Small Investors' Internet Sentiment and Return Predictability

Antti Klemola[1]

January 18, 2018

Preliminary Draft

Abstract

We propose a novel and direct measurement of small investor sentiment in the equity market. We construct a weekly small investor sentiment that is based on the individual investors' internet search activity for search terms as "bear market" and "bull market". Unexpected increase in the search popularity of "bear market", is negatively associated with the next week's equity market returns. Unexpected increase in the spread (the difference in popularities between "bull market" and "bear market") is positively associated with the next week's equity market returns. We find that the effects are stronger for small-sized companies.

Keywords: Small Investor Sentiment, Internet Searches, Equity Market Returns, Return Predictability

[1] Antti Klemola. University of Vaasa, Department of Accounting and Finance, P.O. Box 700, FIN-65101, Vaasa, Finland. E-mail: antti.klemola@uva.fi

Traditionally an investor sentiment is measured by two alternative approaches. The first is the survey based investor sentiment approach, measured either from small investors[2] or more sophisticated investors[3]. These surveys are the likes of *Consumer Confidence*, *American Association of Individual Investor* (AAII) and *Investors Intelligence*. The second is market data based investor sentiment approach[4]. These are the likes of VIX, put-call ratio, a discount of closed-end funds and mutual funds flows. Several previous studies do find that the investor sentiment is related to contemporaneous and future stock market returns[5].

In this paper, we propose a novel and more direct measurement of small investor sentiment. We construct a weekly small investor sentiment based on the individual investors' internet search activity for such search terms as "bear market" and "bull market". We argue that our Small Investors' Internet Sentiment (SIIS) measures the current market view of individual investors' in more timely fashion. As Baker and Wurgler (2007) state in their study: "Now the question is no longer, as it was a few decades ago whether investor sentiment affects stocks prices, but rather how to measure investor sentiment and quantify its effects."

We find that unexpected change in our SIIS, when inferred from the search term "bear market", is negatively associated with next week's equity market returns. One-standard-deviation unexpected increase in the search volumes of "bear market" is associated with 17 (13) basis points lower return for small (large)-sized companies and 15 basis points lower size premium for the

[2] (see, e.g., De Bondt, 1993; Fisher and Statman, 2000; Brown and Cliff, 2004; Wang et al. 2006; Verma and Soydemir, 2006; Kurov, 2008; Verma and Verma, 2008)
[3] (see, e.g., Solt and Statman, 1988; Clarke and Statman, 1998; Fisher and Statman, 2000; Brown and Cliff, 2004; Kurov, 2008; Verma and Verma, 2008) .
[4] (see, e.g., Lee et al., 1991; Chen et al., 1993; Swaminathan, 1996; Neal and Wheatley, 1998; Elton et al., 1998; Whaley, 2000; Baker and Wurgler, 2000; Keim and Madhavan 2000; Simon and Wiggins III, 2001; Giot, 2005; Brown and Cliff, 2005; Cornelli et al. 2006; Frazzini and Lamont, 2008; Beaumont et al., 2008; Feldman, 2010; Ben-Rephael et al., 2012)
[5] (see, e.g Lee et al., 1991; Brown and Cliff, 2005; Kumar and Lee, 2006; Lemmon and Portniaquina, 2006; Baker and Wurgler 2006; Baker, Wang and Wurgler, 2008; Baker, Wurgler and Yuan, 2012; Stambaugh, Yu and Yuan, 2012)

forthcoming week. When the SIIS is the difference between the popularities of “bull market” and “bear market” (known as the spread onwards), the unexpected change in the SIIS is positively associated with the next week’s equity market returns. One-standard-deviation unexpected increase in the spread is associated with 13 (12) basis points higher equity market returns for small (large)-sized companies, and eight basis points higher size premium for the forthcoming week.

We find that when the large-sized companies are experiencing highly negative returns, the effect of unexpected change in SIIS on forthcoming returns of small-sized companies becomes stronger. That suggests that the small investors form their short-term investor sentiment more based on the high negative returns of large-sized companies. In other words, unexpected popularity of search term “bear market” increases contemporaneously with the high negative returns of large-sized companies. This unexpected pessimistic increase in the small investors’ equity market views then reflects more to the forthcoming returns of small-sized companies, as suggested by the classical noise trader model.

We also find that the unexpected changes in the SIIS contain more information that helps predicting the future equity market movements than unexpected changes in the AAII survey. Investors need lags of two to four weeks of unexpected changes in the SIIS to help forecasting next week’s equity market movements. Whereas, the investors need lags of four to six weeks of unexpected changes in AAII survey to help forecasting next week’s equity market movements. These results suggest that our SIIS measures the sentiment changes of small investors and its effect on equity market returns in more timely fashion.

Why should one then measure or at least be interested in the internet search-based investor sentiment instead of the more traditional ones? For example, Da, Engelberg, and Gao (2015) point out some important reasons why search-based sentiment might have an advantage over market-based and survey-based sentiments. First, the market-based sentiment might be the equilibrium outcome of many different economic forces and hence not purely reflect the current investor sentiment. Second, some survey-based sentiments are conducted on too low frequency, like on a monthly basis. Third, respondents of surveys might not answer truthfully to the survey questions, especially if the incentive for telling the truth is low. Finally, the search-based sentiment also reveals real attitudes than just inquires about them like the survey-based sentiments.

In recent years a new line of academic research has emerged from utilizing data from Google searches volumes, known as Google Search Volume Index (SVI). For example, Da, Engelberg, and Gao (2011) find a positive relationship between the SVI for stock tickers of Russell 3000 companies and their subsequent returns for the next two weeks. Da et al. (2011) also document that increased SVI for the stock tickers of IPO companies predict higher first-day IPO returns. Furthermore, Vozlyublennaia (2014) finds that the SVI is not only related to the performance of individual stocks but also to the performance of stock indices and commodities.

The previous studies that use the SVI consider themselves more as a market attention studies than an investor sentiment studies. Da, Engelberg, and Gao (2015) construct a market-level sentiment (known as FEARS) by aggregating the SVIs of such as “recession”, “unemployment” and “bankruptcy”. They find that increase in this market-level sentiment predicts return reversals, increasing volatility and mutual fund flows out from equity funds to bond funds.

The purpose of this paper is to extend the study of Da et al. (2015) more towards small investor sentiment in the equity market. Instead of using macroeconomic related search terms such as the “recession”, “unemployment” and “bankruptcy”, we use more equity market-related search terms such as "bear market" and "bull market". The choice of search words is chosen so that they are closely related to the terminology used in *AAII*'s survey questions. In the *AAII* survey, the investors are asked if they are bullish, neutral or bearish for the market movements for the next six months.

Our paper contributes to the existing literature in several ways. First, we propose a new and novel measurement of small investor sentiment. Second, we extend the idea of Da et al. (2015) more towards small investor sentiment in the equity market. Third, we analyze the effect of SVI has on small-sized companies and size premium especially. Previous studies that use the SVI focuses mainly on its effect on large stocks or stock indices. The SVI is being used to forecast or explain stock returns[6], volatility[7], trading activity[8] or liquidity[9]. Instead, our study also analyzes small-sized companies and size premium.

Theoretical Background

The theoretical background of our study is based on the two theories how the behavior of small investors can affect the equity market returns. The first theory is based on the sentiment of small investors and equity market returns. The second theory is based on market attention, related to Google searches, of small investors and equity market returns.

[6] (see, e.g., Da, Engelberg and Gao, 2011; Joseph, Wintoki and Zhang , 2011; Bank, Larch and Peter, 2011; Vozlyublennaia, 2014; Takeda and Wakao, 2014; Da, Engelberg and Gao, 2015; Klemola, Nikkinen and Peltomäki, 2016; Bijl, Kringhaug, Molnár and Sandvik, 2016; Tantaopas, Padungsaksawasdi and Treepongkaruna, 2016; Chen, 2017)
[7] (see, e.g., Vlastakis and Markellos, 2012; Aouadi, Arouri and Teulon, 2013; Vozlyublennaia, 2014; Da, Engelberg and Gao, 2015;Peltomäki and Vähämaa, 2015; Tantaopas, Padungsaksawasdi and Treepongkaruna, 2016; Peltomäki, Graham and Hasselgren, 2017)
[8] (see, e.g., Joseph, Wintoki and Zhang , 2011; Vlastakis and Markellos, 2012;Takeda and Wakao, 2014; Tantaopas, Padungsaksawasdi and Treepongkaruna, 2016)
[9] (see, e.g., Joseph, Wintoki and Zhang , 2011; Bank, Larch and Peter, 2011; Aouadi, Arouri and Teulon, 2013; Ding and Hou, 2015)

De Long, Shleifer, Summers, and Waldmann (1990) present a theory that the investor sentiment of so-called *noise traders* can affect on asset prices if more rational investors are unable to balance the asset prices due to the limits of arbitrage. Barber and Odean (2008) present a theory and find that individual investors are net buyers of attention-grabbing stocks, hence makes the price of such stocks to deviate from their more fundamental value. That causes the attention-grabbing stocks to face a liquidity shock as described by Campbell, Grossman, and Wang (1993). Yuan (2015) finds that the individual investors might not be just net buyers, but potentially also net sellers. Yuan (2015) argues that during market-wide attention events, the investors increase the attention they pay on their portfolio and rebalance it, which then leads to increased trading. In fact, Yuan (2015) finds that certain front-page news events can increase the selling orders from individual investors. Kumar and Lee (2006) also find that the small investors tend to trade in concert.

We now argue the following: First, past aggregate equity market returns grab small investors' attention. For example, terms such as "bear market" and "bull market" can be used the financial media that grab the attention of small investors. Second, the small investors then use Google to look for information of such terminology or the news related to them, causing an unexpected change in search volumes. Third, the small investors then form their short-term equity market sentiment based on the searched information on which they act on, whether to sell or buy to re-balance their current portfolio. Finally, this then causes irrational liquidity shock to the equity market, leading to negative or positive equity market movements. This effect should be stronger for small-sized companies since they tend to carry more noise-trading risk. The effect should also be stronger after extreme returns of large-sized companies, since those returns and their corresponding terminology are more likely to be reported in financial media that catches the attention of small investors.

Hypothesis

Based on the investor sentiment theory by De Long et al. (1990) and the SVI findings by Da et al. (2011), Vozlyublennaia (2014) and Da et al. (2015) we form the following hypothesis:

H1: Unexpected change in the SIIS, measured as the popularity of “bear market”, has a negative relationship with the next week’s equity market returns.

H2: Unexpected change in the SIIS, measured as the popularity of “bull market”, has a positive relationship with the next week’s equity market returns.

H3: Unexpected change in the SIIS, measured as the popularity difference (the spread) between “bull market” and “bear market”, has a positive relationship with the next week’s equity market returns.

H4: The effect of unexpected change in the SIIS is stronger for small-sized companies.

H5: The effect of unexpected change in the SIIS is stronger after periods of highly negative or positive returns.

Small Investor Sentiment and Equity Market Returns

Generally two investor sentiments are being considered as a small investor sentiment: The small investor sentiment survey conducted by the AAII and consumer confidence surveys. In fact, Fisher and Statman (2003) do find that the AAII survey and the consumer confidence surveys in the U.S move contemporaneously.

Fisher and Statman (2000) find that high (low) level of small investor sentiment (the AAII survey) during the present month is associated with negative (positive) returns for the S&P 500 index for the next month. However, they find no statistically significant association between the present level of small investor sentiment and the returns of small-cap stocks for the next month. They find no statistically significant results that the change of small investor sentiment would forecast the next month's returns.

Consistently with the Fisher and Statman (2000), also Schmeling (2007) find in more global setup (Germany, Europe, USA, and Japan) that the level of U.S. small investor sentiment is associated negatively with global stock market returns. Whereas, Verma and Soydemir (2006) come to the conflicting conclusion when they find that that one standard deviation increase in the U.S. small investor sentiment has a positive effect not only on U.S. stock market but also on U.K stock markets.

Contradicting the previously mentioned findings, Brown and Cliff (2004) find no evidence that either the level or change in the U.S. small investor sentiment is associated with future stock market returns.

An alternative proxy to measure the small investor sentiment is a consumer confidence. For example, Charoenrook (2003) finds that positive changes in the consumer confidence predict negative excess stock market returns on one-month and one-year time horizons in the U.S. also, Lemmon and Portniaquina (2006) find a negative linkage between lagged consumer confidence and small-stock premium with lags of 3, 6 12 months. They also find that lagged *excessive sentiment* (residuals when macroeconomic variables are regressed on consumer confidence) is negatively associated with future small-stock premium.

In more recent study Schmeling (2009) also finds a negative association with the consumer confidence and global stock market returns for the forecast horizons of 1, 6, 12 and 24 months. They also detect that the consumer confidence negatively correlated with the size premium for forecast horizon of one and six months. Whereas, Zouaoui, Nouyrigat, and Beer (2011) find that consumer confidences in Europe and the United States positively affects for the probability of stocks market crises within a one-year period.

Otoo (1999) and Jansen and Nahuis (2003) present contradicting results since they do not find any statistically significant association between the present consumer confidence and future stock market returns in the U.S. or Europe.

Where the relation between the present small investor sentiment (AAII/consumer confidence) and future stock market returns is inconclusive, the relation between lagged or contemporaneous stock market returns and the present small investor sentiment (AAII/consumer confidence is more consistent). Results from De Bondt (1993), Fisher and Statman (2000), Brown and Cliff (2004) and Verma and Verma (2008) suggest that the U.S small investor sentiment (AAII) is affected by past stock market returns. Whereas, Otoo (1999) and Jansen and Nahuis (2003) find that the consumer confidence is affected by lagged or contemporaneous stock market returns.

Google Search Volumes and Stock Returns

Da et al. (2011) propose a new and alternative method to measure investor attention by using Google Search Volume Index (SVI) for stock tickers of Russell 3000 stocks. They state that using the SVI as a proxy of investor attention has two main arguments. First, the investors use the Google to collect and search information. Second, and more critically, Google searches are materialized investor attention; if you google it, you are paying attention to it.

Da et al. (2011) find that abnormal increase in the SVI for stock tickers predicts positive stock returns for Russell 3000 companies within the next two weeks. The abnormal increase in SVI is associated with 0.3 % characteristic-adjusted outperformance during the next two weeks. Also, as a robustness check, Da et al. (2011) also find that higher SVI for the stock tickers is associated with higher first-day returns for IPO companies. The IPO companies with the highest abnormal SVI a week before the listing day outperform the lowest abnormal SVI companies as much as by 6 % during the IPO-day.

Joseph, Wintoki and Zhang (2011) form quintiles portfolios of S&P 500 companies based on their stock ticker SVI. They find that the quintile portfolio with the highest SVI has statistically significant weekly risk-adjusted (by market, size, value, and momentum) alpha of 0.04 %. Also, they report that the zero-cost portfolio (the highest SVI minus the lowest SVI portfolio) also has statistically significant positive risk-adjusted weekly alpha of 0.03 %.

Bank, Larch, and Peter (2011) extend the topic to German stock market. They construct a double-sorted zero-cost portfolio that goes long on high SVI companies with high market value and short on low SVI companies with low market value for one month. They find that the alpha of such portfolio is positive (0.77 % per month) and significant, even after controlling for market, size, value and momentum factors. Also, Bank, Larch, and Peter (2011) find that a double-sorted zero-cost portfolio that goes long on high SVI companies with low market-to-book ratio and short on low SVI companies with high market-to-book ratio yields a monthly alpha of 1.9 %, even after controlling the market, size, value and momentum factors. However, Bank, Larch, and Peter (2011) note that performances of such portfolios deteriorate quickly if positions are held longer than few months.

Takeda and Wakao (2014) extend the topic to Japan stock market. They also find that the quartile portfolio that holds stocks with the highest SVI yields positive risk-adjusted (by market, size, and value) alpha. However, the risk-adjusted alpha between the highest and the lowest SVI portfolios is not statistically significant as reported by Joseph, Wintoki, and Zhang (2011) and Bank, Larch and Peter (2011) for the USA and German stock markets.

However, in the study by Bijl, Kringhaug, Molnár, and Sandvik (2016) with the more recent date they find that that high SVI for companies predicts lower future excess returns for the next 1 to 3 weeks. Although the difference compared to the previous studies could be due to the standardization of SVI.

Instead of the SVI for individual stocks, Vozlyublennaia (2014) focuses more on broader markets such as market indices, commodities, and bonds. They find that generally the high SVI for market indices (S&P 500, Dow and NASDAQ) forecast negative market returns for the next one to two weeks. Although, return reversal will materialize within a month. Also, Chen (2017) find a negative association between the SVI and global stock market returns.

Tantaopas, Padungsaksawasdi, and Treepongkaruna (2016) test the linkage between the SVI and future stock market index movements in more global aspect. They find that the SVI effects the future market index movements in most analyzed stock markets within the next three weeks. Although, they conclude that the causality is more one-way, from returns to the SVI. They also report that there is no consistent difference between the developed and developing markets.

Data and methodology

The data used in this study are obtained from several sources. We begin by briefly describing the data and then continue by the discussing the construction of SIIS.

Data

The data for an annual Google search volumes are downloaded from Google Trends.[10] The search terms used in this study are "bear market" and "bull market". Furthermore, the popularity of searches is limited to cover only the United States and its finance-related searches. The search volumes are scaled to range from 0 to 100, where zero represents a low relative popularity, and 100 represents a high relative popularity for given search terms during the week in question. [11]

Data for different size portfolio returns are downloaded from Kenneth R. French Data Library[12]. The size portfolios are divided into bottom 30 %, middle 40 %, and top 30 % companies by market equity. Although, in empirical analysis only returns from bottom 30 % and top 30 % companies are used.

---

[10] The data is available at: https://trends.google.com/trends/
[11] In total, the data set consists of 704 weekly observations, from 1/4/2004 to 6/25/2017.
[12] The data is available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

For the set of control variables, we follow the Da et al. (2015) study. For volatility and "fear gauge" control variable we use the Chicago Board Options Exchange volatility index (VIX)[13]. For macroeconomic condition control variable, we use the ADS index developed by Aruoba, Diebold, and Scotti (2009). [14] The ADS contains information on several seasonally adjusted macroeconomic activities, like weekly initial jobless claims, monthly payroll employment, industrial production, real gross domestic product, etc. On average, the ADS has a value of zero. Values below zero indicate worse-than-average conditions and values above zero indicate better-than-average macroeconomic conditions. As a control variable for economic uncertainty, we use US Economic Policy Uncertainty Index (EPU). [15] It is developed by Baker, Bloom, and Davis (2016) and is based on newspaper coverage frequency of policy-related economic news. In other words, what type of policy-related economic news and how extensively they are reported in the US newspapers. As an additional control variable, we also use US Equity Market Uncertainty Index (EMU).[16] The methodology is closely related to the US Economic Policy Uncertainty Index. Instead of measuring the policy-related economic news, the US Equity Market Uncertainty Index measures news more related to equity markets. As an additional investor sentiment variable, this study uses sentiment data of American Individual Investors survey[17].

The construction of SIIS

[13] The VIX data is downloaded from Datastream.
[14] The data is available at https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index.
[15] The data ís available at http://www.policyuncertainty.com/us_daily.html.
[16] The data ís available at http://www.policyuncertainty.com/equity_uncert.html.
[17] The AAII survey data is downloaded from Datastream.

We use the relative search popularity of Google search terms “bear market” and “bull market” to construct a Small Investor Internet Sentiment, SIIS. In this study, we use three alternative methods to calculate the SIIS. In the first two methods the relative popularity of search terms “bear market” and “bull market” are used as standalone variables for the SIIS. It should measure how pessimistic (bear market) or optimistic (bull market) investors currently are. This approach should closely follow the method used in more classical investor sentiment surveys, where participated investors are asked whether they are bullish, bearish or neutral for future stock market movements. For example, Fisher and Statman (2000) use a percentage of bullish investors as their investor sentiment.

In the third method, we use the difference, or the spread, between the relative popularities of search terms “bull market” and “bear market”. It should indicate if investors are currently more bullish or bearish. For example, Brown and Cliff (2004) and Verma and Soydemir (2006), Schmeling (2007), Verma and Verma (2008) use the difference between bullish and bearish investors as their investor sentiment.

We model the SIIS into two separate components; expected SIIS and unexpected SIIS. To capture the unexpected SIIS, we follow the method as applied by Peltomäki, Graham, and Hasselgren (2017), who use the residuals from AR(1) process to capture an unexpected Google search volumes for a given search term at the certain time.

We model the AR(1) process as:

(1) $$\mathrm{SIIS}_{j,t} = c_j + \rho \mathrm{SIIS}_{j,t-1} + u_{j,t} ,$$

where $SIIS_{j,t}$ is the Google Search Volume Index at time t for a given search term j. c_j is the constant for search term j, $SIIS_{j,t-1}$ is the lagged Google Search Volume Index for search term j. $u_{j,t}$ is the residual for the search term j.

We define the expected level SIIS as:

(2) $$E[SIIS_{j,t}] = c_i + \rho SIIS_{j,t-1},$$

and we define unexpected SIIS as:

(3) $$UE[SIIS_{j,t}] = u_{j,t}$$

The descriptive data of study is presented in table one. From the table, we can see that on average value for search term "bull market" is higher than it is for the "bear market". The same can also be said for the AAII survey, on average more investors are bullish than bearish. The expected SIIS/AAII (E[SIIS]/E[AAII]) seems closely to follow the process of original time series, as suggested by the low values of unexpected SIIS/AAII (UE[SIIS]/UE[AAII]). The unexpected component of investor sentiments varies only from -0.03 to 0.04 on average[18].

[Table 1 Descriptive Statistics]

[18] None of the average UE[.] values differ from zero with statistical significance.

To test the possible interdependencies between equity market returns and the unexpected SIIS, we employ vector autoregressive models as in Vozlyublennaia (2014). The estimated models are following:

(4) $R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS]_{j,t-g} + e_{i,t}$

(5) $UE[SIIS]_{j,t} = c_j + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{t=g}^{4} \gamma_g UE[SIIS]_{j,t-g} + e_{j,t},$

where $R_{i,t}$ is the return of size portfolio i at time t. $UE[SIIS_{j,t}]$ is the unexpected Small Investor Internet Sentiment at time t inferred from search term j. c_i is the constant, $R_{i,t-s}$ are the lagged returns of given size portfolio i. $UE[SIIS_{j,t-g}]$ are the lagged UE[SIIS]s inferred from given search term j. In addition to the vector autoregressive model, we also conduct pairwise Granger causality tests to empirically analyze if the lagged unexpected SIIS or equity market returns contain some information that helps to predicting the future equity market returns or the unexpected SIIS. In addition, we conduct pairwise Granger causality tests between the equity market returns and unexpected components of AAII survey to test if our unexpected SIIS measure is able to forecast future equity market returns in more timely-fashion.

If the lagged returns affect on investor sentiment, as previous studies suggest[19], we account this effect by including an interaction term between lagged returns and the UE[SIIS]. Bearish (bullish) sentiment should have stronger effect after highly negative (positive) equity market returns. For example, if ongoing week's returns are highly negative (positive) it should associate with the

[19] (see, e.g., De Bondt , 1993; Brown and Cliff, 2004; Verma and Verma, 2008; Vozlyublennaia, 2014)

unexpected increase in popularity of search term “bear market” (“bull market”). This increased bearish (bullish) small investor sentiment then leads to negative (positive) equity market returns for the following week. In light of in Vozlyublennaia (2014), we perform following regression model with a closely similar set of control variables as used by Da et al. (2015).

$$(6) \qquad R_{i,t} = C_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS_{j,t-g}] + \sum_{l=1}^{4} \lambda_l UE[SIIS_{j,t-l}] * D(R_{i,t-l}) + \sum_{h=1}^{4} \nu_h Control_{h,t-1} + e_{i,t} \,,$$

where $R_{i,t}$ is the return of size portfolio i at the time t and $R_{i,t-s}$ are its lagged returns. $UE[SIIS_{j,t-g}]$ denotes the lagged UE[SIIS]s inferred from the search term j. Coefficient λ measures the interaction between the lagged portfolio returns and the lagged UE[SIIS]. The set of control variables are the Aruoba-Diebold-Scotti (ADS) business conditions index, a news-based measure of equity market uncertainty index (EMU), a news-based measure of economic uncertainty index (EPU) and CBOE volatility index (VIX). The estimated coefficient λ measures how the contemporaneous returns effects on the magnitude of UE[SIIS]. $D(R_{i,t-l})$ is dummy variable for the 10 % decile of lowest or highest weekly returns.

Results

We begin our analysis by first estimating the dynamic relationships between the returns of different size portfolios and the UE[SIIS]. We then continue our analysis by conditioning the effect of UE[SIIS] on lagged portfolio returns.

Statistical causality between the unexpected changes in SIIS and equity market returns

Table two presents estimates from vector autoregressive model (see equations 4 and 5) for the UE[SIIS] that is formed on the popularity of search term “bear market”. We find that the one-week lagged unexpected SIIS is negatively associated with next week’s returns for both size portfolios. The estimated coefficients vary from -0.03 to -0.02, the effect being stronger for the small-sized companies. This is further supported by the negative estimated coefficient for the lowminushigh (LMH) portfolio[20]. These results indicate that one unit increase in the unexpected popularity of Google search term “bear market” forecasts two to three basis points lower equity market returns for the forthcoming week. However, the initial negative shock of unexpected SIIS on the equity market returns is counterbalanced after four weeks.

[Table 2 VAR (Bear Market)]

When analyzing the effects that the past equity market returns have on the UE[SIIS], we find no statistically significant evidence that the previous week’s equity market returns are associated with the UE[SIIS].

Table three presents estimates from vector autoregressive model for the UE[SIIS] that is formed based on the popularity of search term “bull market”. We do not find that the unexpected SIIS has any predictive power over future equity market returns. We do however find some weak evi-

[20] Formed by subtracting the returns of top 30 % companies by market equity from returns of bottom 30 % companies by market equity .

dence that past equity market returns, with lags of two to three weeks, affect negatively to the unexpected popularity of search term “bull market”.

[Table 3 VAR (Bull Market)]

Table four presents estimates from vector autoregressive model for the UE[SIIS] that uses the difference between the popularity of search terms “bull market” and “bear market”, also known as the spread. We find a positive and statistically significant estimated coefficient for the unexpected SIIS with one-week lag when regressed on returns of different size portfolios. The estimated coefficients vary from 0.02 to 0.01. Also in this case, the effect seems to be stronger for the small-sized companies, as indicated by the statistically significant estimated positive coefficient for the LMH portfolio. These results indicate that unexpected increase (decrease) in the spread forecasts positive (negative) equity market returns for the forthcoming week. Also, just like in the case of “bear market” UE[SIIS], the spread UE[SIIIS] has a return reversal after four weeks.

[Table 4 VAR (Spread)]

When analyzing the effect that the past returns have on the unexpected spread, we find that returns with one (two) weeks lag are positively (negatively) associated with the UE[SIIS] inferred from the spread.

To test the potential causality between the unexpected SIIS and the equity market returns, we employ Granger causality test. Table five presents the results from pairwise Granger causality tests between the portfolio returns and the UE[SIIS]s inferred from “bear market”, “bull market” and the spread.

[Table 5 Pairwise Granger Causality tests]

The results reported in table five suggest that both UE[SIIS]s inferred from either “bear market” or from the spread have some predictive power over future equity market returns. The results are consistent with whether we use the UE[SIIS] information either from the previous two or four weeks. The UE[SIIS] inferred from “bear market” also has predictive power for the LMH portfolio. The UE[SIIS] inferred from “bull market” does not contain any information that helps to predict future equity market movements.

As a robustness check, the investor sentiments based on the percentage of bearish AAII’s survey respondents and the AAII’s survey spread contain information that helps to predict the future equity market returns, but only with the lags of four weeks.[21] Either of the AAII investor sentiment measurements does not contain information that helps to predict the size premium. Hence, the results suggest that the unexpected component of SIIS, which is based on the search popularity of “bear market” or the spread, do perform better compared to the more classical AAII’s investor sentiment. Especially, in the context how many weekly lags have to be used for the forecastings.

[21] The statistical significance is higher with lags up to six weeks. These results are available upon request.

The effect of UE[SIIS] on portfolio returns conditional on past returns.

We now focus more on detail how the UE[SIIS] effects on the future equity market returns when conditioned on past equity market returns. For example, it can be argued, that contemporaneous negative equity market returns increase the search popularity of search term “bear market”, which then leads to increase in UE[SIIS] inferred from “bear market”. That then potentially leads to negative equity market returns for the forthcoming week. Thus the effect of UE[SIIS] inferred from “bear market” on future equity market returns should be stronger after highly negative equity market returns. To account this effect, we include interaction coefficients between the lagged UE[SIIS] and the lagged returns. Also, we use a model with a dummy variable for those weeks when the equity market returns belong to the lowest or the highest decile of returns.

Table six reports coefficient estimates when the UE[SIIS] is inferred from the search term “bear market”. In general, the results from model l are consistent with the previously reported findings and suggest that the UE[SIIS] with one-week lag is negatively and statistically significantly associated with next week’s equity market returns. The estimated coefficients for UE[SIIS] are varying from -0.0260 to -0.015, being larger for small-sized companies. As suggested by the LMH portfolio that has a negative and statistically significant coefficient. That indicates that one-standard-deviation increase in the UE[SIIS] forecast 17 (small companies) to 13 (large companies) basis points lower equity market returns for the forthcoming week, and 15 basis points lower size premium. As also suggested by the previous finding, the return reversal occurs after four weeks.

As previously argued, the popularity of search term “bear market” should increase contemporaneously with negative equity market returns. For this reason, we focus on model 2 to analyze the interaction term between the UE[SIIS] and negative equity market returns (the lowest decile of weekly returns). First, the estimated coefficient for UE[SIIS] itself remains negative and statistically significant for the small-sized companies, but not for large-sized companies. Second, the interaction term is negative and statistically significant only for large-sized companies. That indicates that the previously found negative association between the UE[SIIS] and next week's equity market returns of large-sized companies is mainly driven by the interaction term of lagged UE[SIIS] and preceding week's low returns. The estimated interaction term for the large-sized companies is -0.051. That indicates that one-standard-deviation increase in the UE[SIIS], contemporaneously with negative equity market returns, predicts 16 (nine) basis points lower equity market returns for the forthcoming week.

The estimated coefficient for UE[SIIS] on returns of small-sized companies is -0.022 and statistically significant, whereas the estimated interaction term is not statistically significant. The small-sized companies are also more affected by the UE[SIIS] as a standalone variable, as suggested by the negative and statistically significant estimated coefficient for LMH portfolio. These results indicate that one-standard-deviation increase in the UE[SIIS] is associated with 14 basis points lower returns for small-sized companies for the forthcoming week, and 15 basis points lower size premium for the next week.

Together these findings suggest that the returns of small companies are more prone to the unexpected changes in the popularity of search term "bear market" as a standalone variable. Whereas the large-sized companies are only affected by the unexpected changes in popularity of search term "bear market" during periods of low equity market returns.

[Table 6 UE[Bear Market] OLS]

Table seven reports result when the UE[SIIS] is formed on the popularity of search term "bull market". The results from model 1 are consistent with the previously reported findings and suggest that the UE[SIIS] is not statistically significantly related to next week's equity market returns on any of the size portfolios. When the UE[SIIS] is conditioned on the highest decile of returns (model 2), we find either no statistically significant relationship between the UE[SIIS] and forthcoming equity market returns.

[Table 7 UE[Bull Market] OLS]

Table eight reports result when the UE[SIIS] is formed on the spread, the difference between popularities of "bull market" and "bear market". For the model 1, we find positive and statistically significant estimated coefficients for the UE[SIIS], with a one-week lag, for both size portfolios and for the LMH portfolio. A one-standard-deviation increase in the UE[SIIS] is associated with 13 (small-sized companies) to 11 (large-sized companies) basis points higher returns for the forthcoming week[22]. The effect of UE[SIIS] on equity returns is larger for the small-sized companies, as suggested by the positive and statistically significant estimated UE[SIIS] coefficient for the LMH portfolio. A one-standard-deviation increase in the UE[SIIS] forecasts eight basis

[22] From "bear market" perspective, one-standard-deviation decrease is associated with 13 to 11 basis points lower returns for the forthcoming week.

points higher size premium for the next week. As in the case of “bear market” UE[SIIS], we find return reversal after four weeks.

When the UE[SIIS] is conditioned on the decile of lowest returns (model 2), we find statistically significant positive interaction term between the UE[SIIS] and the returns for both portfolios. This finding indicates that the effect of UE[SIIS] on future returns is stronger by magnitude after a week of negative returns. The effect is stronger for the large-sized companies. As the interaction term indicates that one-standard-deviation increase in UE[SIIS], contemporaneously with negative equity market returns, is associated with 17 (large-sized companies) to nine (small-sized companies) basis points higher return for the forthcoming week.

The estimated coefficients for the UE[SIIS] itself are positive and statistically significant for the small-sized companies, but not for the large-sized companies. That implies that one-standard-deviation increase in the UE[SIIS] is associated with eight (small-sized companies) basis points higher returns for the forthcoming week, and ten basis points higher size premium for the next week.

This finding is similar that we previously found for the UE[SIIS] that is inferred from the popularity of search term “bear market”. The association between the UE[SIIS] and future equity market returns is stronger and more robust for the small-sized companies. Whereas, the effect of UE[SIIS] on large-sized companies is generally limited to those weeks that follow the weeks of negative returns.

[Table 8 UE[Spread] OLS]

As the previous findings suggest, the forthcoming returns of small-sized companies are more affected by the UE[SIIS], when the SIIS is inferred either from “bear market” or the spread. Also, the UE[SIIS] affects only to the forthcoming returns of large-sized companies when conditioned on past highly negative returns. One could argue that small investor form their short-term sentiment SIIS more based on the past returns of large-sized companies, which are also more likely to be reported in the financial media. This SIIS is then reflected more to the forthcoming returns of small-sized companies, as suggested by the traditional noise trader model. In table nine, we test this relation when we condition the UE[SIIS] on the past highly negative returns of large-sized companies.

Table nine reports result when the UE[SIIS] is conditioned on the lowest decile of returns of large-sized companies. The interaction term between the UE[SIIS] and return of small-sized companies is negative and statistically significant when the UE[SIIS] is inferred either from the “bear market” or the spread. These results implies that the UE[SIIS] has an even stronger effect on the forthcoming returns of small-sized companies when the large-sized companies have experienced relatively high negative returns.

Hence, it can be argue that the channel how the UE[SIIS] affects on future returns of small-sized companies stems from the low contemporaneous correlation of returns of large-sized companies and the UE[SIIS]. In other words, the relatively high negative returns, bear market, of large-size companies is being reported in the financial media and catch small investors attention. Then the small investors use Google to search related information more in detail. Based on the searched information, the small investors form their short-term sentiment and rebalance their portfolios.

[Table 9]

Conclusions

Da et al. (2011) proposed an alternative method to capture investors' attention in the equity market by utilizing data from Google search volumes. They find that this market attention captured by Google Search Volume Index (SVI) is related to future stock market returns. To be more precise, increase search volumes for stock tickers of Russell 3000 index companies predicts a higher return for the next two weeks. They also link this relationship also to the first-day returns for IPO-companies.

Instead of using Google search volume data to only measure investors' market attention, Da et al. (2015) highlighted several reasons why search-based investor sentiment might be a better alternative to measure the investor sentiment than more classical market-based or survey-based investor sentiments. Hence Da et al. (2015) construct a market-level sentiment (FEARS) from a set of search terms and their popularity in Google searches. They find that this FEARS-sentiment is negatively associated with contemporaneous stock market returns and predicts positive stock market returns for the next two days. They also conclude that the FEARS forecasts increasing volatility and mutual fund flow from bond mutual funds to equity mutual funds.

The purpose of this paper is to extend the Da et al. (2015) study more towards small investor sentiment. Da et al. (2015) use more search terms related to the macroeconomic condition, such as "recession", "unemployment" and "inflation rate", whereas we focus more towards the equity market condition. We choose the set of search words so that they are closely related to the terminology used in the AAII survey for individual investors. The search terms we use are "bear market" and "bull market". Based on the popularities of those search terms, we construct a novel and new small investor sentiment, Small Investor's Internet Sentiment (SIIS).

We find that unexpected change in pessimism of small investors, measured as popularity of Google search term "bear market", is negatively associated with next week's equity market returns. One-standard-deviation unexpected increase in the search volumes of "bear market" is associated with 17 (13) basis points lower return for small (large)-sized companies and 15 basis points lower size premium for the forthcoming week.

When the SIIS measured as the difference between the popularities of "bull market" and "bear market" (spread), the unexpected change is positively associated with the next week's equity market returns. One-standard-deviation unexpected increase in the spread is associated with 13 (12) basis points higher equity market returns for small (large)-sized companies, and eight basis points higher size premium for the forthcoming week.

We argued that the effect of UE[SIIS] on next week's equity market returns is stronger by magnitude when financial media or other sources report news to capture small investors' attention. Terminologies as "bull market" or "bear market" are more likely to be used during periods of high or low equity market returns. Which then reflects to Google search volumes, made by the small investors. This then reflects more to the future returns of small-sized companies that carry more of so-called noise-trader risk.

We find that when the large-sized companies are experiencing low returns, the effect of unexpected change in SIIS, inferred from "bear market" or the spread, on the forthcoming returns of small-sized companies is stronger. That suggests that the small investors form their short-term investor sentiment more based on the low returns of large-sized companies. In other words, unexpected popularity of search term “bear market” increases contemporaneously with the low returns of large-sized companies. This unexpected pessimistic increase in the small investors’ equity market views then reflects more to the forthcoming returns of small-sized companies, as suggested by the classical noise trader model.

The findings also suggest that our SIIS measures the small investor sentiment in more timely-fashion than the more traditional AAII survey. Making the unexpected changes in the SIIS to be more associated with the forthcoming equity market returns in short time-horizon. Based on the results, we can accept hypothesis numbers 1, 3, 4 and 5. We reject the hypothesis number 2.

References

Aouadi, A, M. Arouri and F. Teulon. 2013. “Investor attention and stock market activity: Evidence from France.” *Economic Modelling*, vol. 35, no. 1 (September): 674-681.

Aruoba, S., F. Diebold and C. Scotti. 2009. “Real-time measurement of business conditions.” *Journal of Business & Economic*, vol. 27, no.4 (4^{th} issue): 417-427.

Baker, M. and J. Wurgler. 2000. “The Equity Share in New Issues and Aggregate Stock Returns.” *The Journal of Finance*, vol. 55, no. 5 (October): 2219-2257.

Baker, M. and J. Wurgler. 2006. “Investor Sentiment and the Cross-Section of Stock Market Returns.” *The Journal of Finance*, vol.61, no.4 (August): 1645-1680.

Baker, M. and J. Wurgler. 2007. “Investor Sentiment in the stock market.” *Journal of Economic Perspective*, vol.21, no.2 (Spring): 129-151.

Baker, M., J. Wang and J. Wurgler 2008. “How Does Investor Sentiment Affect the Cross-Section of Returns.” *Journal of Investment Management*, vol.6, no.2 (Second Quarter): 57-72.

Baker, M., J. Wurgler and Y. Yuan. 2012. “Global, Local, and Contagious Investor Sentiment.” *The Journal of Financial Economics*, vol.104, no.2 (May): 272-287.

Bank, M., M. Larch and G. Peter. 2011. “Google search volume and its influence on liquidity and return of German stocks.” *Financial Markets and Portfolio Management*, vol.25, no.3 (September): 239-264.

Baker, S., N. Bloom and S. Davis. 2016. “Measuring Economic Policy Uncertainty.” *The Quarterly Journal of Economics*, vol.131, no.4 (November): 1593-1636.

Barber, B. and T. Odean. 2008. “All That Glitters: The Effect of Attention and News on the Buying of Individual and Institutional Investors.” *The Review of Financial Studies*, vol.21, no.2 (April): 785-818.

Beaumont, R., M. van Daele, B. Frijns, T. Lehnert and A. Muller. 2008. “Investor Sentiment, Mutual Fund Flows and Its Impact on Returns and Volatility.” *Managerial Finance*, vol.34, no.11 (Issue 11): 772-785.

Ben-Rephael, A., S. Kandel and A. Wohl. 2012. “Measuring Investor Sentiment with Mutual Fund Flows.” *The Journal of Financial Economics*, vol.104, no.2 (May): 363-382.

Bijl, L., G. Kringhaug, P. Molnár and E. Sandvik. 2016. “Google searches and stock returns.” *International Review of Financial Analysis*, vol.45, no.1 (May): 150-156.

Brown, G. and M. Cliff. 2004. “Investor sentiment and the near-term stock market.” *Journal of Empirical Finance*, vol.11, no.1 (January): 1-27.

Brown, G. and M. Cliff. 2005. "Investor Sentiment and Asset Valuation." *Journal of Business,* vol.78, no.2 (March): 405-440.

Campbell, J., S. Grossman and J. Wang. 1993. "Trading Volume and Serial Correlation in Stock Returns." *Quarterly Journal of Economics*, vol.108, no.4 (November): 905-939.

Charoenrook, A. 2005. "Does Sentiment Matter?" *Unpublished Working Paper*.

Chen, N-F., R. Kan and M. Miller. 1993. "Are the Discounts on Closed-End Funds a Sentiment Index?" *The Journal of Finance,* vol.48, no.2 (June): 795-800.

Chen, T. 2017. "Investor Attention and Global Stock Returns." *Journal of Behavioral Finance,* vol.18, no.3 (Issue 3): 358-372.

Clarke G. and M. Statman. 1998. "Bullish or Bearish?" *Financial Analysts Journal*, vol.54, no.3 (May/June): 63-72.

Cornelli, F., D. Goldreich and A. Ljungqvist. 2006. "Investor Sentiment and Pre-IPO Markets." *The Journal of Finance,* vol.61, no.3 (May): 1187-1216.

Da, Z., J. Engelberg, and P. Gao. 2011. "In Search of Attention." *The Journal of Finance,* vol.66, no.5 (September): 1461-1499.

Da, Z., J. Engelberg, and P. Gao. 2015. "The Sum of All FEARS Investor Sentiment and Asset Prices." *The Review of Financial Studies*, vol.28, no.1 (January): 1-32.

De Bondt, W. 1993. "Betting on Trends: Intuitive Forecasts of Financial Risk and Return." *International Journal of Forecasting*, vol.9, no.3 (November): 355-371.

De Long, J., A. Shleifer, L. Summers and R. Waldmann. 1990. "Noise Trader Risk in Financial Markets." *Journal of Political Economy*, vol.98, no.4 (August): 703-738.

Ding, R. and W. Hou. 2015. "Retail investor attention and stock liquidity. *Journal of International Financial Markets, Institutions & Money*, Vol.37, (July): 12-26.

Elton, E. J., M. J. Gruber and J. A. Busse. 1998. "Do Investors Care about Sentiment." *The Journal of Business,* vol.71, no.4 (October): 477-500.

Feldman, T. 2010. "A More Predictive Index of Market Sentiment." *The Journal of Behavioral Finance*, vol.11, no.4 (Issue 4): 211-223.

Fisher, K. and M. Statman. 2000. "Investor Sentiment and Stock Returns." *Financial Analysts Journal*, vol.56, no.2 (March/April): 16-23.

Fisher, K. and M. Statman. 2003. "Consumer Confidence and Stock Returns." *The Journal of Portfolio Management*, vol. 30, no.1 (Fall): 115-127.

Frazzini, A. and O. A. Lamont. 2008. “Dumb Money: Mutual Fund Flows and the Cross-section of Stock Returns.” *The Journal of Financial Economics*, vol.88, no.2 (May): 299-322.

Giot, P. 2005. “Relationships Between Implied Volatility Indexes and Stock Index Returns.” *The Journal of Portfolio Management*, vol.31, no.3 (Spring): 92-100.

Jansen, W. and N. Nahuis. 2003. “The Stock Market and Consumer Confidence: European Evidence.” *Economic Letters*, vol.79, no.1 (April): 89-98.

Joseph, K., M. Wintoki, and Z. Zhang. 2011. “Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search.” *International Journal of Forecasting*, vol.27, no.4 (October-December): 1116-1127.

Keim, D. and A. Madhavan. 2000. “The Relation between Stock Market Movements and NYSE Seat Prices.” *The Journal of Finance*, vol.55, no.6 (December): 2817-2840.

Klemola, A., J. Nikkinen and J. Peltomäki. 2016. “Changes in Investors’ Market Attention and Near-Term Stock Market Returns.” *Journal of Behavioral Finance*, vol.17, no.1 (Issue 1): 18-30.

Kumar, A. and C. Lee. 2006. “Retail Investor Sentiment and Return Comovements.” *Journal of Finance*, vol.61, no.5 (October): 2451-2486.

Kurov, A. 2008. “Investor Sentiment, Trading Behavior and Informational Efficiency in Index Futures Markets.” *The Financial Review*, vol.43, no.1 (February): 107-127.

Lee, C., A. Shleifer and R. Thaler. 1991. “Investor Sentiment and the Closed-End Fund Puzzle.” *The Journal of Finance*, vol.46, no.1 (March): 75-109.

Lemmon, M. and E. Portniaguina. 2006. “Consumer Confidence and Asset Prices: Some Empirical Evidence.” *The Review of Financial Studies*, vol.19, no.4 (December): 1499-1529.

Neal, R. and S. Wheatley. 1998. “Do Measures of Investor Sentiment Predict Returns?” *Journal of Financial and Quantitative Analysis*, vol.33, no.4 (December): 523-547.

Otoo, M. 1999. “Consumer Sentiment and The Stock Market.” *FEDS Working Paper*.

Peltomäki, J. and E. Vähämaa. 2015. “Investor attention to the Eurozone crisis and herding effects in national bank stock indexes.” *Finance Research Letters*, 14, (August): 111-116.

Peltomäki, J., M. Graham and A. Hasselgren. 2017. “Investor attention to market categories and market volatility: The case of emerging markets.” *Research in International Business and Finance*, Forthcoming.

Schmeling, M. 2007. “Institutional and individual sentiment: Smart money and noise trader risk?” *International Journal of Forecasting*, vol.23, no.1 (January-March): 127-145.

Schmeling, M. 2009. “Investor Sentiment and Stock Returns: Some International Evidence.” *Journal of Empirical Finance*, vol.16, no.3 (June): 394-408.

Simon, D. and R. Wiggins III. 2001. “S&P Futures Returns and Contrary Sentiment Indicators.” *The Journal of Futures Markets*, vol.21, no.5 (May): 447-462.

Solt, M. and M. Statman. 1988. “How Useful is the Sentiment Index.” *Financial Analysts Journal*, vol.44, no.5 (September-October): 45-55.

Stambaugh, R. F., J. Yu, and Y. Yuan. 2012. “The Short of It: Investor Sentiment and Anomalies.” *The Journal of Financial Economics*, vol.104, no.2 (May): 288-302.

Swaminathan, B. 1996. “Time-Varying Expected Small Firm Returns and Closed-End Fund Discounts.” *The Review of Financial Studies*, vol.9, no.3 (July): 845-887.

Tantaopas, P., C. Padungsaksawasdi and S. Treepongkaruna. 2016. “Attention effect via intern search intensity in Asia-Pacific stock markets.” *Pacific-Basin Finance Journal*, vol.38, (June); 107-124.

Takeda, F. and T. Wakao. 2014. “Google search intensity and its relationship with returns and trading volume of Japanese stocks.” *Pacific-Basin Finance Journal*, vol.27, (April): 1-18.

Verma, R. and G. Soydemir. 2006. “The Impact of U.S. Individual and Institutional Investor Sentiment on Foreign Stock Markets.” *The Journal of Behavioral Finance*, vol.7, no.3 (Issue 3): 128-144.

Verma, R., and P. Verma. 2008. “Are Survey Forecasts of Individual and Institutional Sentiments Rational?” *International Review of Financial Analysis*, vol.17, no.5 (December): 1139-1155.

Vlastakis, N. and R. Markellos. 2012. “Information demand and stock market volatility.” *Journal of Banking & Finance*, vol.36, no.6 (June): 1808-1821.

Vozlyublennaia, N. 2014. “Investor attention, index performance, and return predictability.” *Journal of Banking & Finance*, vol.41, (April): 17-35.

Wang, Y.-H., A. Keswani and S. Taylor. 2006. “The Relationships between Sentiment, Returns and Volatility.” *International Journal of Forecasting*, vol.22, no.1 (January-March): 109-123.

Whaley, R. 2000. “The Investor Fear Gauge.” *The Journal of Portfolio Management*, vol.26, no.3 (Spring): 12-17.

Yuan, Y. 2015. “Market-wide attention, trading, and stock returns.” *Journal of Financial Economics*, vol.116, no.3 (June): 548-564.

Zouaoui, M., G. Nouyrigat and F. Beer. 2011." How Does Investor Sentiment Affect Stock Market Crises? Evidence from Panel Data." *The Financial Review*, vol.46, no.4 (November): 723-747.

Table 1. Descriptive statistics.

	N	Mean	Std.Dev	Min	Max
SIIS					
SIIS_Bear	704	40.04	23.06	0.00	100.00
E[SIIS_Bear]	704	40.00	12.44	18.46	72.37
UE[SIIS_Bear]	704	0.04	19.42	-58.34	73.57
SIIS_Bull	704	49.21	20.95	0.00	100.00
E[SIIS_Bull]	704	49.23	8.19	29.98	69.08
UE[SIIS_Bull]	704	-0.02	19.29	-59.30	56.91
SIIS_Spread	704	9.16	28.00	-92.00	89.00
E[SIIS_Spread]	704	9.22	11.90	-33.82	43.14
UE[SIIS_Spread]	704	-0.06	25.37	-97.30	81.38
AAII					
AAII_Bear	704	33.21	9.39	10.10	70.27
E[AAII_Bear]	704	33.18	6.65	16.81	59.43
UE[AAII_Bear]	704	0.03	6.64	-19.07	24.86
AAII_Bull	704	38.19	9.09	16.50	69.50
E[AAII_Bull]	704	38.22	6.30	23.18	59.91
UE[AAII_Bull]	704	-0.03	6.58	-17.86	26.90
AAII_Spread	704	4.98	16.72	-51.35	56.20
E[AAII_Spread]	704	5.04	11.34	-33.15	39.73
UE[AAII_Spread]	704	-0.06	12.33	-41.78	45.60
Portfolio Returns					
Low 30	704	0.163	3.07	-18.04	13.80
Med 40	704	0.193	2.89	-19.97	14.50
High 30	704	0.161	2.33	-21.94	10.87
LMH	704	0.002	1.41	-4.48	7.26
Control Variables					
VIX	704	18.73	9.14	9.75	79.13
ADS	704	-0.32	0.78	-4.08	0.93
EPU	704	123.78	71.61	19.34	472.47
EMU	704	44.82	55.72	7.46	823.76

This table reports the descriptive statistics for all the variables used in this study. SIIS_Bear, SIIS_Bull are Google search volumes for “bear market” and “bull market” search terms. SIIS_Spread is the difference between search volumes for the “bull market” and “bear market” search terms. AAII is the survey of American Association of Individual Investors. AAII_Bear (AAII_Bull) is the percentage of respondents who are bearish (bullish) on their market view for the next six months. AAII_Spread is the difference between AAII_Bull and AAII_Bear. E[.] is the expected search volume for given search term using AR(1) process. UE[.] is the unexpected search volume for given search term using AR(1) process, i.e., the residual. Low 30, Med 40 and High 30 are portfolio returns for the bottom 30 %, middle 40 % and top 30 % companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. VIX is the CBOE Volatility Index. ADS is the Aruoba-Diebold-Scotti Business Conditions Index. EPU is the news based Economic Policy Uncertainty index. EMU is the news based Equity Market Uncertainty index. The data is in weekly form from 4/1/204 to 6/25/2017.

Table 2. Vector Autoregressive estimates between the unexpected changes in "bear market" popularity and equity market returns.

	Low 30		High 30		LMH	
	UE [$SIIS_t$]	R_t	UE [$SIIS_t$]	R_t	UE [$SIIS_t$]	R_t
Intercept	-0.03	0.15	-0.08	0.18	0.03	-0.01
	(-0.04)	(1.32)	(-0.10)	(2.00)	(0.04)	(-0.11)
UE[$SIIS_{t-1}$]	-0.15	**-0.03**	-0.16	**-0.02**	-0.15	**-0.01**
	(-4.05)	(-4.24)	(-4.14)	(-3.33)	(-3.96)	(-3.75)
UE[$SIIS_{t-2}$]	0.08	0.00	0.08	0.00	0.08	-0.00
	(2.08)	(0.10)	(2.13)	(0.80)	(2.12)	(-1.51)
UE[$SIIS_{t-3}$]	0.22	0.01	0.23	0.01	0.21	-0.00
	(5.99)	(1.19)	(6.13)	(1.73)	(5.74)	(0.09)
UE[$SIIS_{t-4}$]	0.14	**0.02**	0.114	**0.01**	0.14	**0.01**
	(3.83)	(3.45)	(3.82)	(2.84)	(3.63)	(2.97)
R_{t-1}	-0.09	-0.01	-0.24	-0.08	0.25	-0.03
	(-0.40)	(-0.28)	(-0.79)	(-2.03)	(0.50)	(-0.66)
R_{t-2}	0.08	0.04	0.31	0.04	-0.38	0.03
	(0.36)	(1.00)	(1.02)	(1.16)	(-0.76)	(0.92)
R_{t-3}	**0.44**	-0.07	**0.66**	-0.08	0.32	0.01
	(1.89)	(-1.89)	(2.15)	(-2.23)	(0.64)	(0.27)
R_{t-4}	-0.09	0.03	-0.10	-0.01	-0.01	-0.02
	(-0.40)	(0.85)	(-0.32)	(-0.23)	(-0.19)	(-0.49)
Adj. R^2	0.070	0.034	0.073	0.033	0.067	0.019
F-Stat	7.60	4.08	7.89	3.99	7.25	2.71

This table reports estimates from following vector autoregressive models:

$$\mathrm{UE}[\mathrm{SIIS}_{j,t}] = c_j + \sum_{s=1}^{4} \beta_s R_{i,t-1} + \sum_{t=g}^{4} \gamma_g \mathrm{UE}[\mathrm{SIIS}_{j,t-g}] + e_{j,t}$$

$$R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g \mathrm{UE}[\mathrm{SIIS}_{j,t-g}] + e_{i,t}$$

where $SIIS_{i,t}$ is the Google Search Volume Index at time t for a search term "bear market". $R_{i,t}$ is the return for given size portfolio at time t. UE[.] is the unexpected search volume for the search term "bear market" using AR(1) process, i.e., the residual. Low 30 is the portfolio consisting of the bottom 30 % companies by market equity. High 30 is the portfolio consisting of the top 30 % companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. The data is in weekly form from 4/1/204 to 6/25/2017. T-stats are reported in parentheses.

Table 3. Vector Autoregressive estimates between the unexpected changes in “bull market” popularity and equity market returns.

	Low 30		High 30		LMH	
	UE $[SIIS_t]$	R_t	UE $[SIIS_t]$	R_t	UE $[SIIS_t]$	R_t
Intercept	-0.13	0.16	-0.16	0.18	-0.12	-0.01
	(-0.19)	(1.33)	(-0.22)	(2.02)	(-0.17)	(-0.11)
$UE[SIIS_{t-1}]$	-0.09	-0.00	-0.09	0.00	-0.09	-0.00
	(-2.29)	(-0.27)	(-2.28)	(0.22)	(-2.42)	(-1.23)
$UE[SIIS_{t-2}]$	0.11	-0.00	0.11	-0.00	0.12	-0.00
	(3.03)	(-0.43)	(2.92)	(-0.31)	(3.15)	(-0.63)
$UE[SIIS_{t-3}]$	0.12	0.00	0.12	0.00	0.12	-0.00
	(3.21)	(0.31)	(3.31)	(0.61)	(3.26)	(-0.30)
$UE[SIIS_{t-4}]$	0.13	-0.00	0.13	-0.00	0.13	0.00
	(3.60)	(-0.46)	(3.61)	(-0.61)	(3.53)	(0.15)
R_{t-1}	0.34	0.00	0.33	-0.06	0.59	-0.02
	(1.49)	(0.08)	(1.09)	(-1.65)	(1.17)	(-0.42)
R_{t-2}	**-0.42**	0.04	**-0.59**	0.04	-0.32	0.04
	(-1.83)	(0.93)	(-1.95)	(1.05)	(-0.63)	(0.92)
R_{t-3}	-0.14	-0.09	0.10	-0.10	**-0.98**	0.01
	(-0.60)	(-2.31)	(0.34)	(-2.62)	(-1.95)	(0.14)
R_{t-4}	0.31	0.01	0.38	-0.03	0.41	-0.02
	(1.36)	(0.39)	(1.25)	(-0.66)	(0.81)	(-0.62)
Adj. R^2	0.049	-0.001	0.049	0.008	0.048	-0.007
F-Stat	5.54	0.92	5.45	1.72	5.39	0.40

This table reports estimates from following vector autoregressive models:

$$UE[SIIS_{j,t}] = c_j + \sum_{s=1}^{4} \beta_s R_{i,t-1} + \sum_{t=g}^{4} \gamma_g UE[SIIS]_{j,t-g} + e_{j,t}$$

$$R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS]_{i,t-g} + e_{i,t}$$

where $SIIS_{i,t}$ is the Google Search Volume Index at time t for a search term “bull market”. $R_{i,t}$ is the return for given size portfolio at time t. UE[.] is the unexpected search volume for the search term “bull market” using AR(1) process, i.e., the residual. Low 30 is the portfolio consisting of the bottom 30 % companies by market equity. High 30 is the portfolio consisting of the top 30 % companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. The data is in weekly form from 4/1/204 to 6/25/2017. T-stats are reported in parentheses.

Table 4. Vector Autoregressive estimates between the unexpected changes in the spread and equity market returns.

	Low 30		High 30		LMH	
	UE [$SIIS_t$]	R_t	UE [$SIIS_t$]	R_t	UE [$SIIS_t$]	R_t
Intercept	-0.10	0.15	-0.09	0.18	-0.13	-0.01
	(-0.12)	(1.33)	(-0.10)	(2.02)	(-0.15)	(-0.10)
UE[$SIIS_{t-1}$]	-0.17	**0.02**	-0.17	**0.01**	-0.17	**0.00**
	(-4.60)	(3.16)	(-4.55)	(2.80)	(-4.53)	(2.09)
UE[$SIIS_{t-2}$]	0.13	-0.00	0.13	-0.00	0.13	0.00
	(3.60)	(-0.50)	(3.59)	(-1.00)	(3.58)	(0.67)
UE[$SIIS_{t-3}$]	0.29	-0.01	0.29	-0.01	0.28	-0.01
	(8.02)	(-1.14)	(8.06)	(-1.29)	(7.85)	(-0.51)
UE[$SIIS_{t-4}$]	0.18	**-0.02**	0.17	**-0.01**	0.18	**-0.00**
	(4.77)	(-3.23)	(4.66)	(-2.94)	(4.74)	(-2.21)
R_{t-1}	**0.55**	-0.00	**0.71**	-0.07	0.52	-0.02
	(1.90)	(-0.00)	(1.85)	(-1.76)	(0.82)	(-0.53)
R_{t-2}	-0.45	0.03	**-0.83**	0.03	0.12	0.03
	(-1.56)	(0.71)	(-2.16)	(0.87)	(0.20)	(0.83)
R_{t-3}	**-0.58**	-0.07	-0.55	-0.08	**-1.32**	0.01
	(-1.99)	(-1.86)	(-1.43)	(-2.22)	(-2.09)	(0.22)
R_{t-4}	0.31	0.03	0.39	-0.02	0.32	-0.01
	(1.08)	(1.33)	(1.01)	(-0.51)	(0.50)	(-0.33)
Adj. R^2	0.125	0.023	0.125	0.029	0.118	0.001
F-Stat	13.47	3.04	13.51	3.60	12.73	1.07

This table reports estimates from following vector autoregressive models:

$$UE[SIIS_{j,t}] = c_j + \sum_{s=1}^{4} \beta_s R_{i,t-1} + \sum_{t=g}^{4} \gamma_g UE[SIIS]_{j,t-g} + e_{j,t}$$

$$R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS]_{j,t-g} + e_{i,t}$$

where $SIIS_{i,t}$ is the difference between Google Search Volume Indices at time t for search terms "bull market" and "bear market". $R_{i,t}$ is the return for given size portfolio at time t. UE[IS] is the unexpected SIIS using AR(1) process, i.e., the residual. Low 30 is the portfolio consisting of the bottom 30 % companies by market equity. High 30 is the portfolio consisting of top 30 % companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. The data is in weekly form from 4/1/204 to 6/25/2017. T-stats are reported in parentheses.

Table 5. Pairwise Granger causality tests between unexpected SIIS, unexpected AAII and equity market returns.

	Panel A: Dependent Variable		
	Low 30	High 30	LMH
2 Weeks			
UE[SIIS_Bear]	**5.76*** **	**4.26*** **	**5.04*** **
UE[SIIS_Bull]	0.19	0.21	0.85
UE[SIIS_Spread]	**3.24** **	**3.42** **	1.07
UE[AAII_Bear]	0.22	0.09	0.28
UE[AAII_Bull]	0.14	0.20	0.45
UE[AAAII_Spread]	0.19	0.17	0.33
4 Weeks			
UE[SIIS_Bear]	**6.43*** **	**4.72*** **	**5.10*** **
UE[SIIS_Bull]	0.17	0.26	0.49
UE[SIIS_Spread]	**4.38*** **	**3.96*** **	1.84
UE[AAII_Bear]	**2.18* **	1.35	1.23
UE[AAII_Bull]	1.53	1.27	1.05
UE[AAII_Spread]	**2.11* **	1.50	1.24

This table report results from Granger Causality tests with lags of two and four weeks. Low 30 is the portfolio consisting of bottom 30 % companies by market equity. High 30 is the portfolio consisting of the top 30 % companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. UE[SIIS] is the unexpected SIIS inferred from search terms “bear market”, “bull market” and their spread (“bull market” minus “bear market”). UE[AAII] is the unexpected AAII, measured as a percentage of bearish or bullish respondents and their difference (the spread). The unexpected components are the residuals from AR(1) process. *, **, *** refers to statistical significance at the 10 %, 5 % and 1 % level.

Table 6. Unexpected change in “bear market” popularity and future equity market returns.

	Low 30		High 30		LMH	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Constant	0.148	0.170	0.176*	0.197**	-0.006	-0.005
	(1.23)	(1.43)	(1.86)	(2.08)	(-0.11)	(-0.09)
UE[$SIIS_{t-1}$]	-0.026***	-0.022***	-0.015***	-0.007	-0.011***	-0.011***
	(-4.88)	(-3.54)	(-4.02)	(-1.56)	(-3.22)	(-3.59)
UE[$SIIS_{t-2}$]	0.001	0.002	0.004	0.006	-0.004	-0.003
	(0.17)	(0.36)	(0.82)	(1.23)	(-1.40)	(-0.88)
UE[$SIIS_{t-3}$]	0.008	0.012*	0.008*	0.007	0.000	0.001
	(1.24)	(1.66)	(1.75)	(1.43)	(-0.08)	(0.38)
UE[$SIIS_{t-4}$]	0.022***	0.019***	0.014***	0.009***	0.009***	0.009***
	(3.59)	(3.42)	(3.41)	(2.56)	(2.85)	(3.07)
R_{t-1}	0.045	0.051	-0.065	-0.065	-0.023	-0.028
	(0.73)	(0.77)	(-0.83)	(-0.87)	(-0.50)	(-0.59)
R_{t-2}	0.023	0.015	0.034	0.018	0.036	0.033
	(0.44)	(0.29)	(0.58)	(0.30)	(0.88)	(0.84)
R_{t-3}	-0.072*	-0.081**	-0.084*	-0.085*	0.011	0.016
	(-1.93)	(-2.14)	(-1.70)	(-1.85)	(0.21)	(0.30)
R_{t-4}	0.035	0.038	-0.005	-0.006	-0.017	-0.016
	(0.59)	(0.64)	(-0.10)	(-0.12)	(-0.38)	(-0.35)
UE[$SIIS_{t-1}$]		-0.028		-0.051**		0.006
*D(R_{t-1})		(-1.25)		(-2.56)		(0.57)
UE[$SIIS_{t-2}$]		-0.003		0.000		-0.012
*D(R_{t-2})		(-0.15)		(0.01)		(-1.22)
UE[$SIIS_{t-3}$]		-0.031		-0.002		-0.009
*D(R_{t-3})		(-1.54)		(-0.18)		(-1.20)
UE[$SIIS_{t-4}$]		0.021		0.021		-0.009
*D(R_{t-4})		(0.72)		(1.06)		(-0.92)
ADS_{t-1}	-2.432	-2.524	-2.235	-2.173	-0.305	-0.262
	(-1.18)	(-1.23)	(-1.12)	(-1.11)	(-0.62)	(-0.55)
EMU_{t-1}	0.063	0.075	0.008	0.018	0.060	0.058
	(0.58)	(0.69)	(0.10)	(0.23)	(1.18)	(1.12)
EPU_{t-1}	-0.126	-0.142	-0.126	-0.110	0.022	0.026
	(-0.51)	(-0.57)	(-0.74)	(-0.65)	(0.19)	(0.22)
VIX_{t-1}	1.976*	2.367**	0.483	0.922	0.024	-0.026
	(1.81)	(2.03)	(0.47)	(0.95)	(0.05)	(-0.06)
Adj R^2	0.040	0.044	0.037	0.056	0.016	0.017
F-Statistics	3.40	3.03	3.25	3.61	1.95	1.75
Obs	700	700	700	700	700	700

This table reports results from following model:

$$R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS_{j,t-g}] + \sum_{l=1}^{4} \lambda_l UE[SIIS_{j,t-l}] * D(R_{i,t-l}) + \sum_{h=1}^{4} \nu_h Control_{h,t-1} + e_{i,t}$$

where $R_{i,t}$ is the weekly return for size portfolio i at time t and $R_{i,t-s}$ are its lagged returns. UE[$SIIS_{j,t-g}$] are the lagged unexpected components of SIIS, inferred from search popularity of search term “bear market”. Control variables are: ADS is a weekly change in Aruoba-Diebold-Scotti business condition index, EMU is the weekly change in the news-based measure of equity market uncertainty index, EPU is the weekly change in the news-based measure of economic uncertainty index and VIX is the weekly change CBOE volatility index. D is a dummy variable for those weekly stock returns that belong to the lowest 10 % decile. Low 30, High 30 are portfolio returns for the bottom 30 % and top 30 % companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. All standard errors are corrected for both heteroskedasticity and autocorrelation by the White diagonal method. * refers to statistical significance at the 0.1 level; ** refers to statistical significance at the 0.05 level; *** refers to statistical significance at the 0.01 level.

Table 7. Unexpected change in "bull market" popularity and future equity market returns.

	Low 30		High 30		LMH	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Constant	0.152	0.150	0.181*	0.176*	-0.006	-0.006
	(1.25)	(1.16)	(1.87)	(1.80)	(-0.11)	(-0.10)
$UE[SIIS_{t-1}]$	-0.002	-0.002	0.002	0.002	-0.003	-0.003
	(-0.28)	(-0.31)	(0.35)	(0.49)	(-1.15)	(-1.16)
$UE[SIIS_{t-2}]$	-0.003	-0.004	-0.001	-0.004	-0.002	-0.001
	(-0.55)	(-0.75)	(-0.32)	(-0.90)	(-0.57)	(-0.32)
$UE[SIIS_{t-3}]$	0.002	0.003	0.003	0.003	-0.001	-0.002
	(0.45)	(0.43)	(0.77)	(0.75)	(-0.41)	(-0.79)
$UE[SIIS_{t-4}]$	-0.002	-0.001	-0.003	-0.004	0.000	0.001
	(-0.34)	(-0.20)	(-0.55)	(-0.74)	(0.16)	(0.42)
R_{t-1}	0.049	0.048	-0.057	-0.054	-0.018	-0.016
	(0.78)	(0.75)	(-0.71)	(-0.66)	(-0.41)	(-0.35)
R_{t-2}	0.022	0.019	0.030	0.027	0.036	0.038
	(0.45)	(0.30)	(0.53)	(0.48)	(0.90)	(0.96)
R_{t-3}	-0.088**	-0.090**	-0.099**	-0.102**	0.008	0.003
	(-2.32)	(-2.18)	(-2.05)	(-2.05)	(0.15)	(0.05)
R_{t-4}	0.018	0.017	-0.022	-0.022	-0.022	-0.019
	(0.31)	(0.30)	(-0.41)	(-0.42)	(-0.48)	(-0.41)
$UE[SIIS_{t-1}]$		0.006		-0.007		0.004
$*D(R_{t-1})$		(0.31)		(-0.49)		(0.37)
$UE[SIIS_{t-2}]$		0.016		0.030		-0.010
$*D(R_{t-2})$		(0.54)		(1.35)		(-0.81)
$UE[SIIS_{t-3}]$		-0.005		-0.001		0.013
$*D(R_{t-3})$		(-0.16)		(-0.07)		(1.31)
$UE[SIIS_{t-4}]$		-0.010		0.012		-0.009
$*D(R_{t-4})$		(-0.36)		(0.50)		(-0.74)
ADS_{t-1}	-2.523	-2.493	-2.273	-2.270	-0.380	-0.396
	(-1.22)	(-1.19)	(-1.13)	(-1.12)	(-0.76)	(-0.78)
EMU_{t-1}	0.023	0.021	-0.021	-0.038	0.050	0.062
	(0.21)	(0.20)	(-0.25)	(-0.47)	(0.99)	(1.20)
EPU_{t-1}	-0.062	-0.056	-0.085	-0.055	0.041	0.026
	(-0.26)	(-0.23)	(-0.50)	(-0.31)	(0.36)	(0.24)
VIX_{t-1}	1.693	1.703	0.374	0.405	-0.104	-0.119
	(1.51)	(1.50)	(0.36)	(0.39)	(-0.24)	(-0.28)
Adj R^2	0.003	-0.002	0.012	0.011	-0.010	-0.011
F-Statistics	1.17	0.93	1.71	1.51	0.40	0.52
Obs	700	700	700	700	700	700

This table reports results from following model:

$$R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS_{j,t-g}] + \sum_{l=1}^{4} \lambda_l UE[SIIS_{j,t-l}] * D(R_{i,t-l}) + \sum_{h=1}^{4} \nu_h Control_{h,t-1} + e_{i,t}$$

where $R_{i,t}$ is the weekly return for size portfolio i at time t and $R_{i,t-s}$ are its lagged returns. $UE[SIIS_{j,t-g}]$ are the lagged unexpected components of SIIS, inferred from search popularity of search term "bull market" . Control variables are: ADS is a weekly change in Aruoba-Diebold-Scotti business condition index, EMU is the weekly change in the news-based measure of equity market uncertainty index, EPU is the weekly change in the news-based measure of economic uncertainty index and VIX is the weekly change CBOE volatility index. D is a dummy variable for those weekly stock returns that belong to the highest 10 % decile. Low 30 and High 30 are portfolio returns for the bottom 30 % and top 30 % companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. All standard errors are corrected for both heteroskedasticity and autocorrelation by the White diagonal method. * refers to statistical significance at the 0.1 level; ** refers to statistical significance at the 0.05 level; *** refers to statistical significance at the 0.01 level.

Table 8. Unexpected change in the spread and future equity market returns.

	Low 30		High 30		LMH	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Constant	0.151	0.146	0.179**	0.171*	-0.005	-0.005
	(1.25)	(1.20)	(1.89)	(1.80)	(-0.10)	(-0.10)
UE[$SIIS_{t-1}$]	0.015***	0.009**	0.010***	0.004	0.005*	0.005**
	(3.44)	(2.22)	(3.10)	(1.28)	(1.87)	(2.13)
UE[$SIIS_{t-2}$]	-0.003	-0.001	-0.004	-0.003	0.001	0.002
	(-0.59)	(-0.15)	(-1.11)	(-0.94)	(0.63)	(0.69)
UE[$SIIS_{t-3}$]	-0.005	-0.008	-0.005	-0.004	-0.001	-0.001
	(-1.10)	(-1.50)	(-1.20)	(-0.92)	(-0.57)	(-0.63)
UE[$SIIS_{t-4}$]	-0.015***	-0.011**	-0.011**	-0.006	-0.005**	-0.006**
	(-2.63)	(-2.30)	(-2.45)	(-1.61)	(-2.08)	(-2.47)
R_{t-1}	0.041	0.077	-0.062	-0.019	-0.024	-0.028
	(0.66)	(1.11)	(-0.78)	(-0.23)	(-0.54)	(-0.60)
R_{t-2}	0.015	0.007	0.023	0.020	0.033	0.031
	(0.29)	(0.14)	(0.42)	(0.38)	(0.83)	(0.76)
R_{t-3}	-0.070**	-0.061*	-0.084*	-0.063*	0.011	0.012
	(-1.99)	(-1.76)	(-1.80)	(-1.71)	(0.21)	(0.22)
R_{t-4}	0.029	0.029	-0.016	-0.022	-0.010	-0.008
	(0.50)	(0.55)	(-0.31)	(-0.46)	(-0.22)	(-0.18)
UE[$SIIS_{t-1}$]		0.031*		0.044***		-0.005
*D(R_{t-1})		(1.71)		(2.71)		(-0.60)
UE[$SIIS_{t-2}$]		-0.013		-0.009		-0.002
*D(R_{t-2})		(-0.61)		(-0.52)		(-0.27)
UE[$SIIS_{t-3}$]		0.025		-0.002		0.002
*D(R_{t-3})		(1.46)		(-0.15)		(0.22)
UE[$SIIS_{t-4}$]		-0.023		-0.023		0.006
*D(R_{t-4})		(-1.02)		(-1.53)		(0.73)
ADS_{t-1}	-2.640	-2.729	-2.307	-2.339	-0.445	-0.418
	(-1.31)	(-1.35)	(-1.17)	(-1.19)	(-0.92)	(-0.89)
EMU_{t-1}	0.037	0.067	-0.009	0.017	0.052	0.051
	(0.34)	(0.61)	(-0.11)	(0.21)	(1.04)	(1.02)
EPU_{t-1}	-0.057	-0.100	-0.088	-0.098	0.048	0.052
	(-0.24)	(-0.40)	(-0.52)	(-0.57)	(0.43)	(0.46)
VIX_{t-1}	1.545	2.172*	0.327	0.915	-0.173	-0.197
	(1.38)	(1.86)	(0.31)	(0.95)	(-0.40)	(-0.45)
Adj R^2	0.027	0.040	0.033	0.059	-0.002	-0.006
F-Statistics	2.62	2.84	2.99	3.76	0.88	0.74
Obs	700	700	700	700	700	700

This table reports results from following model:

$$R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS_{j,t-g}] + \sum_{l=1}^{4} \lambda_l UE[SIIS_{j,t-l}] * D(R_{i,t-l}) + \sum_{h=1}^{4} \nu_h Control_{h,t-1} + e_{i,t}$$

where $R_{i,t}$ is the weekly return for size portfolio i at time t and $R_{i,t\text{-}s}$ are its lagged returns. UE[$SIIS_{j,t\text{-}g}$] are the lagged unexpected components of SIIS, inferred from search popularity difference between search term “bull market” and “bear market”. Control variables are: ADS is a weekly change in Aruoba-Diebold-Scotti business condition index, EMU is the weekly change in the news-based measure of equity market uncertainty index, EPU is the weekly change in the news-based measure of economic uncertainty index and VIX is the weekly change CBOE volatility index. D is a dummy variable for those weekly stock returns that belong to the lowest 10 % decile. Low 30 and High 30 are portfolio returns for the bottom 30 % and top 30 % companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. All standard errors are corrected for both heteroskedasticity and autocorrelation by White diagonal method. * refers to statistical significance at the 0.1 level; ** refers to statistical significance at the 0.05 level; *** refers to statistical significance at the 0.01 level.

Table 9. Interaction of returns of large-sized companies and unexpected changes in SIIS on future returns of small-sized companies.

	SIIS[Bear Market]		SIIS[Spread]	
	Low 30	LMH	Low 30	LMH
Constant	0.159	-0.007	0.145	-0.006
	(1.30)	(-0.13)	(1.21)	(-0.12)
$UE[SIIS_{t-1}]$	-0.018***	-0.010***	0.008*	0.004*
	(-2.82)	(-3.14)	(1.79)	(1.81)
$UE[SIIS_{t-2}]$	0.002	-0.003	-0.001	0.002
	(0.37)	(-1.15)	(-0.26)	(0.88)
$UE[SIIS_{t-3}]$	0.006	0.000	-0.005	-0.001
	(0.96)	(-0.15)	(-0.92)	(-0.49)
$UE[SIIS_{t-4}]$	0.016***	0.007***	-0.009*	-0.004*
	(2.78)	(2.14)	(-1.85)	(-1.71)
R_{t-1}	0.046	-0.024	0.069	-0.024
	(0.71)	(-0.51)	(1.00)	(-0.53)
R_{t-2}	0.016	0.036	0.012	0.033
	(0.31)	(0.88)	(0.23)	(0.78)
R_{t-3}	-0.072*	0.012	-0.054	0.010
	(-1.93)	(0.22)	(-1.59)	(0.19)
R_{t-4}	0.038	-0.017	0.021	-0.010
	(0.64)	(-0.36)	(0.41)	(-0.22)
$UE[SIIS_{t-1}]$	-0.052**	-0.002	0.046***	0.001
$*D(HR_{t-1})$	(-2.10)	(-0.19)	(2.70)	(0.05)
$UE[SIIS_{t-2}]$	0.004	-0.003	-0.016	-0.005
$*D(HR_{t-2})$	(0.17)	(-0.33)	(-0.76)	(-0.54)
$UE[SIIS_{t-3}]$	-0.003	0.001	0.000	-0.001
$*D(HR_{t-3})$	(-0.14)	(0.11)	(0.01)	(-0.15)
$UE[SIIS_{t-4}]$	0.033	0.007	-0.033*	-0.009
$*D(HR_{t-4})$	(1.18)	(0.69)	(-1.65)	(-0.96)
ADS_{t-1}	-2.367	-0.302	-2.792	-0.541
	(-1.16)	(-0.62)	(-1.37)	(-1.09)
EMU_{t-1}	0.074	0.059	0.071	0.055
	(0.70)	(1.15)	(0.66)	(1.11)
EPU_{t-1}	-0.116	0.019	-0.080	0.038
	(-0.47)	(0.16)	(-0.32)	(0.33)
VIX_{t-1}	2.452**	0.056	2.019*	-0.159
	(2.19)	(0.13)	(1.77)	(-0.36)
Adj R^2	0.052	0.012	0.047	-0.004
F-Statistics	3.38	1.52	3.17	0.82
Obs	700	700	700	700

This table reports results from following models:

$$R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS_{j,t-g}] + \sum_{l=1}^{4} \lambda_l UE[SIIS_{j,t-l}] * D(R_{hr,t-l}) + \sum_{h=1}^{4} \nu_h Control_{h,t-1} + e_{i,t}$$

where $R_{i,t}$ is the weekly return for size portfolio i at time t and $R_{i,t-s}$ are its lagged returns. $UE[SIIS_{j,t-g}]$ are the lagged unexpected components of SIIS. Control variables are: ADS is a weekly change in Aruoba-Diebold-Scotti business condition index, EMU is the weekly change in the news-based measure of equity market uncertainty index, EPU is the weekly change in the news-based measure of economic uncertainty index and VIX is the weekly change CBOE volatility index. HR is the return for size portfolio with top 30 % companies by market equity. D1 is a dummy variable for those weekly stock returns that belong to the lowest 10 % decile. Low 30 is portfolio return for the bottom 30 % companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. All standard errors are corrected for both heteroskedasticity and autocorrelation by the White diagonal method. * refers to statistical significance at the 0.1 level; ** refers to statistical significance at the 0.05 level; *** refers to statistical significance at the 0.01 level.