w/o Google Interest)	2,628,680.79***	0.15	
PSEC (w/ Google Interest)	194,408.87**	0.05	64528.53***
SHLD (w/o Google Interest)	651,166.94***	0.35**	
SHLD (w/ Google Interest)	-221,004.64	0.3**	19309.58***
SJM (w/o Google Interest)	365,644.65***	0.38***	
SJM (w/ Google Interest)	316,388.16**	0.38***	742.37
SPLS (w/o Google Interest)	7,872,009***	0.3**	
SPLS (w/ Google Interest)	-2,007,832.66	0.25**	240421.48***

*Appendix 1 shows the parameter estimates for volume using prior week's volume lag and Google interest data. ***, ** and * indicate significance at the 1%, 5% and 10% levels.*

Appendix 2: Price Model

Company and Model Used	Intercept	Lag of Closing Price	Google Interest
ANF (w/o Google Interest)	4.58*	0.9***	
ANF (w/ Google Interest)	1.14	0.89***	0.05
BBY (w/o Google Interest)	-0.2	1.03***	
BBY (w/ Google Interest)	-0.63	1.02***	0.01
DKS (w/o Google Interest)	12.89**	0.74***	
DKS (w/ Google Interest)	13.26**	0.75***	-0.01
EV (w/o Google Interest)	2.47*	0.94***	
EV (w/ Google Interest)	1.99	0.92***	0.02
GPS (w/o Google Interest)	1.07	0.98***	
GPS (w/ Google Interest)	1.53	0.98***	-0.01
HD (w/o Google Interest)	4.21*	0.94***	
HD (w/ Google Interest)	5.71**	0.89***	0.03**
HPQ (w/o Google Interest)	0.67	0.97***	
HPQ (w/ Google Interest)	1.29	0.96***	-0.01
JCP (w/o Google Interest)	1.63	0.9***	
JCP (w/ Google Interest)	5.24***	0.78***	-0.04***
LOW (w/o Google Interest)	1.42	0.97***	
LOW (w/ Google Interest)	2.7	0.97***	-0.02
P (w/o Google Interest)	0.24	0.99***	
P (w/ Google Interest)	-0.15	0.97***	0.01
PSEC (w/o Google Interest)	2.16**	0.8***	
PSEC (w/ Google Interest)	2.28**	0.8***	0
SHLD (w/o Google Interest)	6.33	0.87***	
SHLD (w/ Google Interest)	10.71***	0.88***	-0.1***
SJM (w/o Google Interest)	1.51	0.99***	
SJM (w/ Google Interest)	1.53	0.98***	0.01
SPLS (w/o Google Interest)	0.88	0.94***	
SPLS (w/ Google Interest)	1.39***	0.96***	-0.02***

*Appendix 2 shows the parameter estimates for price using prior week's price lag and Google interest data. ***, ** and * indicate significance at the 1%, 5% and 10% levels.*

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BIOGRAPHY

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