Google Search Volume Index:
Predicting Returns, Volatility and Trading Volume of Tech Stocks

Economics Honors Thesis 2015[1]

Xu Rui, Trinity'15

Faculty Advisor: Prof. Edward Tower

Duke University Economics Department

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Abstract

This paper investigates the efficacy of using Google Search Volume Index (SVI), a publicly available tool Google provides via Google Trends, to predict stock movements within the tech sector. Relative changes in weekly search volume index are recorded from April 2004 to March 2015 and correlated with weekly returns, realized volatility and trading volume of 10 actively traded tech stocks. Correlations are drawn for three different time periods, each representing a different stage of the financial business cycle, to find out how Search Volume Index correlates with stock market movements in economic recessions and booms. When the 10 stocks are aggregated, we find a strong positive correlation between Google SVI and weekly trading volume as well as stock returns across all 3 periods from 2004 to 2015. On aggregate, Google SVI is also positively correlated with weekly realized volatility, and this relationship grows significantly stronger over the 3 periods, presumably with the rise in popularity of Google search in recent years. These strong results on an aggregate level are tempered by the fact that individual stock movements exhibit greater variations in their relationships with Google SVI, and strong positive relationships are found only in about half of the stocks sampled. The regression model was also a better fit before and during the recession, suggesting the possibility of stronger "herding" behavior during those periods than in recent years.

1. Introduction

Asset-pricing models are traditionally based on the Efficient Market Hypothesis, an investment theory that postulates that it is impossible to gain abnormal returns because existing share prices incorporate all relevant information [Fama, 1998]. In order to obtain higher returns, investors would have to take on higher risks. In reality however, individual investors do not always have access to all the information they need, and instead selectively allocate their attention to stocks they are interested in and react to new information as they see fit [Kahneman, 1973]. This undermines the Efficient Market Hypothesis and suggests that investor attention plays a potentially significant role in asset movements in the stock market.

In 1987, Merton proposed a model of capital market equilibrium under incomplete information with the goal of explaining the remaining variation in stock returns [Merton, 1987]. Holding fundamentals constant, he demonstrated that a firm's value increases with increasing investor recognition. The investor recognition hypothesis has since become one of the most widely cited theories in the field. Despite subsequent studies on the theory, it has long remained notoriously difficult to properly quantify degrees of investors' attention. Researchers have used indirect proxies for investor attention, such as trading volume [Barber et al., 2008], news and headline counts as well as advertising expenses [Thomans et al., 2009]. In the paper *In Search of Attention* published in 2011, Zhi Da *et al.* point out that these proxies make the assumption that investors have necessarily paid attention to excess movements in the market or news items in the media. This may not be true especially in the information age, where consumers are increasingly bombarded with excess information [Da et al., 2011].

By 2004 however, the advent of the Internet and more importantly, the emergence of search engines have given data scientists a new means of directly tracking consumer behavior and trends. Even better, Google has made part of the search engine data they accrue available to the public, initially through Google Insights, which was later renamed Google Trends. Unlike previous proxies of investor attention, Google search volume quantifies proactive user quest for information on a specific topic, which translates directly to investor time and attention. Even more importantly, it quantifies the trends and behavior of individual retail investors, who rely heavily on search engines to obtain information for guiding their investments.

This thesis has two main objectives. Firstly, it intends to study the correlation between Google Search Volume Index and three key characteristics of 10 tech stocks – weekly returns, realized volatility and trading volume. Secondly, it aims to compare these correlations in the setting of three different time periods – (1) April 2004 to November 2007, (2) December 2007 to March 2009 and (3) April 2009 to March 2015. These periods were selected in accordance to business cycle dates provided by the National Bureau of Economic Research to represent the downward sloping, trough and upward sloping periods of the business cycle respectively, with adjustments made according to historical data of the NASDAQ and DOW indices. In particular, the differences in correlation behavior between stock prices and search volume in each period may reveal patterns of speculative and “herding” behavior in the years leading to the stock market crash.

High profile tech stocks were chosen for two primary reasons. Many of the companies are web-based or have a strong online presence, relying on a large Internet user group for both retail and marketing. Tech stocks in general have also received large amounts media attention on the Internet, especially with high profile IPOs in recent years for companies like Twitter and Alibaba. Assuming that individual retail investors are using search engines as an essential tool for investment research, it is reasonable to assume that retail investors in tech stocks are ever more likely to be relying on search engines. The 10 tech stocks in this study were chosen based on their high profile in the media and active trading volumes on NASDAQ. These stocks have amongst the highest active share volume by shares and/or dollar volume according to NASDAQ's March 2015 rankings, and are also household names in the tech sector.

2. Literature Review

In 2011, Da *et al.* proposed the use of Google Search Volume Index as a new and direct measure of investor attention. They sampled Russell 3000 stocks from 2004 to 2008, and found a correlation with existing proxies of investor attention. Google SVI was found to be a likely measure of retail investor attention, and captures it in a timelier manner than other proxies do. They also provided evidence that an increase in SVI predicted higher stock prices in subsequent weeks. The paper concluded that SVI increases first-day returns of IPOs but undermines long-run performance for a sample of IPO stocks. This finding aligns with that of a 2011 study done by Chemmanur and Yan, who found that a higher level of advertising growth is associated with higher contemporaneous stock returns but lower ex-post long run stock returns [Thomas et al., 2009].

These conclusions align largely with Merton's investor recognition theory. In 1987, Merton proposed the hypothesis that a security's value initially increases along with the degree of investor recognition of the security, measured as the number of investors who know about the security. He explained that if relatively few investors know about a particular security, the market can only clear if large undiversified positions on the security are taken by these investors, who would in turn expect a higher return to compensate them for the increased risk. Stock value would thus increase with the degree of investor recognition, but stock returns in equilibrium would in turn decrease as increased investor attention pushes the price to the point where future returns are small.

In 2014, Vozlyublennaia explored the link between Google search probability and performances of security indexes in broad investment categories. The paper found that a short-term increase in investor attention is followed by a significant short-term surge in index returns. The shock in returns would lead to a long-term increase in attention, which reduces investor speculations using information on lagged values or from values of a different index. This diminishes index volatility and ultimately improves market efficiency, hence offering evidence that a short-term increase in investor attention can increase market efficiency [Vozlyublennaia, 2014].

Google search intensity and its relationship with returns and trading volume have also been studied in the context of Japanese stocks. In a paper published by Takeda and Wakao in 2013, 189 Japanese stocks searched between 2008 and 2011 were studied. Search intensity was found to be strongly and positively correlated with trading volume and weakly but positively correlated with stock returns. They concluded that increases in Google search activity is likely to be associated with increases in trading activity, but not with raising stock prices. On the other hand, Curme, Peis, Stanley and Moat, in an article contributed in 2013, investigated links between Internet searches relating to politics or business and subsequent stock market movements [Curme et al, 2014]. In their study, they analyzed historic data from 2004 to 2012 and found that an increase in search volume for these topics precedes stock market falls.

One potential reason for this disparity may be the difference in search behavior of Japanese investors. Another obvious reason may be the date range of the data analyzed. Between 2004 and 2012 lies a period of economic recession and stock market crash from 2007-2008, and the increased volatility in that period is likely to have resulted in the dip in stock market following intense investor interest in the bad news. To account for the possibility of different behavioral links during different periods of the economy, this study breaks down the data into 3 periods – pre-recession, recession and post-recession respectively, relative to the 2007-2009 financial crisis.

A major challenge that has been recognized by past research lies in the definition of keywords used to query the search volume index. Takeda et al. made a list of abbreviations of company names and excluded words such as "Co", "Ltd", "Inc." and "Holdings" from their keyword search. Da. et al. used simple stock tickers as their query keyword, but noted the problems with using tickers with generic meanings like "GPS" and "DNA" and flagged those out. While past studies took such steps to optimize the choice of keywords, such processes have an inherent uncertainty. As Vozlyublennaia pointed out in her article, one cannot be certain that agents who search for company information use it to make trading decisions.

3. METHODOLOGY

3.1 CHOICE OF TECH STOCKS AND SEARCH TERMS

To minimize the above-mentioned uncertainties, this study chose 10 tech stocks from NASDAQ 100 with unambiguous tickers and high active trading volume. The former significantly reduces the uncertainty that agents are searching for company information or for the actual retail or web site. For instance, an Amazon shopper is less to type “AMZN” into the search field than to type “Amazon”. For the stocks used in the analysis, typing in their tickers also directly returns a summary of the stock information as the first Google search result, a further indication of the query keyword is likely to be used by potential investors. Stocks with tickers such as “ADI” or “AMAT” were not considered as they could refer to multiple companies or names. As such, we can reasonably make the assumption that users searching for “AMZN”, “GOOG”, “AAPL” and such are highly likely to be looking for stock information.

Stocks with high active trading volume guarantee a sizable pool of interested individual retail investors that are likely to seek information on these stocks. The stocks used in the analysis have, presently and historically, the highest active share and dollar volumes according to the official NASDAQ site. This provides us with a good sample size to observe variations in investor interest.

Table 1. List of stocks used and their active dollar volume listed on NASDAQ, April 2015

Company Name	Ticker	Search Term	Dollar Volume (Million)
Apple Inc.	AAPL	AAPL	$1,644.87
Amazon.com Inc.	AMZN	AMZN	$186.28
Baidu.com, Inc.	BIDU	BIDU	$232.99
Cisco Systems Inc.	CSCO	CSCO	$126.39
Gilead Sciences, Inc	GILD	GILD	$1088.43
Google Inc Class A	GOOGL	GOOGL	$231.90
Intel Corporation	INTC	INTC	$185.13
Microsoft Corporation	MSFT	MSFT	$314.96
Netflix, Inc.	NFLX	NFLX	1023.83
Qualcomm, Inc.	QCOM	QCOM	$759.55

3.2 Google Search Volume Index

Data is collected from Google Trends, a public web tool provided by Google that shows how often a specific search term is searched relative to the total search volume across the world, over a defined date range that the user inputs. This is quantified with Search Volume Index, which is calculated first using daily search interest and then normalized to control for the overall increase in number of Internet searches over time.

$$\boldsymbol{Search\ Interest} = \frac{\boldsymbol{\#\ queries\ for\ specific\ keyword}}{\boldsymbol{Total\ Google\ search\ queries}} \tag{1}$$

Each search interest data point is then divided by the highest point of interest for the specific keyword within the defined date range. Search interest is then indexed to values ranging from 0 – 100 on a relative scale, which allows us to gauge relative changes in search interest over that time period. Google Trends provides weekly data on the recorded indexes. For each data point, the SVI of the previous week is also recorded as *SVI_pre* in order to correlate changes in SVI with stock movements in the subsequent week.

$$\boldsymbol{Weekly\ Change\ in\ SVI} = \Delta\,\boldsymbol{SVI_w} = \boldsymbol{log}\left(\frac{\boldsymbol{SVI_w}}{\boldsymbol{SVI_{w-1}}}\right) \tag{2}$$

where SVI_w is the Google search volume index for week w.

3.3. Measuring Stock Market Activity

A series of metrics for measuring stock market activity are used for correlating with SVI. Data on daily open, close, high low and volume of the stocks are obtained from Yahoo! Finance. Weekly data were derived by consolidating consecutive trading weekdays on Excel and matched with the corresponding week in the Google data. I adjusted for stock splits in the calculation of derived values such as daily returns to avoid sudden spikes in stock return values.

3.3.1 Trading Activity

In order to measure trading activity, we measure average weekly traded volume. Average volumes are used instead of total trading volume because certain weeks only have 4 business days instead of 5, resulting in a lower total trading volume in that week simply because of fewer days of trading. Changes in trading volume across weeks are then calculated and natural log is taken to normalize the data.

$$\boldsymbol{Average\ trading\ Volume = ATV_w = \frac{\sum_n TV_t}{n}} \tag{3}$$

where ATV_w is the average trading volume for week *w, n* is the number of trading days and TV_t is the trading volume for day *t* in week *w.* Hence,

$$\boldsymbol{Weekly\ change\ in\ trading\ volume = \Delta\, ATV_w = log\left(\frac{ATV_w}{ATV_{w-1}}\right)} \tag{4}$$

3.3.2 Calculating Weekly Stock Returns

Daily returns are first calculated by taking the log of the ratio between closing prices of day *t* and day *t-1.* Weekly returns on a stock are measured by taking the natural log of the ratio of the closing price of the current week to the closing price of the week before.

$$\boldsymbol{Daily\ Returns = r_{t,w} = log\left(\frac{P_{close,t}}{P_{close,t-1}}\right)} \tag{5}$$

where $r_{t,w}$ is the daily returns of day t of week w and $P_{close,t}$ is the closing price for day t for a particular stock.

$$\boldsymbol{Weekly\ Returns = R_w = log\left(\frac{P_{close,w}}{P_{close,w-1}}\right)} \tag{6}$$

where R_w is the weekly returns for day t of week w and $P_{close,w}$ is the closing price of week *w.*

3.3.3 Realized Volatility

A popular measure of historical volatility is realized volatility, which measures the daily standard deviation of log returns of the stock over a defined period. According to NASAQ, while implied volatility refers to the market's assessment of future volatility, realized volatility measures what actually happened in the past. According to Andersen et al, realized volatilities and correlations show strong temporal dependence and are well described by long-memory processes. This makes it appropriate for our purpose of correlating it with SVI [Andersen et al., 2001].

$$\boldsymbol{Realized\ Volatility = RV_w = \sum_{t=1}^{n} {r_{t,w}}^2} \tag{7}$$

where $\boldsymbol{RV_w}$ is the realized volatility for week w, n is the number of trading days in week w and r_t is the daily log returns.

3.4 Time Periods

The regressions were run over 3 time periods, representing the years pre-recession, during the recession and post-recession respectively. This is to compare any potential differences in how stock market movements correlate to SVI according to the times. The time periods were selected based on data from the National Bureau of Economic Research on the month and year of peaks and troughs of the US business cycle. A cross comparison was drawn between these dates and trends in the NASDAQ price history over those years. Since Google was founded only in 2004, our data extends from April 2004 and ends on March 2015. Period 1 is defined as April 2004 to November 2007, period 2 as Dec 2007 to April 2009 and period 3 as May 2009 to March 2015.

Table 2. US Business Cycle by Month and Year. *(Duration measured in weeks.)*

Peak month	Trough month	Duration, peak to trough	Duration, trough to peak	Duration, peak to peak	Duration, trough to trough
Mar 2001	Nov 2001	8	120	128	128
Dec 2007	Jun 2009	18	73	91	81

Source: The National Bureau of Economic Research, 2015

Table 3. Breakdown of 3 time periods

Period	Period Start	Period End	Duration (Weeks)	Cycle Stage	Significance
1	Apr 2004	Nov 2007	191	Peak to Trough	Pre-recession
2	Dec 2007	Apr 2009	74	Trough	Recession
3	May 2009	Mar 2015	308	Trough to Peak	Post-recession

3.5 Regression Models

The following multivariate regressions were conducted for each of the 3 time periods. Correlations were drawn between SVI and each of trading volume, returns and volatility for the corresponding week. Regressions were run for all 10 stocks as an aggregate, and subsequently for each stock to investigate differences in relationships between SVI and stock movements between the 10 stocks.

3.5.1 Correlating Stock Price and Returns with SVI

Weekly returns are regressed against weekly changes in SVI, ΔSVI, to test for the relationship between changes in stock returns and search interest. Weekly realized volatility is included in the regression model as an explanatory variable for stock returns. Trading volume is excluded from the regression model as it is historically associated with volatility, and its inclusion would result in multicollinearity.

The absolute level of weekly search interest is also regressed with weekly closing price, as well as closing prices of the subsequent week. This tests for predictive properties of SVI towards future stock price movements.

$$\boldsymbol{R_{s,w} = \gamma_0 + \gamma_1 \Delta SVI_{s,w} + \gamma_2 RV_{s,w} + \zeta_{s,w}} \tag{8}$$

$$\boldsymbol{P_{close,s,w} = \theta_0 + \theta_1 SVI_{s,w} + \theta_2 RV_{s,w} + \kappa_{s,w}} \tag{9}$$

$$\boldsymbol{P_{close,s,w} = \rho_0 + \rho_1 SVI_{s,w-1} + \rho_2 RV_{s,w} + \epsilon_{s,w}} \tag{10}$$

where $R_{s,w}$ is the change in volume of stock *s* shares traded, $SVI_{s,w}$ is the Google search volume index for week *w,* and $RV_{s,w}$ is the realized volatility of stock *s* over week *w.*

3.5.2 *Correlating Trading Volume with SVI*

Changes in average trading volume are regressed with changes in search volume to see if a spike in search interest is correlated with a surge in trading volume.

$$\Delta\, \boldsymbol{ATV_{s,w}} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1}\Delta \boldsymbol{SVI_{s,w}} + \boldsymbol{\alpha_2 R_{s,w}} + \boldsymbol{\varepsilon_{s,w}} \tag{11}$$

where $\Delta\, ATV_{s,w}$ is the change in volume of stock *s* shares traded, $\Delta SVI_{s,w}$ is the Google search volume index for week *w,* $R_{intra,s,w}$ is the intra-week weekly return on stock *s* and $RV_{s,w}$ is the realized volatility of stock *s* over week *w.*

3.5.3 *Correlating Volatility with SVI*

Weekly realized volatility is regressed on changes in search volume to see if a spike in search interest is related to higher volatility in the stock pricing.

$$\boldsymbol{RV_{s,w}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\Delta \boldsymbol{SVI_{s,w}} + \boldsymbol{\beta_2}\Delta\, \boldsymbol{ATV_{s,w}} + \boldsymbol{\tau_{s,w}} \tag{12}$$

where $R_{s,w}$ is the change in share volume of stock *s* traded, $SVI_{s,w}$ is the Google search volume index for week *w,* $\Delta\, ATV_{s,w}$ is the change in volume of stock *s* shares traded and $RV_{s,w}$ is the realized volatility of stock *s* over week *w.*

4. Results and Discussion

4.1 Search Volume Index and Weekly Price and Returns

Table 4 shows the regression results of Equation (8) across the 3 time periods of interest. The regression was first run across the aggregation of all 10 stocks, AGG, to find a general trend. I aggregated by averaging returns and volatilities of the stocks. In all 3 periods, there was a positive partial correlation between weekly returns and change in Google Search Volume Index for the stocks in aggregate. For AGG in period 3 for instance, a 1% increase in the SVI holding realized volatility constant is associated with 0.744% increase in SVI, and this is significant at a 99% confidence level. However, during period 2 where the economy was at a trough, this correlation was the weakest, where SVI was a significant regressor only at the 90% confidence level. Weekly returns over this period were also observed to be strongly but negatively correlated with realized weekly volatility, which was consistent with the stock market movements during the financial market recession.

When model (8) is run on each of the individual stocks however, there is no clear pattern in the significance of correlations across periods. In periods 1 and 2, 4 out of the 10 stocks showed significant partial correlations between weekly returns and change in SVI. In period 3, this count rose marginally to 5 out of 10. All of them were positive partial correlations, except for Apple during period 2. Interestingly, Apple (AAPL) was the only stock to have a significant coefficient on *Change_SVI* across all 3 periods.

Table 4. Significant stocks

	Weekly Stock Returns					
PERIOD 1	**AGG**	**AAPL**	**CSCO**	**GOOGL**	**MSFT**	
Change_SVI	**0.688*** **	**1.931** **	**1.306*** **	**3.833*** **	**0.761** **	
	(0.220)	(0.773)	(0.386)	(1.317)	(0.314)	
Realized_Weekly_Vol	0.00135	0.000386	-0.0821***	0.0759***	-0.0487	
	(0.00534)	(0.0458)	(0.0308)	(0.0274)	(0.0346)	
Constant	0.153**	0.403	0.236*	0.131	0.128	
	(0.0673)	(0.344)	(0.137)	(0.193)	(0.103)	
Observations	1,674	190	190	170	190	
R-squared	0.006	0.040	0.068	0.095	0.033	
PERIOD 2	**AGG**	**AAPL**	**AMZN**	**BIDU**	**GILD**	
Change_SVI	**0.701* **	**-2.573* **	**2.173** **	**14.09** **	**3.903** **	
	(0.409)	(1.465)	(0.953)	(6.251)	(1.701)	
Realized_Weekly_Vol	-0.0291***	-0.0752***	-0.0354	-0.0608***	-0.00410	
	(0.00698)	(0.0236)	(0.0252)	(0.0184)	(0.0300)	
Constant	0.193	0.529	0.418	1.084	-0.00650	
	(0.139)	(0.414)	(0.515)	(0.689)	(0.339)	
Observations	729	73	73	73	73	
R-squared	0.024	0.202	0.081	0.164	0.070	
PERIOD 3	**AGG**	**CSCO**	**INTC**	**MSFT**	**NFLX**	**QCOM**
Change_SVI	**0.744*** **	**1.492*** **	**1.010*** **	**1.100*** **	**1.044** **	**0.987*** **
	(0.207)	(0.314)	(0.284)	(0.304)	(0.488)	(0.298)
Realized_Weekly_Vol	-0.0110**	-0.108***	0.0285	-0.161***	-0.00639	-0.151***
	(0.00554)	(0.0169)	(0.0392)	(0.0300)	(0.00810)	(0.0225)
Constant	0.145**	0.350***	0.0476	0.413***	0.406*	0.421***
	(0.0604)	(0.0989)	(0.113)	(0.0939)	(0.225)	(0.0983)
Observations	3,070	307	307	307	307	307
R-squared	0.004	0.125	0.054	0.094	0.016	0.130

Standard errors in parentheses; AGG = Aggregation of all 10 stocks
*** p<0.01, ** p<0.05, * p<0.1

4.1.1 "Herding Behavior"

The absolute value of weekly SVI directly gauges overall search interest in a particular stock relative to the time period. Table 5, summarizing the results for Equation (10), shows a strongly positive partial correlation between weekly closing price and the corresponding week's Google Search Volume Index for at least 6 of the 10 stocks in each period. This strong correlation also holds when weekly closing price is regressed against the previous week's SVI, SVI_pre, (summarized in Table 6) suggesting the potential for referencing past week's search interest in gauging the following week's stock prices. These results suggest that a higher level of Google search interest is correlated with a higher closing price in both the current and the following week. This aligns with Merton's investor recognition theory and provides evidence for his prediction that increased investor attention increases stock value.

For regression model (9), R^2 values range from 16.3% to 90.6% for the 7 stocks with significant coefficients in period 1, suggesting a fairly good fit for the model. In period 2, 8 out of the 10 stocks have significant partial correlations between weekly prices and SVI_pre, with most R^2 values between 35% and 45%. During this time, 9 out of 10 stocks have weekly closing price strongly correlated with the absolute level of search interest. By period 3 however, R^2 values range only from 0.2% to 43.1%. While there are many possibilities for this decrease in goodness of fit, this may hint at stronger herding behavior pre- and during-recession as opposed to post-recession.

Table 5. Significant stocks

				Log_Close						
PERIOD 1	**AGG**	**AAPL**	**AMZN**	**BIDU**	**CSCO**	**GILD**	**GOOGL**	**INTC**		
log_SVI	**0.464*** **	**0.448*** **	**0.430*** **	**1.357*** **	**0.180*** **	**0.406*** **	**0.793*** **	**-0.116*** **		
	(0.0338)	(0.0208)	(0.0590)	(0.0636)	(0.0252)	(0.0690)	(0.0205)	(0.0150)		
Realized_ Weekly_ Vol	0.000288	-0.0106***	0.00146	-0.00407***	-0.00321	-0.00710	0.00143	-0.000469		
	(0.00115)	(0.00330)	(0.00118)	(0.000701)	(0.00318)	(0.00538)	(0.00186)	(0.00253)		
Constant	2.202***	2.915***	2.191***	-0.226	2.489***	2.380***	2.779***	3.532***		
	(0.121)	(0.0639)	(0.216)	(0.229)	(0.0839)	(0.269)	(0.0821)	(0.0525)		
Observations	1,688	191	191	121	191	184	171	191		
R-squared	0.101	0.711	0.228	0.794	0.214	0.163	0.906	0.247		
PERIOD 2	**AGG**	**AAPL**	**BIDU**	**CSCO**	**GILD**	**GOOGL**	**INTC**	**MSFT**	**NFLX**	**QCOM**
log_SVI	**1.107*** **	**0.433*** **	**-1.308*** **	**0.375*** **	**0.185*** **	**-1.330*** **	**0.378*** **	**0.343*** **	**0.147** **	**0.240*** **
	(0.0709)	(0.0657)	(0.182)	(0.0577)	(0.0603)	(0.232)	(0.0700)	(0.0761)	(0.0613)	(0.0404)
Realized_ Weekly_ Vol	-0.00173	-0.0106***	-0.00234**	-0.0118***	-0.00332***	-0.00611***	-0.0130***	-0.00937***	-0.00264**	-0.00361***
	(0.00206)	(0.00182)	(0.00115)	(0.00181)	(0.000928)	(0.00214)	(0.00207)	(0.00200)	(0.00107)	(0.00127)
Constant	-0.0910	3.409***	11.11***	1.808***	3.100***	11.88***	1.714***	1.946***	2.955***	2.935***
	(0.268)	(0.234)	(0.775)	(0.204)	(0.262)	(1.002)	(0.241)	(0.291)	(0.204)	(0.135)
Observations	740	74	74	74	74	74	74	74	74	74
R-squared	0.251	0.454	0.472	0.518	0.249	0.367	0.426	0.312	0.115	0.345
PERIOD 3	**AGG**	**AAPL**	**AMZN**	**CSCO**	**GILD**	**GOOGL**	**NFLX**	**QCOM**		
log_SVI	**0.199*** **	**0.530*** **	**0.646*** **	**-0.148*** **	**-0.865*** **	**0.498*** **	**0.679*** **	**0.432*** **		
	(0.0297)	(0.0866)	(0.0430)	(0.0278)	(0.175)	(0.0389)	(0.0537)	(0.0329)		
Realized_ Weekly_ Vol	0.00421**	-0.0136	-0.0183***	0.000783	0.00506	-0.00448	-0.00907***	-0.0216***		
	(0.00191)	(0.0109)	(0.00248)	(0.00169)	(0.00348)	(0.00327)	(0.00128)	(0.00264)		
Constant	3.805***	3.989***	3.341***	3.536***	7.637***	4.317***	3.669***	2.524***		
	(0.108)	(0.282)	(0.136)	(0.0883)	(0.740)	(0.166)	(0.117)	(0.119)		
Observations	3,080	308	308	308	308	308	308	308		
R-squared	0.016	0.114	0.431	0.105	0.077	0.354	0.350	0.389		

Standard errors in parentheses; AGG = Aggregation of all 10 stocks

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

4.2 Search Volume Index and Weekly Traded Volume

Results presented in Table 9 show that across all 3 periods, an increase in SVI from the previous to current week is significantly correlated with a surge in trading volume over the week for 8 of the 10 stocks, where $\Delta \boldsymbol{SVI}_{s,w}$ is a significant predictor of change in average trading volume of stock *s* in week *w* at the 99% confidence level. This result is consistent with that of other studies, which found that if many people were searching for a company's stocks in one week, the volume of the company's shares traded for the following week would also increase.

4.3 Search Volume Index and Realized Volatility

In Table 10, we see that a strongly positive relationship between $\Delta \boldsymbol{SVI}_{s,w}$ and weekly realized volatility across the aggregated data becomes significant only from period 2. In periods 1 and 2, only 2 and 3 stocks had a significant and positive correlation between $\Delta \boldsymbol{SVI}_{s,w}$ and realized volatility. In period 3 however, 7 out of the 10 stocks showed a strong positive correlation between change in weekly Google SVI and realized volatility, with the coefficient on the aggregated level being significant at a 99% confidence level. This hints at the growing potential for SVI to be a good predictor of stock volatility, perhaps in a booming economy where the financial market is relatively more stable. This increase in the strength of SVI as a predictor may have also arisen from the increased use of Google search as a highly accessible source of stock information for common investors. We can also note the historically positive association between trading volume and volatility, with significantly positive correlations between the two variables for almost all the stocks in all periods.

5. CONCLUSION

This study introduces a novel approach to selecting stocks for studies on search volume, as it uses active trading volume and the appearance of stock ticker summary as the selection criteria for stocks. This serves to maximize the accuracy of using Google SVI as a measure of investor interest. This study also offers evidence on positive relationships between Google SVI and weekly traded volume, realized volatility and weekly close price for specifically actively traded stocks in the tech sector. The positive relationship between Google SVI and weekly returns is shown to be slightly more prevalent amongst the tech stocks during times of economic stability and boom. Furthermore, this study presents new evidence that Google SVI has become an increasingly significant predictor of realized weekly volatility in the stock market over the years. Results also suggest more significant “herding” behavior before and during the recession, than in the years after the recession. This may be a result of a less speculative market in the aftermath of the 2008 financial market crash.

There is likely to be increasingly prevalent research in this field as public tools for mining data become more widely available, but for the time being studies using Google Trends data can only test broad hypotheses. When Google SVI and weekly returns are contemporaneous in the regression model, it is impossible to predict weekly returns using SVI. This is because the predictive power of Google search volume depends largely on finding its correlation with stock movements in subsequent time periods. However, there remains the question of how much time lag there exists between fluctuations in search volume and observed subsequent changes in stock movements.

On an intuitive level, taking on a non-contemporaneous approach with weekly stock data and SVI is non-optimal, since investors are unlikely to wait a week between researching and making investment decisions. However, public data on Google search volume is only available as a weekly breakdown as of May 2015. Greater granularity in search data is therefore needed to improve the predictive power of Google SVI, such as data of daily or even hourly changes in search volume. This would allow us to more closely observe the relationship between search volume and stock movements, and determine the time lag between the two. Such studies would allow Google SVI to gauge market interests in a timelier manner, since investors are likely to make investment decisions within hours or days. We also have to note the possibility of non-stationary behaviors in shorter time series, which may include deterministic trends and cycles in both Google and stock data that can produce spurious forecasting. This can be avoided by applying detrending and differencing in future research. With increasing collaboration and availability of more granular data, researchers might just be able to predict movements in the notoriously complex stock market not too far into the future.

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APPENDIX

Table 6. Relationship between Weekly Returns and Change in SVI

	AGG	AAPL	AMZN	BIDU	CSCO	GILD	GOOGL	INTC	MSFT	NFLX	QCOM
					Close_Diff						
Period 1											
Change_SVI	**0.688*** **	**1.931** **	0.150	1.762	**1.306*** **	-0.252	**3.833*** **	0.522	**0.761** **	0.537	0.0217
	(0.220)	(0.773)	(0.756)	(1.773)	(0.386)	(1.122)	(1.317)	(0.363)	(0.314)	(0.705)	(0.538)
Realized_Weekly_Vol	0.00135	0.000386	0.0183	-0.0133	-0.0821***	0.0509	0.0759***	-0.219***	-0.0487	-0.00184	0.0937
	(0.00534)	(0.0458)	(0.0125)	(0.0113)	(0.0308)	(0.0785)	(0.0274)	(0.0364)	(0.0346)	(0.0186)	(0.0568)
Constant	0.153**	0.403	0.0217	0.716*	0.236*	-0.245	0.131	0.526***	0.128	0.0929	-0.221
	(0.0673)	(0.344)	(0.213)	(0.378)	(0.137)	(0.375)	(0.193)	(0.141)	(0.103)	(0.283)	(0.238)
Observations	1,674	190	190	120	190	182	170	190	190	125	127
R-squared	0.006	0.040	0.012	0.015	0.068	0.002	0.095	0.165	0.033	0.005	0.023
Period 2											
Change_SVI	**0.701***	**-2.573***	**2.173** **	**14.09** **	0.117	**3.903** **	2.077	-0.886	-0.684	1.340	-0.288
	(0.409)	(1.465)	(0.953)	(6.251)	(1.133)	(1.701)	(5.214)	(1.302)	(1.133)	(1.030)	(0.751)
Realized_Weekly_Vol	-0.0291***	-0.0752***	-0.0354	-0.0608***	-0.00475	-0.00410	0.0461	-0.0312	0.00741	-0.0266	0.0209
	(0.00698)	(0.0236)	(0.0252)	(0.0184)	(0.0307)	(0.0300)	(0.0280)	(0.0320)	(0.0258)	(0.0206)	(0.0251)
Constant	0.193	0.529	0.418	1.084	-0.160	-0.00650	-0.795*	-0.0411	-0.383	0.788	-0.180
	(0.139)	(0.414)	(0.515)	(0.689)	(0.386)	(0.339)	(0.414)	(0.445)	(0.367)	(0.529)	(0.368)
Observations	729	73	73	73	73	73	73	73	73	73	72
R-squared	0.024	0.202	0.081	0.164	0.000	0.070	0.040	0.030	0.006	0.033	0.011
Period 3											
Change_SVI	**0.744*** **	0.0900	0.214	-4.031	**1.492*** **	2.274	0.555	**1.010*** **	**1.100*** **	**1.044** **	**0.987*** **
	(0.207)	(0.993)	(0.327)	(5.471)	(0.314)	(1.392)	(3.864)	(0.284)	(0.304)	(0.488)	(0.298)
Realized_Weekly_Vol	-0.0110**	-0.0217	0.0501***	-0.171***	-0.108***	-0.0470*	0.0501	0.0285	-0.161***	-0.00639	-0.151***
	(0.00554)	(0.1000)	(0.0158)	(0.0536)	(0.0169)	(0.0250)	(0.0387)	(0.0392)	(0.0300)	(0.00810)	(0.0225)
Constant	0.145**	0.0497	0.00716	0.985**	0.350***	0.268*	-0.0636	0.0476	0.413***	0.406*	0.421***
	(0.0604)	(0.393)	(0.128)	(0.461)	(0.0989)	(0.156)	(0.157)	(0.113)	(0.0939)	(0.225)	(0.0983)
Observations	3,070	307	307	307	307	307	307	307	307	307	307
R-squared	0.004	0.000	0.052	0.037	0.125	0.019	0.006	0.054	0.094	0.016	0.130

Standard errors in parentheses; AGG = Aggregation of all 10 stocks

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

Table 7. Relationship between Weekly Close Price and Weekly SVI

	AGG	AAPL	AMZN	BIDU	CSCO	GILD	GOOGL	INTC	MSFT	NFLX	QCOM
					log_Close						
Period 1											
log_SVI	0.464***	0.448***	0.430***	1.357***	0.180***	0.406***	0.793***	-0.116***	0.00990	0.00914	-0.0102
	(0.0338)	(0.0208)	(0.0590)	(0.0636)	(0.0252)	(0.0690)	(0.0205)	(0.0150)	(0.0123)	(0.0388)	(0.0425)
Realized_Weekly_Vol	0.000288	-0.0106***	0.00146	-0.00407***	-0.00321	-0.00710	0.00143	-0.000469	0.00134	-0.00152***	-0.00521*
	(0.00115)	(0.00330)	(0.00118)	(0.000701)	(0.00318)	(0.00538)	(0.00186)	(0.00253)	(0.00238)	(0.000353)	(0.00314)
Constant	2.202***	2.915***	2.191***	-0.226	2.489***	2.380***	2.779***	3.532***	3.269***	3.122***	3.786***
	(0.121)	(0.0639)	(0.216)	(0.229)	(0.0839)	(0.269)	(0.0821)	(0.0525)	(0.0418)	(0.133)	(0.167)
Observations	1,688	191	191	121	191	184	171	191	191	128	129
R-squared	0.101	0.711	0.228	0.794	0.214	0.163	0.906	0.247	0.007	0.136	0.028
Period 2											
log_SVI	1.107***	0.433***	0.0976	-1.308***	0.375***	0.185***	-1.330***	0.378***	0.343***	0.147**	0.240***
	(0.0709)	(0.0657)	(0.0590)	(0.182)	(0.0577)	(0.0603)	(0.232)	(0.0700)	(0.0761)	(0.0613)	(0.0404)
Realized_Weekly_Vol	-0.00173	-0.0106***	-0.00798***	-0.00234**	-0.0118***	-0.00332***	-0.00611***	-0.0130***	-0.00937***	-0.00264**	-0.00361***
	(0.00206)	(0.00182)	(0.00139)	(0.00115)	(0.00181)	(0.000928)	(0.00214)	(0.00207)	(0.00200)	(0.00107)	(0.00127)
Constant	-0.0910	3.409***	3.999***	11.11***	1.808***	3.100***	11.88***	1.714***	1.946***	2.955***	2.935***
	(0.268)	(0.234)	(0.208)	(0.775)	(0.204)	(0.262)	(1.002)	(0.241)	(0.291)	(0.204)	(0.135)
Observations	740	74	74	74	74	74	74	74	74	74	74
R-squared	0.251	0.454	0.317	0.472	0.518	0.249	0.367	0.426	0.312	0.115	0.345
Period 3											
log_SVI	0.199***	0.530***	0.646***	-0.0710	-0.148***	-0.865***	0.498***	-0.0580	0.00371	0.679***	0.432***
	(0.0297)	(0.0866)	(0.0430)	(0.117)	(0.0278)	(0.175)	(0.0389)	(0.0415)	(0.0475)	(0.0537)	(0.0329)
Realized_Weekly_Vol	0.00421**	-0.0136	-0.0183***	-0.000680	0.000783	0.00506	-0.00448	-0.00245	-0.00539	-0.00907***	-0.0216***
	(0.00191)	(0.0109)	(0.00248)	(0.00492)	(0.00169)	(0.00348)	(0.00327)	(0.00530)	(0.00484)	(0.00128)	(0.00264)
Constant	3.805***	3.989***	3.341***	5.376***	3.536***	7.637***	4.317***	3.369***	3.421***	3.669***	2.524***
	(0.108)	(0.282)	(0.136)	(0.484)	(0.0883)	(0.740)	(0.166)	(0.144)	(0.168)	(0.117)	(0.119)
Observations	3,080	308	308	308	308	308	308	308	308	308	308
R-squared	0.016	0.114	0.431	0.002	0.105	0.077	0.354	0.010	0.005	0.350	0.389

Standard errors in parentheses; AGG = Aggregation of all 10 stocks

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

Table 8. Relationship between Weekly Close Price and SVI of Week before

	AGG	AAPL	AMZN	BIDU	CSCO	GILD	GOOGL	INTC	MSFT	NFLX	QCOM
						log_Close					
Period 1											
log_SVI_pre	**0.456*** **	**0.427*** **	**0.441*** **	**1.261*** **	**0.178*** **	**0.413*** **	**0.780*** **	**-0.119*** **	0.0109	-0.0375	-0.0358
	(0.0338)	(0.0220)	(0.0603)	(0.0752)	(0.0249)	(0.0686)	(0.0210)	(0.0148)	(0.0120)	(0.0406)	(0.0390)
Realized_Weekly_Vol	0.00664***	0.000961	0.00212*	-0.000168	0.00232	-0.00361	0.00239	-0.00453*	0.00157	-0.000266	-0.00534*
	(0.00170)	(0.00347)	(0.00119)	(0.000825)	(0.00314)	(0.00535)	(0.00190)	(0.00250)	(0.00232)	(0.00130)	(0.00309)
Constant	2.201***	2.919***	2.149***	0.0685	2.483***	2.340***	2.834***	3.551***	3.265***	3.267***	3.889***
	(0.122)	(0.0705)	(0.221)	(0.274)	(0.0847)	(0.269)	(0.0841)	(0.0530)	(0.0414)	(0.139)	(0.156)
Observations	1,678	190	190	120	190	183	170	190	190	127	128
R-squared	0.105	0.668	0.230	0.706	0.215	0.170	0.899	0.263	0.007	0.008	0.031
Period 2											
log_SVI_pre	**1.087*** **	**0.348*** **	-0.00609	**-1.359*** **	**0.320*** **	**0.124***	**-1.307*** **	**0.235*** **	**0.248*** **	0.0481	**0.230*** **
	(0.0709)	(0.0697)	(0.0581)	(0.176)	(0.0618)	(0.0634)	(0.233)	(0.0735)	(0.0767)	(0.0614)	(0.0405)
Realized_Weekly_Vol	0.00202	-0.00814***	-0.00725***	-0.00290**	-0.0103***	-0.00346***	-0.00603***	-0.00948***	-0.00730***	-0.00187*	-0.00255**
	(0.00205)	(0.00190)	(0.00137)	(0.00110)	(0.00193)	(0.000966)	(0.00212)	(0.00216)	(0.00201)	(0.00106)	(0.00128)
Constant	-0.0622	3.685***	4.355***	11.33***	1.988***	3.365***	11.77***	2.178***	2.294***	3.281***	2.958***
	(0.270)	(0.252)	(0.209)	(0.750)	(0.221)	(0.275)	(1.007)	(0.260)	(0.297)	(0.211)	(0.137)
Observations	729	73	73	73	73	73	73	73	73	73	72
R-squared	0.247	0.348	0.285	0.505	0.441	0.195	0.358	0.291	0.228	0.057	0.333
Period 3											
log_SVI_pre	**0.210*** **	**0.444*** **	**0.521*** **	-0.0883	**-0.149*** **	**-0.887*** **	**0.490*** **	-0.0687*	-0.0153	**0.516*** **	**0.340*** **
	(0.0300)	(0.0806)	(0.0437)	(0.116)	(0.0234)	(0.174)	(0.0390)	(0.0382)	(0.0424)	(0.0526)	(0.0345)
Realized_Weekly_Vol	0.00635***	0.00627	-0.00319	-0.000711	-0.00334**	0.00434	-0.00462	-0.00340	-0.00514	-0.00270**	-0.00978***
	(0.00193)	(0.0101)	(0.00252)	(0.00488)	(0.00142)	(0.00347)	(0.00328)	(0.00498)	(0.00431)	(0.00125)	(0.00276)
Constant	3.762***	4.231***	3.683***	5.448***	3.550***	7.734***	4.353***	3.410***	3.490***	3.949***	2.830***
	(0.110)	(0.270)	(0.143)	(0.482)	(0.0763)	(0.738)	(0.167)	(0.137)	(0.153)	(0.121)	(0.127)
Observations	3,070	307	307	307	307	307	307	307	307	307	307
R-squared	0.017	0.096	0.325	0.002	0.137	0.082	0.346	0.012	0.005	0.248	0.277

Standard errors in parentheses; AGG = Aggregation of all 10 stocks

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

Table 9. Relationship between Change in Trading Volume and Change in SVI

	AGG	AAPL	AMZN	BIDU	CSCO	GILD	GOOGL	INTC	MSFT	NFLX	QCOM
						Change_Volume					
Period 1											
Change_SVI	**0.231*** **	**0.323*** **	0.0247	**0.798*** **	**0.256*** **	**0.0914* **	0.0278	**0.156*** **	**0.157*** **	**0.415*** **	**0.188*** **
	(0.0142)	(0.0262)	(0.0592)	(0.107)	(0.0287)	(0.0497)	(0.103)	(0.0259)	(0.0275)	(0.0541)	(0.0348)
Close_Diff	**0.00805*** **	0.00284	0.0159***	0.0189***	-0.0141**	0.00311	0.0163***	-0.00530	0.0149**	0.00728	0.00630
	(0.00159)	(0.00271)	(0.00571)	(0.00599)	(0.00567)	(0.00333)	(0.00577)	(0.00508)	(0.00654)	(0.00731)	(0.00594)
Constant	-0.00198	-0.00242	-0.00177	-0.00779	0.000114	-0.00277	-0.00735	-0.000464	-0.000674	-0.00135	0.000984
	(0.00406)	(0.00889)	(0.0154)	(0.0219)	(0.00892)	(0.0120)	(0.0124)	(0.00827)	(0.00819)	(0.0194)	(0.0108)
Observations	1,674	190	190	120	190	182	170	190	190	125	127
R-squared	0.155	0.468	0.041	0.368	0.301	0.023	0.051	0.169	0.186	0.334	0.199
Period 2											
Change_SVI	**0.258*** **	**0.376*** **	**0.242*** **	**0.474*** **	**0.372*** **	-0.0246	-0.368	**0.273*** **	**0.345*** **	**0.288*** **	**0.133*** **
	(0.0154)	(0.0375)	(0.0326)	(0.171)	(0.0366)	(0.0881)	(0.259)	(0.0522)	(0.0395)	(0.039)	(0.0407)
Close_Diff	**-0.00656*** **	-0.00545*	-0.00116	-0.00956***	-0.00993**	-0.0119**	-0.00103	-0.00904*	-0.00646	-0.0015	-0.00589
	(0.0014)	(0.00285)	(0.004)	(0.00304)	(0.0039)	(0.00597)	(0.00582)	(0.00505)	(0.00425)	(0.00482)	(0.00655)
Constant	-0.0000337	-0.000898	0.00339	-0.00954	0.000653	0.00155	-0.00179	0.000602	0.000000521	0.00498	0.00167
	(0.0043)	(0.00826)	(0.0123)	(0.0146)	(0.00943)	(0.0137)	(0.0159)	(0.0135)	(0.0105)	(0.0173)	(0.0154)
Observations	729	73	73	73	73	73	73	73	73	73	72
R-squared	0.291	0.643	0.45	0.176	0.61	0.063	0.029	0.324	0.535	0.438	0.144
Period 3											
Change_SVI	**0.312*** **	**0.307*** **	**0.295*** **	**0.665*** **	**0.360*** **	0.0183	-0.331	**0.305*** **	**0.323*** **	**0.323*** **	**0.302*** **
	(0.00747)	(0.0153)	(0.0147)	(0.148)	(0.0171)	(0.0926)	(0.230)	(0.0215)	(0.0229)	(0.0134)	(0.0220)
Close_Diff	**-0.00203*** **	0.000722	-0.00287	-0.00201	-0.0147***	-0.00178	0.00254	-0.0124***	-0.00593	2.75e-05	-0.0226***
	(0.000704)	(0.000940)	(0.00289)	(0.00154)	(0.00341)	(0.00378)	(0.00341)	(0.00454)	(0.00450)	(0.00189)	(0.00428)
Constant	-0.000758	-0.00155	-0.000630	-0.00180	0.000816	-0.000329	-0.000565	0.000966	0.000525	-0.000659	0.000923
	(0.00220)	(0.00484)	(0.00561)	(0.00908)	(0.00552)	(0.00887)	(0.00799)	(0.00623)	(0.00615)	(0.00670)	(0.00661)
Observations	3,071	307	307	307	307	307	307	307	307	307	308
R-squared	0.362	0.571	0.573	0.070	0.596	0.001	0.009	0.398	0.396	0.658	0.407

Standard errors in parentheses; AGG = Aggregation of all 10 stocks

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

Table 10. Relationship between Weekly Realized Volatility and Change in SVI

	AGG	**AAPL**	**AMZN**	**BIDU**	**CSCO**	**GILD**	**GOOGL**	**INTC**	**MSFT**	**NFLX**	**QCOM**
						Realized_Weekly_Vol					
Period 1											
Change_SVI	0.462	1.537	4.271	23.86	**2.134****	0.864	2.324	**1.413****	**1.234***	0.958	0.710
	(0.985)	(1.377)	(3.503)	(15.15)	(0.931)	(0.943)	(3.427)	(0.650)	(0.664)	(3.557)	(0.840)
Change_Volume	27.79***	18.02***	44.75***	42.63***	10.64***	10.05***	13.99***	13.08***	7.230***	26.42***	9.222***
	(1.566)	(2.861)	(4.241)	(10.39)	(2.017)	(1.402)	(2.578)	(1.675)	(1.610)	(4.869)	(1.943)
Constant	4.835***	5.448***	6.610***	15.81***	2.535***	3.349***	4.043***	2.452***	1.368***	8.075***	3.049***
	(0.261)	(0.346)	(0.911)	(2.536)	(0.250)	(0.226)	(0.412)	(0.190)	(0.182)	(1.047)	(0.236)
Observations	1,674	190	190	120	190	182	170	190	190	125	127
R-squared	0.183	0.335	0.378	0.249	0.253	0.235	0.155	0.337	0.162	0.276	0.211
Period 2											
Change_SVI	**5.375****	12.21	-0.652	41.83	7.047	-0.341	19.24	**11.00****	5.015	**12.23***	2.154
	(2.458)	(11.59)	(5.78)	(39.92)	(6.679)	(6.656)	(21.31)	(5.356)	(7.382)	(7.233)	(3.782)
Change_Volume	23.92***	12.85	34.74**	53.66**	-3.927	16.46*	28.42***	11.8	10.83	24.68	14.66
	(5)	(23.07)	(16.17)	(25.79)	(13.63)	(9.067)	(9.7160)	(10.17)	(15.25)	(16.7)	(10.36)
Constant	11.71***	11.01***	14.36***	24.05***	8.375***	6.562***	9.515***	9.824***	8.589***	15.34***	9.458***
	(0.587)	(1.627)	(1.67)	(3.361)	(1.121)	(1.071)	(1.281)	(1.161)	(1.346)	(2.412)	(1.329)
Observations	729	73	73	73	73	73	73	73	73	73	72
R-squared	0.068	0.082	0.1	0.09	0.024	0.046	0.111	0.141	0.047	0.175	0.047
Period 3											
Change_SVI	**10.40*****	**2.056****	**6.916*****	4.126	**4.823*****	2.487	0.542	**1.358*****	**2.418*****	**30.13*****	**2.194*****
	(0.772)	(0.811)	(1.550)	(5.370)	(1.344)	(2.796)	(5.204)	(0.476)	(0.664)	(4.900)	(0.829)
Change_Volume	12.29***	4.260**	11.83***	17.15***	13.42***	16.62***	10.46***	4.511***	5.404***	10.58	9.484***
	(1.491)	(1.991)	(4.005)	(2.011)	(2.879)	(1.737)	(1.292)	(1.013)	(1.298)	(12.30)	(1.659)
Constant	3.952***	2.603***	4.291***	6.002***	2.748***	3.208***	2.139***	2.075***	1.897***	12.10***	2.363***
	(0.182)	(0.168)	(0.390)	(0.319)	(0.286)	(0.268)	(0.180)	(0.111)	(0.139)	(1.430)	(0.200)
Observations	3,070	307	307	307	307	307	307	307	307	307	307
R-squared	0.163	0.128	0.272	0.212	0.315	0.233	0.178	0.189	0.212	0.312	0.227

Standard errors in parentheses; AGG = Aggregation of all 10 stocks

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

Figure 1. Using NASDAQ trends to determine the 3 time periods

```
*do-file for STATA regressions

gen Change_SVI = log(SVI/SVI_pre)

gen log_SVI = log(SVI)

gen log_SVI_pre = log(SVI_pre)

gen Close_Diff = Close_Close_Diff*100

gen log_Close = log(Close)


*Eqn 1

reg Change_Volume Change_SVI Close_Diff

outreg2 using Change_Volume.xls, append


*Eqn 2a,b


reg log_Close log_SVI Realized_Weekly_Vol

outreg2 using Close.xls, append

reg log_Close log_SVI_pre Realized_Weekly_Vol

outreg2 using Close_pre.xls, append


*Eqn 3

reg Close_Diff Change_SVI Realized_Weekly_Vol

outreg2 using Close_Diff.xls, append


*Eqn 4a


reg Realized_Weekly_Vol Change_SVI Change_Volume

outreg2 using Realized_Weekly_Vol.xls, append
```