The Sum of All FEARS: Investor Sentiment and Asset Prices*

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Abstract

We use daily internet search volume from millions of households to reveal market-level sentiment. By aggregating the volume of queries related to household concerns (e.g. "recession", "unemployment" and "bankruptcy"), we construct a Financial and Economic Attitudes Revealed by Search (FEARS) index as a new measure of investor sentiment. Between 2004 and 2011, we find FEARS (1) predict short-term return reversals, (2) predict temporary increases in volatility and (3) predict mutual fund flows out of equity funds and into bond funds. Taken together, the results are broadly consistent with theories of investor sentiment.

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1 Introduction

John Maynard Keynes (1936) argued that markets can fluctuate wildly under the influence of investors' "animal spirits" which move prices in a way unrelated to fundamentals. Fifty years later, De Long, Shleifer, Summers and Waldmann (1990, hereafter, DSSW) formalized the role of investor sentiment in financial markets. DSSW demonstrate that if uninformed noise traders base their trading decisions on sentiment and risk-averse arbitrageurs encounter limits-to-arbitrage, sentiment changes will lead to more noise trading, greater mispricing and excess volatility. While the survival of noise traders in the long-run remains open for debate (e.g., Kogan, Ross, Wang and Westerfield, 2006, 2009), there is a growing consensus that noise traders can induce large price movements and excess volatility in the short-run.[1] As Baker and Wurgler (2007) put it in their survey article: "Now, the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather *how to measure investor sentiment and quantify its effects*" (italics added).

In this paper we propose a possible answer: investor sentiment can be directly measured through the internet search behavior of households. We aggregate the volume of internet search queries such as "recession", "bankruptcy" and "unemployment" from millions of US households to construct a Financial and Economic Attitudes Revealed by Search (FEARS) index. We then quantify the effects of FEARS on asset prices, volatility and fund flows. We find that FEARS predict return reversals: although increases in FEARS correspond with low market-level returns today, they predict high returns (reversal) over the next few days. Moreover, increases in FEARS coincide with only temporary increases in market volatility and predict mutual fund flow out of equity funds and into bond funds.

The appeal of our search-based sentiment measure is more transparent when compared with alternatives. Traditionally, empiricists have taken two approaches to measuring investor sentiment. Under the first approach, empiricists proxy for investor sentiment with market-based measures such as trading volume, closed-end fund discount, IPO first-day returns, IPO volume, option implied volatilities (VIX) or mutual fund flows (see, Baker and Wurgler (2007) for a comprehensive survey

[1] A particularly interesting thread of this literature examines sentiment following non-economic events such as sports (Edmans, Garcia, and Norli (2007)), aviation disasters (Kaplanski and Levy (2010)), weather conditions (Hirshleifer and Shumway (2003)), seasonal affective disorder (SAD, Kamstra, Kramer and Levi (2003)), and shows these sentiment-changing events cause changes in asset prices.

of the literature). Although market-based measures have the advantage of being readily available at a relatively high frequency, they have the disadvantage of being the equilibrium outcome of many economic forces *other than investor sentiment*. Qiu and Welch (2006) put it succinctly: "How does one test a theory that is about inputs → outputs with an output measure?"

Under the second approach, empiricists use survey-based indices such as the University of Michigan Consumer Sentiment Index, the UBS/GALLUP Index for Investor Optimism, or investment newsletters (Brown and Cliff (2004), Lemmon and Portniaguina (2006), and Qiu and Welch (2006)). Compared to survey-based measures of investor sentiment, the search-based sentiment measure we propose has several advantages. First, search-based sentiment measures are available at a high frequency.[2] Survey measures are often available monthly or quarterly. In fact, we find that our daily FEARS index can *predict* monthly survey results of consumer confidence and investor sentiment. Second, search-based measures *reveal* attitudes rather than inquire about them. Although many people answer survey questions for altruistic reasons, there is often little incentive to answer survey questions carefully or truthfully, especially when questions are sensitive (Singer (2002)). Search volume has the potential to reveal more personal information where non-response rates in surveys are particularly high or the incentive for truth-telling is low. For example, eliciting the likelihood of job loss via survey may be a sensitive topic for a respondent. On the other hand, aggregate search volume for terms like "find a job", "job search" or "unemployment" *reveals* concern about job loss. Finally, some economists have been skeptical about answers in survey data which are not "cross-verif(ied) with data on actual (not self-reported) behavior observed by objective external measurement" (Lamont in Vissing-Jorgensen (2003)). Search behavior is an example of such objective, external verification.

Google, the largest search engine in the world, makes public the Search Volume Index (SVI) of search terms via its product Google Trends (http://www.google.com/trends/).[3] When a user inputs a search term into Google Trends, the application returns the search volume history for that term scaled by the time-series maximum (a scalar). As an example, Figure 1 plots the SVI for "recession" and "bankruptcy" respectively. The plots conform with intuition. For example, the

[2] To date, high-frequency analysis of investor sentiment is only found in laboratory settings. For example, Bloomfield, O'Hara and Saar (2009) use laboratory experiments to investigate the impact of uninformed traders on underlying asset prices.

[3] By February 2009, Google accounted for 72.11% of all search queries performed in the US, according to Hitwise, which specializes in tracking Internet traffic.

SVI for "recession" began rising in the middle of 2007 and then increased dramatically beginning in 2008. All of this was well before the NBER announced in December 2008 that the U.S. had been in a recession since December of 2007. The SVI for "bankruptcy" peaks once during 2005 and once again during 2009 before falling off. According to the American Bankruptcy Institute, actual bankruptcies in the United Stated follow a similar pattern with peaks in 2005 and 2009/2010.[4]

At the monthly frequency, SVI correlates well with alternative measures of market sentiment. For example, Figure 2 plots the monthly log SVI for "recession" (with a minus sign since higher SVI on "recession" signals pessimism) against the monthly University of Michigan Consumer Sentiment Index (MCSI) which asks households about their economic outlook. During our sample period from January 2004 to December 2011, the two times series are highly correlated with a correlation coefficient of 0.858. When we use the log change in "recession" SVI this month to predict next month's log change in the MCSI, we find an increase in SVI predicts a decrease in the MCSI (t-value = 2.56). This predictive result suggests that SVI, revealing household sentiment at a high-frequency, leads survey-based sentiment measures by at least a month.

The key to the construction of our FEARS index is the identification of relevant sentiment-revealing search terms. To identify search terms in a way that is as objective as possible, we begin with well-known dictionaries in the finance and textual analytics literature (Tetlock (2007)) and select the set of words which are classified as "economic" words with either "positive" or "negative" sentiment. This provides us with a list of 149 words such as "crisis", "gold", "inflation", "recession" and "security." Second, we download the associated top ten related search terms (provided by Google) in order to see how these economic words are used by search engine users in practice. Finally, we eliminate non-economic search terms and search terms with too few valid SVIs. This procedure results in a list of 118 search terms for which we calculate daily log-differences. To make these 118 terms comparable, we winsorize, remove intra-week and intra-year seasonality and standardize each time series (as in Baker and Wurgler (2006)). Finally, we run backward-looking rolling regressions to let the data tell us which of the 118 terms are most important. For example, when thinking about our FEARS list in January 2011, we run a regression to determine the historical relationship between search and contemporaneous market return for all of our search terms during

[4] See http://www.abiworld.org/AM/AMTemplate.cfm?Section=Home&CONTENTID=65139&TEMPLATE =/CM/ContentDisplay.cfm

the period between January 1, 2004 and December 31, 2010. Only the search terms which have historically been related to returns (through December 31, 2010) are used for our FEARS list beginning in January 2011. This procedure produces a dynamic list of 30 search terms whose search volume changes are then averaged to produce our FEARS index.

We then relate our FEARS index to asset prices. In Section 3, we find a negative contemporaneous correlation between FEARS and stock market returns. Increases (decreases) in FEARS correspond with low (high) returns. However, in the days following, this relationship reverses. Increases in FEARS today predict increases in stock market returns in the following two days, which is consistent with sentiment-induced temporary mispricing. Moreover, this reversal is strongest among stocks with higher beta, higher volatility and greater downside risk, consistent with the predictions in Baker and Wurgler (2006, 2007). We find similar spike-reversal patterns among other asset classes. For example, among treasury bonds, we find a *positive* contemporaneous correlation with FEARS (i.e. increases in FEARS correspond with high treasury bond returns) consistent with the notion of flight-to-safety. Again, this relationship reverses in the following days.

In Section 4 we consider the prediction that sentiment swings generate excess volatility. We find a significant positive contemporaneous correlation between our FEARS index and daily market volatility measured as either realized volatility on a S&P500 ETF or the Chicago Board of Exchange (CBOE) market volatility index (VIX). Because volatility displays seasonal patterns and is well-known to be persistent and long-lived (Engel and Patton (2001) and Andersen et al. (2001, 2003)), we account for this long-range dependence through the fractional integrated autoregressive moving average (ARFIMA) model, $ARFIMA(1, d, 1)$. We also examine the daily returns on a tradable volatility-based contract, the Chicago Board of Exchange (CBOE) VIX futures. When we relate our FEARS index to these daily VIX futures returns, we first confirm the strong contemporaneous correlation between our FEARS index and VIX futures returns. As before, we find our FEARS index predicts a reversal in VIX futures returns during the next two trading days.

As a more direct test of the "noise trading" hypothesis, we examine daily mutual fund flows in Section 5. Since individual investors hold about 90% of total mutual fund assets and they are more likely to be "noise" traders, daily flows to mutual fund groups likely aggregate "noise" trading at the asset class level.[5] We examine two groups of mutual funds that specialize in equity and

[5] Source: 2007 Investment Company Fact Book by the Investment Company Institute.

intermediate Treasury bonds. We document strong persistence in fund flows and again use the $ARFIMA$ model to extract daily innovations to these fund flows. Our results suggest significant outflow from the equity market one day after an increase in FEARS. We also observe a significant inflow to bond funds one day after a significant withdrawal from equity funds. Taken together, the evidence indicates a flight to safety with investors shifting their investments from equities to bonds after a spike in FEARS.

2 Data and Methodology

Although the data for this study come from a variety of sources, we begin by discussing the construction of our FEARS index which is the main variable in our analysis.

2.1 Construction of FEARS Index

Our objective is to build a list of search terms that reveal sentiment towards economic conditions. We follow the recent text analytics literature in finance which uses the Harvard IV-4 Dictionary and the Lasswell Value Dictionary (Tetlock (2007), Tetlock et al. (2008)). These dictionaries place words into various categories such as "positive", "negative", "weak", "strong" and so on. Because we are interested in household sentiment towards the economy, we select the set of words which are "economic" words that also have either "positive" or "negative" sentiment.[6] This results in 149 words such as "bankruptcy", "crisis", "gold", "inflation", "recession", "valuable" and "security."

We call this list the "primitive" word list. Our next task is to understand how these words might be searched in Google by households. To do this, we input each primitive word into Google Trends which, among other things, returns ten "top searches" related to each primitive word.[7] For example, a search for "deficit" results in related searches "budget deficit", "attention deficit", "attention deficit disorder", "trade deficit" and "federal deficit" because this is how the term "deficit" is commonly searched in Google. Our 149 primitive words generate 1,490 related terms which become 1,245 terms after removing duplicates.

[6] Specifically, from http://www.wjh.harvard.edu/~inquirer/spreadsheet_guide.htm we take all economic words (those with tags "Econ@" or "ECON") which also have a positive or negative sentiment tag (those with tags "Ngtv", "Negativ", "Positiv" or "Pstv").

[7] According to Google, "Top searches refers to search terms with the most significant level of interest. These terms are related to the term you've entered... our system determines relativity by examining searches that have been conducted by a large group of users preceding the search term you've entered, as well as after."

Next we remove terms with insufficient data. Of our 1,245 terms only 622 have at least 1000 observations of daily data.[8] Finally, we remove terms which are not clearly related to economics or finance. For example, a search for "depression" results in related searches "the depression", "great depression", "the great depression", "depression symptoms", "postpartum depression", "depression signs", etc. We keep the first three terms (which relate to an economic depression) and remove the last three terms (which relates to the mental disorder of depression). This leaves us with 118 search terms.

We download the SVI for each of these 118 terms over our sample period of 2004/01 - 2011/12 from Google Trends. Google Trends allows users to restrict SVI results to specific countries (e.g. search volume for "recession" from British households). Because most of the dependent variables of interest in this paper are related to U.S. indices, we restrict the SVI results to the U.S. Thus, the measures we construct represent the sentiment of American households. Google Trends also provides SVIs on a daily basis when you download them for a time window less than or equal to a quarter, so we download the daily SVI time series from Google Trends one quarter at a time. Thus, the daily SVIs in a particular quarter are scaled by the time series maximum SVI in that quarter. While this normalization does not affect us in computing daily SVI change within a quarter, it does create a problem when we compute SVI change over consecutive quarters. For this reason, we are not able to compute the daily SVI on the first trading day of a quarter. For other days, we define the daily change in search term j as:

$$\Delta SVI_{j,t} = \ln\left(SVI_{j,t}\right) - \ln(SVI_{j,t-1}). \tag{1}$$

Figure 3 plots the daily log changes for two terms – "Inflation" and "Price of Gold" – during two different quarters in 2006. The figures demonstrate several important features of the search data. The first is seasonality: SVI change rises during the beginning of the week (e.g., Monday and Tuesday) and falls throughout the week which generates the repeated 5-day hump-shaped pattern depicted in Figure 3. Moreover there is a considerable difference in variance across terms. SVI

[8] To increase the response speed, Google currently calculates SVI from a random subset of the actual historical search data. This is why SVIs on the same search term might be slightly different when they are downloaded at different points in time. We believe that the impact of such sampling error is small for our study and should bias against finding significant results. As in Da, Gao, and Engelberg (2011), when we download the SVIs several times and compute their correlation, we find the correlations are usually above 97%.

change for "Inflation"and "Price of Gold" are plotted on the same scale so that the heteroscedasticity is apparent. In fact, the standard deviation of SVI change for "Price of Gold" is nearly three times greater than that of "Inflation." Finally, the SVI change for "Price of Gold" indicates the presence of some extreme values. To mitigate any concerns about outliers and to address the issues of seasonality and heteroscedasticity in the data, we adjust the raw data in the following way. First, we winsorize each series at the 5% level (2.5% in each tail). Then, to eliminate seasonality from $\Delta SVI_{j,t}$ we regress $\Delta SVI_{j,t}$ on weekday dummies and month dummies and keep the residual. Finally, to address heteroscedasticity and make each times series comparable, we standardize each of the time series by scaling each by the time-series standard deviation as in Baker and Wurgler (2006). This leaves us with an adjusted (winsorized, deseasonalized and standardized) daily change in search volume, $\Delta ASVI_t$, for each of our 118 terms.

Our final step is to let the data identify search terms which are most important for returns. To do this we run expanding backward rolling regressions of $\Delta ASVI$ on market returns every six months (every June and December) to determine the historical relationship between search and contemporaneous market return for all 118 of our search terms. When we do this it becomes clear that, given a search term has a strong relationship with the market, the relationship is *almost always negative*. This is despite the fact that we began with economic words of both positive and negative sentiment when selecting words from the Harvard and Lasswell dictionaries. For example, when we use all 118 terms in the full sample (January 2004 – December 2011) we find 0 terms with a t-statistic on $\Delta ASVI$ above 2.5 but 14 terms with a t-statistic below -2.5. These terms include "recession", "great depression", "gold price" and "crisis." As in Tetlock (2007) it appears negative terms in English language are most useful for identifying sentiment. For this reason, we only use the terms which have the largest negative t-statistic on $\Delta ASVI$ to form our FEARS index. Formally, we define FEARS on day t as:

$$FEARS_t = \sum_{i=1}^{30} R^i(\Delta ASVI_t) \tag{2}$$

where $R^i(\Delta ASVI_t)$ is the $\Delta ASVI_t$ for the search term which had a t-statistic rank of i from the period January 2004 through the most recent 6-month period, where ranks run from smallest ($i = 1$) to largest ($i = 118$). For example, at the end of June 2009, we run a regression of $\Delta ASVI$

on contemporaneous market return during the period January 1, 2004 – June 30, 2009 for each of our 118 search terms. Then we rank the t-statistic on $\Delta ASVI$ from this regression from most negative ($i = 1$) to most positive ($i = 118$). We select the 30 most negative terms and use these terms to form our FEARS index for the period July 1, 2009 - December 31, 2009. $FEARS$ on day t during this period is simply the average $\Delta ASVI$ of these 30 terms on day t. Given our relatively short sample period, we choose an expanding rolling window to maximize the statistical power of the selection. Although we choose a cutoff of 30 terms to diversify away any idiosyncratic noise in a given term, results are nearly identical for other cutiff choices (Table 5). Finally, due to the need for an initial window of at least 6 months, our FEARS index begins in July, 2004.

There are several advantages with this historical, regression-based approach for selecting terms. First, using historical regressions to identify the most relevant terms is an objective way to "let the data speak for itself." Kogan, Routledge, Sagi and Smith (2010) take a similar regression approach to identify relevant words in firm 10-Ks and argue this approach not only helps the researcher identify terms that were not ex-ante obvious but also is an objective way to select terms. This is also true in our case. For example, the word "gold" is considered an economic word of *positive* sentiment by the Harvard dictionary, and yet we find a strong *negative* relationship between searches for "gold" and market returns, consistent with the evidence in Baur and Lucey (2010) who argue that gold represents a "safe heaven" in times of distress, at least in view of retail investors who are most likely to be affected by sentiment. This only came to light given our data-driven approach for constructing the FEARS index.

Table 1 displays the top 30 terms over our entire sample (January 2004 - December 2011). The terms which have historically the largest daily correlation with the market include "gold prices" (t-stat = -6.04), "recession" (t-stat = -5.60), "gold price" (t-stat = -4.81), "depression" (t-stat = -4.56) and "great depression" (t-stat = -4.15).

2.2 Other Data

Most of our empirical tests are carried out at the aggregate market or index level. Daily indices are either taken directly from CRSP or calculated from the individual stock prices and returns in the CRSP daily stock file. To ensure that illiquid index component stocks are not driving our results, we also examine four highly liquid index exchange traded funds (ETFs): the SPDR

S&P500 (NYSEARCA: SPY), the PowerShares QQQ Trust (NASDAQ: QQQQ), Russell 1000 Index ETF (NYSEARCA: IWB), and the Russell 2000 Index ETF (NYSEARCA: IWM). We also obtain intraday data on SPY from TAQ in order to estimate realized market volatility. Finally, we obtain Treasury portfolio returns from the CRSP 10-year constant maturity Treasury file.

The Chicago Board Options Exchange (CBOE) daily Market Volatility Index (VIX), which measures the implied volatility of options on the S&P 100 stock index, is well-known as an "investor fear gauge" by practitioners. For example, Whaley (2001) discusses the spikes in the VIX series since its 1986 inception, which captures the crash of October 1987 and the 1998 Long Term Capital Management crisis. Baker and Wurgler (2007) consider it as an alternative market sentiment measure. We include the VIX index as a control variable in most specifications. Later we use our FEARS index to predict VIX, as well as returns from VIX futures traded on the CBOE.

We obtain a high-frequency measure of concurrent macroeconomic coconditions from the Federal Reserve Bank of Philadelphia.[9] Using a dynamic factor model to extract the latent state of macroeconomic activity from a large number of macroeconomic variables, Aruoba, Diebold, and Scoitti (2009) construct a daily measure of macroeconomic activities (the "ADS" index). According to the Federal Reserve Bank of Philadelphia, construction of the ADS index includes a battery of seasonally adjusted macroeconomic variables of mixed frequencies: weekly initial jobless claims; monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales; and quarterly real GDP. The change in the ADS index reflects innovations driven by macroeconomic conditions. An increase in the ADS index indicates progressively better-than-average conditions, while a decrease in ADS index indicates progressively worse-than-average conditions. We also obtain the dates of important macroeconomic announcements about the consumer price index (CPI), the producer price index (PPI), unemployment rates, and interest rates as in Savor and Wilson (2013) for our sample period.

To capture uncertainty related to economic policies, we adopt a news-based measure of economic policy uncertainty (EPU) recently developed by Baker, Bloom, and Davis (2013).[10] This measure is constructed by counting the number of US newspaper articles achieved by the NewsBank Access World News database with at least one term from each of the following three categories:

[9] The data are available at: http://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index/

[10] The data are available at: http://www.policyuncertainty.com/us_daily.html.

(1) “economic” or “economy”; (2) “uncertain” or “uncertainty”; and (3) “legislation”, “deficit”, “regulation”, “congress”, “Federal Reserve” or “White House”. Baker, Bloom, and Davis (2013) provide evidence that the news-based measure of economic policy uncertainty (EPU) seems to capture perceived economic policy uncertainty.

In a robustness table we also use a measure of news-based sentiment. Our news-based sentiment measure is the fraction of negative words in the Wall Street Journal’s “Abreast of the Market” column as in Tetlock (2007). To identify negative words, we follow Tetlock (2007) and use the dictionaries from the General Inquirer program. Loughran and McDonald (2011) argue that some negative words in these dictionaries do not have a truly negative meaning in the context of financial markets. For example, words like “tax”, “cost”, “vice”, and “liability”, simply describe company operations. Instead, they develop an alternative negative word list that better reflects the tone of financial text. We obtain qualitatively similar results when using either word list.

Our daily mutual fund flow data are obtained from TrimTabs, Inc. A description of TrimTabs data can be found in Edelen and Warner (2002) and Greene and Hodges (2002). TrimTabs collects daily flow information for about $1,000$ distinct mutual funds which represent approximately 20% of the universe of US-based mutual funds according to Greene and Hodges (2002). TrimTabs aggregates the daily flows for groups of mutual funds categorized using fund objectives from Morningstar. For our study, we focus on the daily flow of two groups of mutual funds. The first group (Equity) specializes in equity. The second group (MTB) specializes in “Intermediate Treasury Bonds.” For each group, we compute the daily flow as the ratio between dollar flow (inflow minus outflow) and fund Total Net Assets (TNA). The data we received from TrimTabs cover the five-year period from July 2004 to October 2009.

3 FEARS and Asset Returns

We first examine the relationship between FEARS and returns across various asset classes. We then examine how this relationship varies among the cross-section of stocks when we consider limits to arbitrage.

3.1 FEARS and Average Returns

One salient feature of sentiment theories is the heterogeneity of investors. In sentiment models, there is typically one class of investors who suffer from a bias, such as extrapolative expectations about future cash flows. These biases lead investors to make demands for assets which are not reflected by fundamentals and, in the presence of limits to arbitrage, push prices away from fundmantal values. Thus, a central prediction of theories of investor sentiment is reversal. For example, when sentiment is high, prices are temporarily high but later become low.

We look for evidence of return reversals by running the following regressions:

$$return_{i,t+k} = \beta_0 + \beta_1 FEARS_t + \sum_m \gamma_m Control^m_{i,t} + u_{i,t+k}. \quad (3)$$

In regression (3), $return_{i,t+k}$ denotes asset i's return on day $t+k$. We also consider two-day cumulative returns, $return_{i,[t+1,t+2]}$, to gain a perspective on the cumulative effects of return reversals. Control variables ($Control^m_{i,t}$) include lagged asset-class returns (up to five lags), changes in a news-based measure of economic policy uncertainty (EPU), the CBOE volatility index (VIX), and changes in the Aruoba-Diebold-Scotti (ADS) business conditions index.[11] We calculate bootstrapped standard errors and our statistical inference is conservative.[12]

In Table 2, we examine the Standard and Poor's 500 Index. When $k = 0$, the negative and significant coefficient on $FEARS_t$ suggests a negative contemporaneous relationship between FEARS and a broad equity index. Days in which there were sharp declines in the equity index there were also sharp increases in search for terms like "recession", "gold price", "depression" and so on. For example, the first column of Table 2 shows that a one standard deviation increase in FEARS corresponds with a contemporaneous decline of 20 basis points for the daily S&P 500 index, after controlling for lagged returns, contemporaneous VIX, EPU, and ADS.[13] This result is perhaps unsurprising. Recall that the search terms which comprise the FEARS index were selected based

[11] We also find that replacing the VIX index with an increasingly popular alternative sentiment index, the Credit Suisse Fear Barometer (CSFB) has little effect on the results.

[12] For all the empirical results reported in the paper, we have also computed standard errors that are robust to heteroscedasticity and autocorrelations. These unreported standard errors imply even higher t-values in general, thus only strengthen our conclusions.

[13] A one standard deviation change in the FEARS index corresponds to 0.35. Recall that while each individual search term has been standardized so that it's standard deviation is one by construction, the average across search terms will not have a standard deviation of one given correlation among search terms.

on their historical correlation with the market. Table 2 suggests that they continue to be correlated out of sample.

Much of the day 0 effect, however, is temporary. In the following days, the positive and significant coefficient on $FEARS$ suggests increases in FEARS predict *higher* returns. As evident in columns 2 to 4, these reversals are significant on both the first and the second day ($k = 1$ and 2).[14] Specifically, a standard deviation increase in FEARS predicts an *increase* of 7 basis points in the S&P 500 at $k = 1$ (significant at the 10% level), and an *increase* of 8 basis points at $k = 2$ (significant at the 5% level). The cumulative impact of a standard deviation increase in FEARS predicts a cumulative *increase* of 15 basis points in the S&P 500 over days 1 and 2 (significant at the 1% level). In other words, the initial impact of FEARS on the S&P 500 Index on day 0 is almost completely reversed after two days. In Table 2, we also consider longer horizons, ranging from $k = 3$ to $k = 5$ but none of the coefficients on FEARS is statistically significant and point estimates are economically negligible, confirming that the effect of FEARS on asset prices operates mainly during the first three days. We also verify that this is true for other asset classes and, for this reason, we do not report the results for $k > 2$ in other tables.

Table 3 reports results using different test assets. Panels A and B focus on different equity portfolios while Panel C focuses on Treasury securities. The test assets are the CRSP value-weighted and equally-weighted portfolios (Panel A), equity exchange traded funds (Panel B), and the CRSP 10-year constant maturity Treasury portfolio (Panel C). The equity ETFs include the S&P 500 Index ETF (SPY), the NASDAQ 100 ETF (QQQQ), the Russell 1000 Index ETF (IWB), and the Russell 2000 Index ETF (IWM). Across all assets, a contemporaneous increase in FEARS is always associated with a contemporaneous decrease of equity returns, and a contemporaneous increase of Treasury returns. Moreover, an increase in FEARS today (i.e., $k = 0$) always predicts a return reversal in the coming two days (i.e., $k = 1$ and $k = 2$). The effect of FEARS on equities is typically larger in both initial and future returns compared to Treasury securities. A standard deviation increase in FEARS corresponds with a contemporaneous *decrease* of 17 to 20 basis points

[14] Note that search volume and returns are measured over different intervals. Daily search volume is measured over the interval 00:00 - 24:00 PST while returns are measured over the interval 13:00 PST - 13:00 PST. Therefore the return on day t+1 overlaps with some search volume on day t. If FEARS measured after-hours on day t spilled into day t+1 return we would expect a negative coefficient in column 2. We don't find one which suggests the effect from this mismatch in measurement of intervals is small. Moreover, FEARS on day t predicts returns on day t+2 where there is no overlap of measurement intervals.

among equities at $k = 0$ (significant at the 1% significance), and a reversal of 13 to 17 basis points during the next two days ($k = 1$ and 2, significant at the 1% - 5% level). In contrast, a standard deviation increase in FEARS corresponds with a contemporaneous *increase* of 4 basis points for Treasury securities at $k = 0$ (significant at the 1% level), and an almost complete reversal over the next two days (significant at the 5% level). Also, as the portfolios include more small stocks in Panel B (from the S&P 500 Index, to the Russell 1000 Index and then to the Russell 2000 Index) we observe a stronger reversal effect associated with our FEARS index.

Short-term reversals can also be caused by a liquidity shock as in Campbell, Grossman, and Wang (1993, CGW hereafter). Baker and Stein (2004) point out that, as sentiment and liquidity are intertwined, the difference between a sentiment-based story as in DSSW and a liquidity-based story as in CGW boils down how we view liquidity shocks and noise traders. Tetlock (2007) summarizes that "the difference between DSSW and CGW is philosophical rather than economic." While our results may be consistent with changes in investor sentiment triggering a liquidity shock, in section 3.3 we consider the possibility that our results are driven by liquidity shocks following macro announcements and find little evidence to support the hypothesis.

3.2 FEARS and Limits to Arbitrage

As highlighted in Baker and Wurgler (2006, 2007), there are several additional channels which can exacerbate the effect of sentiment investors on asset prices. Perhaps the most important channel is limits to arbitrage (Pontiff, 1996; Shleifer and Vishny, 1997). Arbitrage capital moves slowly to take advantage of the irrational beliefs of sentiment investors. Motivated by limits to arbitrage, we consider several additional testing assets in order to explore the effect of sentiment on asset prices.

The first set of testing assets is the return spread from beta-sorted portfolios obtained from CRSP. CRSP computes a Scholes-Williams (1977) beta for common stocks traded on NYSE and AMEX using daily returns within a year and then forms decile portfolios. We take these beta-sorted decile portfolios, and compute the return spread between high beta stocks and low beta stocks.

According to Baker, Bradley, and Wurgler (2011), high beta portfolios are prone to the speculative trading of sentiment investors. Moreover, high beta stocks may be unattractive to arbitragers who face institutional constraints such as benchmarking. Because these two forces work in the same direction for high beta stocks, it is natural to conjecture that investor sentiment may have a larger impact among high beta stocks than among low beta stocks. Thus, the return spreads between high beta and low beta stock portfolios should be negatively correlated with a contemporaneous increase in FEARS, while future return spreads should be positively correlated with current increases in FEARS. Motivated by Wurgler and Zhuravskaya (2002), we also use total return volatility as a proxy for limits to arbitrage and examine the aforementioned reversal pattern for a portfolio of stocks with high volatility versus a portfolio of stocks with low volatility. The volatility-sorted portfolios are also obtained from CRSP. Using daily stock returns within a calendar year, CRSP computes the total return volatility of common stocks traded on NYSE and AMEX, and creates decile portfolios based on total return volatility.

Panels A from Table 4 confirm the hypothesis. As shown in Panel A, columns 1 and 2, sentiment has a more negative contemporaneous relationship with high-beta stocks. For example, a one standard deviation increase in FEARS is associated with a 23 basis points decrease in the return spread between the high-beta and low-beta stock portfolio (statistically significant at the 1% level). Again, FEARS also predicts future return reversal effects. By $k = 2$, the effect is almost completely reversed. Likewise in columns 3 and 4, we find FEARS to have stronger impact on high-volatility stocks than low-volatility stocks on day (t), while the impact is almost completely reversed by the end of the second day $(k = 2)$.

Certain assets are also prone to "downside" risk. As Ang, Chen, and Xing (2006) observe, "downside" risk is not well captured by conventional beta from the Capital Asset Pricing Model (CAPM). If downside risk is particularly large when investor sentiment is high, we anticipate a portfolio of stocks with high downside risk should underperform a portfolio of stocks with relatively low downside risk because downside risk limits arbitrageurs from correcting mispricing. Following Ang, Chen, and Xing (2006), we consider two measures of "downside risk." The first measure is "downside beta", which was first introduced by Bawa and Lindenberg (1977). Specifically, at the end of each month, we estimate the "downside beta" (i.e., β_i^-) for individual stocks as follows,

$$\beta_i^- = \frac{cov\left(r_i, r_m | r_m < \mu_m\right)}{var\left(r_m | r_m < \mu_m\right)}, \tag{4}$$

using the past one-year of daily returns.

The second measure of downside risk is "downside sigma" (i.e., σ_i^-), which is defined as follows

$$\sigma_i^- = \sqrt{var\left(r_i | r_m < \mu_m\right)}, \tag{5}$$

and it is also estimated using the past one-year of daily returns on a monthly basis.

Analogous to the beta-sorted or the total return volatility sorted portfolios constructed by CRSP, we create decile portfolios on the basis of stock-level estimates of "downside beta" or "downside sigma" for individual stocks. We track daily portfolio returns over the next month, and rebalance the portfolio at the end of next month. The return spreads between the returns of the high "downside beta" and low "downside beta" stock portfolios are the test assets in columns 5 and 6 of Panel A. Similarly, columns 7 and 8 relate FEARS and return spreads between the high "downside sigma" and low "downside sigma" stock portfolios. Sentiment's effect on these return spreads are large. For instance, a one standard deviation increase in FEARS is associated with a 39 basis points decrease in the return spreads between the high downside beta and low downside beta stock portfolio (statistically significant at the 1% level). Again, FEARS also predicts future return reversals. By $k = 2$, the reversal of the return spreads associated with FEARS is about 23 basis points. Thus sentiment has a stronger effect on high downside beta stocks than low downside beta stocks on day (t), while the impact almost completely reverses back by the end of the second day ($k = 2$) after event day (t), or $k = 0$. Similar results are obtained using the High-minus-Low-Downside-Volatility portfolio return spreads.

We have shown earlier that FEARS predict a reversal in market return. Since stocks that are difficult to arbitrage tend to have higher betas, it is perhaps not surprising that FEARS predicts a stronger reversal among these stocks. In other words, the cross-sectional results in Panel A of Table 4 could be driven by a mechanical "beta effect." To examine whether a "beta effect" is driving the results shown in Panel A, we construct a series of double-sorted portfolios to account for potential differences in betas across testing assets. Specifically, at the end of each month, we first compute the Scholes-Williams (1977) beta for each stock, using the past 12-month daily returns. To ensure our sample is comparable to various decile-sorted portfolios constructed by CRSP and further alleviate liquidity concerns, we restrict our sample to stocks from NYSE and AMEX. We sort these stocks into quintile portfolios. Within each quintile portfolio, we further sort stocks into another set of quintile portfolios based on total volatility, downside beta, or downside volatility (as estimated before). From each beta-sorted quintile portfolio, we compute the return spreads between the high and low total volatility, downside beta, or downside volatility portfolios, and take the average across the beta-sorted quintiles. These double-sorted portfolios generate return spreads with varying degrees of limits to arbitrage, but are beta-neutral.

Panel B of Table 4 reports our results. After removing the "beta effect," FEARS still significantly predicts reversals on the three beta-neutral return spreads due to differences in total volatility (columns 1 and 2), downside beta (columns 3 and 4), or downside volatility (columns 5 and 6), although the magnitudes of the reversals are in general smaller than those reported in Panel A. For example, a one standard deviation increase in FEARS is associated with a 24 basis points decrease in the return spreads between the high and low downside-beta stock portfolio (statistically significant at the 1% level). By $k = 2$, the reversal of the return spreads associated with FEARS is about 18 basis points (statistically significant at the 1% level) – or about 74.3% (= 18/24) of reversal of intial return spreads.

Overall, this evidence provides additional support for the sentiment model of Baker and Wurgler (2006, 2007), which highlights the interaction between speculative trading and limits to arbitrage. It also provides cross-sectional evidence for sentiment-induced mispricing. Among the set of stocks for which sentiment is most likely to operate we find the strongest evidence of temporary deviation from fundamentals.

3.3 Robustness Checks

Construction of our FEARS index required several choices and in this section we examine the robustness of our results to those choices and the inclusion of additional control variables.

For example, we use the 30 search terms whose $\Delta ASVI$s are most negatively correlated with the market return in our backward rolling window. Averaging FEARS across many search terms allows us to capture their common variation, and at the same time, alleviate idiosyncratic noise. In Panel A of Table 5, we construct alternative FEARS indices by averaging the top 25 search terms and top 35 search terms. Comparing the results in Table 5 Panel A to those in Table 2, we find the alternative FEARS indices produce very similar results. Moreover, to alleviate the effect from extreme outliers in the construction of the FEARS index, we also winsorized the series for each search term at the 5% level (2.5% in each tail). A potential concern about applying winsorization in the context of predictive regressions is that it could introduce a forward-looking bias. To address this concern, the final columns of Panel A reports the result of using FEARS indices constructed without winsorization. The results are again very similar to those in Panel A of Table 2, if not slightly stronger.

In the main test specifications, we have been using a news-based measure of economic policy uncertainty (EPU), the CBOE volatility index (VIX), and Aruoba-Diebold-Scotti (ADS) business conditions index as our controls for economic uncertainty, investor sentiment and macroeconomic conditions. There are also news-based investor sentiment measures. For example, Tetlock (2007) proposes a news-based sentiment measure using the fraction of negative words in the Wall Street Journal's "Abreast of the Market" column. The news-based investor sentiment measure is available to us through 2010, and this is why we do not include it in our benchmark regressions. Nevertheless, the first two columns of Table 5, Panel B show that in this shorter sample our results are robustness to the inclusion of it as an additional control.

Another potential concern is that FEARS could simply proxy for extreme market returns which are more likely to revert in the future. While we have included the market return and additional lags as control variables in our regressions, one may still be concerned that the FEARS index simply captures a nonlinear effect from large market returns. To address this concern, we include decile dummies for the market return in our regressions in columns 3 and 4 of Panel B. Little changes after the inclusion of these decile dummies.

The next two columns consider the effect of holidays on search and returns. Because search patterns may systematically change around holidays and there is some evidence of holiday-related return phenomenon (see, Ariel (1990) for example), columns 5 and 6 of Panel B removes holiday effects by including additional dummy variables for the trading day before and the trading day after public holidays in our sample. Little changes after the inclusion of holiday controls.

Although we interpret the spike-reversal pattern herein as evidence of sentiment, such a pattern is potentially consistent with a liquidity shock following an economic event. The economic event could trigger both spikes in search volume and liquidity trades, pushing prices away from fundamentals temporarily as in CGW. This would also generate the predictable spike-reversal pattern we find. We address this alternative in a few ways. First, we include the turnover of the S&P500

index as a control variable in columns 7 and 8 of Panel B. Controlling for liquidity in this way does little to change the results. Second, we obtain macro announcement dates as in Savor and Wilson (2013) and remove all observations with macro announcements. The idea is that while periodical macro announcements may affect investor sentiment, they may also induce portfolio rebalancing and generate liquidity shocks. In Table 5, Panel C we find the same spike-reversal pattern among observations without macro announcements. Third, recall that our spike-reversal pattern occurs among all the ETFs we examine. ETFs are less susceptible to liquidity shocks because the supply of ETF shares is not fixed. If many investors wanted to sell shares in an ETF at the same time, the market maker can simply "destroy" existing shares without worrying about finding buyers on the other side. In fact, the bid-ask spread on the SPY ETF is almost always at the minimum tick of 1 cent. Fourth, recall that we find larger effects among the cross-section of stocks prone to speculative trading (Section 3.2). A liquidity hypothesis is unlikely to generate the same cross-sectional pattern in stocks.

Finally, we have been using the FEARS index on day t to "predict" asset returns on days $t+1$ and $t+2$ as we try to understand the economic impact of investor sentiment on contemporaneous and future prices. Because Google releases its SVI data with a one-day delay, these predictive regressions cannot be run in real time. For example, the SVI for a search term on Wednesday, January 23rd will typically be released sometime during the evening of Thursday, January 24th. Moreover, Google only made this data publicly available in June 2006.

Panels C and D demonstrates the robustness of our reversal results when the predictive regressions are implemented when data are available. The final columns of Panel C consider the subset of observations beginning in June 2006 when search data were available and finds little change in the main result. Panel D considers the predictability of day $t+2$ open-to-close returns with day t search volume. Continuing with the earlier example, it means that we use our FEARS index on Wednesday, January 23rd (observable by the evening of Thursday, January 24th) to predict the open-to-close returns on Friday, January 25th. In other words, the predictive variables are strictly observable before the asset return can be computed. Because open prices are needed for this analysis, we focus our attention on ETFs. The results in Panel D confirms the strong and significant reversals across all four ETFs. The regression coefficients are only slightly smaller compared to those in Table 3 Panel B, reflecting the fact that we are using open-to-close returns rather than the standard close-to-close returns.

4 FEARS and Volatility

A long strand of literature starting from Black (1986) suggests that investor sentiment and the resulting noise trading can affect both the level and the volatility of asset prices. If uninformed noise traders base their trading decisions on sentiment, then extreme sentiment changes will temporarily lead to more noise trading, greater mispricing and excessive volatility. To our knowledge, no prior work has examined the relation between sentiment measures and market-level volatility at a high frequency.[15] In this section we examine the relationship between FEARS and various stock market return volatility measures. The results are reported in Table 6.

We start by examining two direct measures of stock market volatility. The first measure is realized volatility (RV) developed by Andersen, Bollerslev, Diebold, and Ebens (2001) and Andersen, Bollerslev, Diebold, and Labys (2003). We implement the realized volatility estimation procedure by closely following Andersen, Bollersleve, Diebold, and Ebens (2001). Since intraday transaction data is needed to calculate daily realized volatilities, we focus our attention on the SPDR S&P500 ETF (NYSEARCA: SPY) as a close proxy for the stock market index. The SPY ETF is extremely liquid. For instance, the bid-ask spread is almost always one cent. Similar to Antweiler and Frank (2004), we choose 15-minute periods when we sample the intraday returns. $r_{t,d}$ denotes the intraday return for SPY during the d-th period on day t. SPY's (annualized) realized volatility on day t is given by

$$rv_t = 250 \sum_{d=1}^{N} r_{t,d}^2. \tag{6}$$

We then compute daily log realized volatility, rv, and remove potential seasonal effects by regressing it on day-of-the-week and month-of-the-year dummies. We focus on the residuals, or the seasonal-adjusted log RV time series (adj_rv). Since volatility is persistent and long-lived (Engel and Patton (2001) and Andersen et al. (2001, 2003)), we also model the long-range dependence

[15] Using Yahoo! message board activities as a proxy for noise trading, Antweiler and Frank (2004) and Koski, Rice, and Tarhouni (2008) confirm the positive relation between noise trading and future volatility at the daily frequency for a small set of individual stocks.

through the fractional integrated autoregressive moving average model, $ARFIMA(1,d,1)$:

$$(1-L)^d\left(adj\_rv_t-\beta_1 FEARS_t-\sum_m \beta_m Control_{i,t}^m\right)=(1-L)\varepsilon_t \tag{7}$$

where the fractional integration parameter is $d\in(0,0.5)$. The control variables are changes in a news-based measure of economic policy uncertainty (EPU), and changes in the Aruoba-Diebold-Scotti (ADS) business conditions index. We estimate (7) using the maximum likelihood method. The key coefficient β_1 identifies the impact of the FEARS index on the realized volatility of the stock market after controlling for the persistent component in volatility, changes in EPU and ADS.

The second measure of the stock market volatility is the Chicago Board Options Exchange (CBOE) daily Market Volatility Index (VIX). As in the case of the realized volatility, we also first compute the seasonal-adjusted log VIX time series (adj_vix) and then estimate a similar $ARFIMA(1,d,1)$ as in (7) except that we replace adj_rv_t with adj_vix_t. The results are reported in Panel B (columns 1 to 3 for the realized volatility and columns 4 to 6 for the VIX). We find that our FEARS index is positively and significantly related to the market volatility measures only contemporaneously (see columns 1 and 4). Controlling for the persistent component in volatility, neither realized volatility nor VIX loads significantly on lagged FEARS index. These results again suggest that our FEARS index only has a transitory impact on the level of stock market volatility.

Second, parallel to our analysis in the previous sections, we also examine daily returns to a tradable asset based on volatility, the Chicago Board of Exchange (CBOE) VIX futures contract. Working with the return series has the benefit of circumventing potential econometric issues associated with the VIX and RV time-series and providing a clear interpretation of asset returns. For a contract with a given settlement date, its daily return is computed as the change of log daily prices.[16] We then use our FEARS index to predict these daily VIX futures returns using the same regression specifications (3). The results are reported in Panel C.

Panel C confirms the strong contemporaneous correlation between FEARS and volatility. For example, a one standard deviation increase in FEARS corresponds with a contemporaneous 43 basis points increase in VIX futures return. In the next two trading days, we again find a reversal

[16] Daily returns are calculated using the contract closest to maturity except when this contract is less than five days away. When the closest to maturity contract is less than five days away daily returns are calculated from the second closest to maturity contract.

pattern. By the end of the second trading day, we observe a total reversal of 31 basis points.

Thus far analyzing both the levels and changes in stock market volatility, our results paint a consistent picture: an increase in our FEARS index coincides with an increase in market volatility which is temporary. To the extent that a spike in our FEARS index coincides with more noise trading, our evidence provides further support for the DSSW model where noise trading leads to excessive volatility temporarily. The DSSW model also predicts a positive relation between the volatility of sentiment and the volatility of the asset price (see equation 11 in DSSW). The intuition is simple: if sentiment contributes to a temporary price deviation from fundamental value, then the more volatile sentiment is, the higher the excessive price volatility should be. While our focus is on the level of investor sentiment as measured by our FEARS index, we also try to analyze the joint volatility dynamics between our FEARS index and market returns. Specifically, we model daily stock market excess return and our FEARS index jointly using a multivariate GARCH with dynamic conditional correlation (see Engle (2000)). Unreported results confirm a significant positive correlation of 7.17% (p-value of 0.002) between the conditional variance of the stock market return and that of the FEARS index.

5 FEARS and Fund Flows

Noise traders affect asset prices via trading. To directly examine the sentiment effects of noise traders we examine daily mutual fund flows in our last set of tests. Since individual investors hold about 90% of total mutual fund assets, and they are more likely to be sentiment traders, daily flows to mutual fund groups likely aggregate noise trading at the asset class level (Brown et al. (2002)). Daily mutual fund flow data are obtained from TrimTabs for two groups of mutual funds that specialize in equity (Equity) and intermediate treasury bonds (MTB).

Bollerslev and Jubinski (1999) and Fleming and Kirby (2006) provide evidence that an individual stock's daily trading volume series exhibits long-run temporary dependencies, which can be modeled using a fractionally integrated processes. Similar to observations made on the volume of individual stocks, we also find very strong persistence and long-memory components in daily fund flows. For this reason, we first demean each of the daily fund flow series, and apply the $ARFIMA(p, d, q)$ models to extract daily fund flow innovations. Our diagnostics indicate that the

$ARFMA(1,d,1)$ model fits the underlying daily fund flows well. The integration parameter values are in the neighborhood of 0.40 and p-value less than 0.1%. In addition, the moving average (MA) as well as the autoregressive (AR) terms are all statistically significant at the 1% level or better.

There is one data issue worth pointing out. TrimTabs mutual fund flow is calculated using both publicly observable net asset value (NAV) and privately reported total asset value (NTA). Despite the obvious accuracy of NAV, the NTA information might be reported with a delay of one day for some funds. Both Edelen and Warner (2001), as well as Greene and Hodges (2002) document this issue, and analyze it in detail. Because of this potential one-day reporting delay, we note that TrimTabs flow in day $t+1$ may actually contain flow in day t (see also Yuan (2008)). We run regressions of contemporaneous fund flows and fund flows 1 to 4 days ahead. In particular, we run the following regression:

$$flow_{i,t+k} = \beta_0 + \beta_1 FEARS_t + \sum_m \gamma_m Control_{i,t}^m + u_{i,t+k} \tag{8}$$

where fund class i includes bond and equity funds. Control variables($Control_{i,t}^m$) include as usual VIX, ΔEPU, ΔADS, and five lags of market returns. The results of these regressions are reported in Table 7.

We find that our FEARS index has significant incremental predictive power for future daily fund flow innovations of both equity and bond funds. In the equity flow regressions the coefficient on FEARS is negative on each day we consider: $t = 0, 1, 2, 3$ and 4 and is statistically significant for days t=2 (p-value $< 5\%$) and t=3 and 4 (p-value $<10\%$). Interestingly, in the bond flow regressions the coefficient on FEARS is positive on all days but only significant on t=3, suggesting a significant inflow to bond funds one day after a significant withdrawl from equity funds. The evidence highlights a flight to safety where investors are shifting their investment from equity to bond after a spike in FEARS.

Considering equity flows, the coefficients on FEARS are economically large. A one standard deviation increase in FEARS is associated with significant equity outflows of $-2.79 \times 10^{-5} (= 0.35 \times -7.98 \times 10^{-5})$. Given the average equity fund flow of -5.06×10^{-5}, this is about 55% of the typical daily flows. Similarly, a one standard deviation increase in FEARS is associated with significant bond inflows of 8.2×10^{-5}, which is slightly larger than the average daily bond flow (7.49×10^{-5}).

While Panel A only reports significant equity outflows one day after the spike in FEARS (recall that the outflow on t+2 may actually contain outflow in day t+1 due to a reporting delay in the TrimTabs data), such outflows are very predictable. As such, while retail investors may wait until tomorrow to actually withdraw their money from the fund, the fund, in anticipation of such a withdrawal, may start to trade stocks today and cause an immediate price impact..

Taken together, the evidence herein suggests that individual investors switch from equity funds to bond funds when negative sentiment is high.

6 Discussion of Alternative Interpretations

Just as many authors have understood the solicitation of household attitudes by survey as a measure of sentiment (e.g., Brown and Cliff (2004), Lemmon and Portniaguina (2006), and Qiu and Welch (2006)), we understand the revelation of household attitudes via search as a measure of sentiment. We then test many of the predictions of sentiment models such as DSSW. So far we have found evidence that the attitudes of households as revealed by their search behavior have predictability for short-term returns, short-term market volatility and both equity and bond mutual fund flows.

6.1 Endogenous Search

Some readers may be concerned that search is endogenous to macroeconomic events. For example, there must be some macro events which coordinate the large spikes in search we observe in Figure 1. This does not disqualify search as a measure of sentiment. In fact, we should expect investor sentiment to be endogenous to macroeconomic events.[17] News arrives daily - some of it will affect investor sentiment and some of it will not. To the extent that daily returns, the policy uncertainty index and the business conditions index measure news arrival, we have explicitly controlled for news events in each of our specifications. Therefore, we can think of our FEARS index as describing the amount of sentiment generated by an event.

Other readers will be concerned about reverse causality in some of our prediction models if events are anticipated. We cannot conclude that sentiment today caused return tomorrow in

[17] Qui and Welch (2006) discuss this issue as well. They argue: "The theories are about sentiment, not about sentiment orthogonal to macroeconomic conditions. In what theory would we expect sentiment not to be related to unemployment, GDP, portfolio returns, wealth changes, etc.? (Answer: None!) Sentiment does not drop like manna from heaven."

the same way we cannot conclude that someone who buys an umbrella today in preparation for rain tomorrow causes the rain tomorrow. However, the predictability for returns (Section 3) likely mitigates such concerns. The fact that we find high FEARS today are correlated with low returns today but predicts high returns tomorrow makes reverse causality unlikely. It is implausible that investors, anticipating a high return tomorrow, would search for terms like "recession" and "inflation" today. Return reversal following a spike in the FEARS index is more consistent with sentiment models which predict temporary deviation from fundamentals.

6.2 Search as a Measure of Sentiment

Beyond endogeneity concerns, there are also other interpretations of our measure and its subsequent predictability for asset volatility. For instance, it is possible that search for terms like "recession" or "great depression" proxy for time-varying risk-aversion. In Campbell and Cochrane (1999), a low surplus consumption ratio will jointly cause risk-aversion and volatility to increase. In Kyle and Xiong (2001) when convergence traders have reduced capital as a result of losses, their risk aversion will increases (due to wealth effects) while asset volatility increases as they liquidate their positions. Both models generate a correlation between risk aversion and volatility in the time series.

While this is a possible interpretation of our evidence, there are two important caveats. First, neither model generates a predictable reversal in prices which is what we find in Section 3. Second, there is little evidence that risk-aversion changes rapidly (see Brunnermeier and Nagel (2008)). Therefore, it seems unlikely that the large daily variation we observe in search volume represents time-varying risk aversion.

Alternatively, FEARS may be proxying for time-varying parameter uncertainty. Uncertainty about the parameters of models governing the dynamics of asset returns can be positively related to future asset volatility (see Veronesi (1999) among others). While the VIX index is commonly viewed as an indicator of aggregate uncertainty, we do not find any evidence that VIX is related to return reversal: FEARS remains a strong predictor of future VIX even after controlling for current VIX. Moreover, our policy uncertainty control variable (EPU) further alleviates this concern.

Finally, some readers may worry that search for FEARS is a neutral activity which does not reflect underlying pessimism or optimism. The argument is that households may search for terms like "inflation" or "recession" not because they are concerned about inflation or a recession but rather because they wish to gather information about inflation or recession. This claim is not supported by the evidence. First, even a cursory look at many of the FEARS components (such as "recession" or "bankruptcy") suggests they increase in bad times (Table 2). For example, (negative) search volume for the term "recession" has an 85.8% correlation with the University of Michigan's Consumer Confidence Index, suggesting most of the time households search for "recession" when they are worried about a recession. Second, recall from Section 3 that we find a contemporaneous, negative relationship between FEARS and equity returns. The days in which equity returns are low are the same days in which households search for terms in our FEARS index.

7 Conclusion

By aggregating queries like "recession", "bankruptcy" and "depression" we construct a Financial and Economic Attitudes Revealed by Search (FEARS) index. We show that FEARS predicts aggregate market returns. In particular, FEARS are correlated with low returns today but predict high returns tomorrow, a reversal pattern that is consistent with sentiment-induced temporary mispricing. Moreover, this effect is strongest among stocks that are favored by sentiment investors and are difficult to arbitrage. In addition, our FEARS index is strongly related to the transitory component of daily volatility, and that its correlation with VIX futures returns also reverse. Finally, using daily aggregate mutual fund flows, we also provide direct evidence for "noise" trading. Increases in FEARS index trigger daily mutual fund flows out of equity funds and into bond funds. The evidence is broadly consistent with the "noise trading" hypothesis of De Long et. al. (1990).

More generally, this paper follows a new strand of the sentiment literature which proposes novel, high-frequency measures that do not rely on market outcomes like return and volume. Tetlock (2007) suggests that a journalist's tone as measured by the frequency of negative words in a *Wall Street Journal* column captures sentiment and also shows that this tone has predictability for returns. Tetlock (2007) argues that "these results have two reasonable interpretations: the media reports investor sentiment before this sentiment is fully incorporated into market prices; or the media directly influences investors' attitudes toward securities. " Although we also find predictability for returns, our results have only one reasonable interpretation because aggregate search volume does not require a journalist or other intermediary. As such this paper underscores the usefulness of search data in financial applications. Search data has the potential to objectively and directly *reveal* to empiricists the underlying beliefs of an entire population of households. Given that many financial models link beliefs to equilibrium outcomes (such as returns or volume), search behavior has the potential to provide sharper tests of economic models. The tests herein constitute one possible application of search data. We leave the many other applications for future research.

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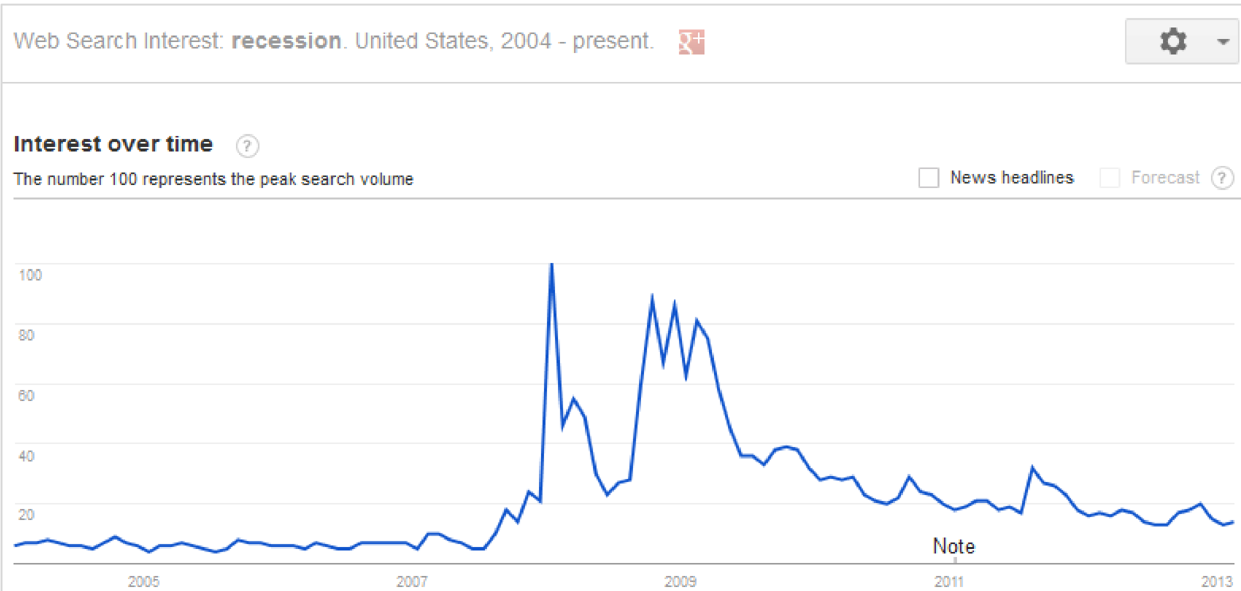
Figure 1: Illustrations of Google Search Volume

The figures represent the graphical output of weekly aggregate search frequency (SVI) from Google Trends (http://www.google.com/trends/). The top (bottom) panel plots weekly SVI for "recession" ("bankruptcy") in the United States. Plotted SVI is weekly search volume scaled by the maximum over the time period.



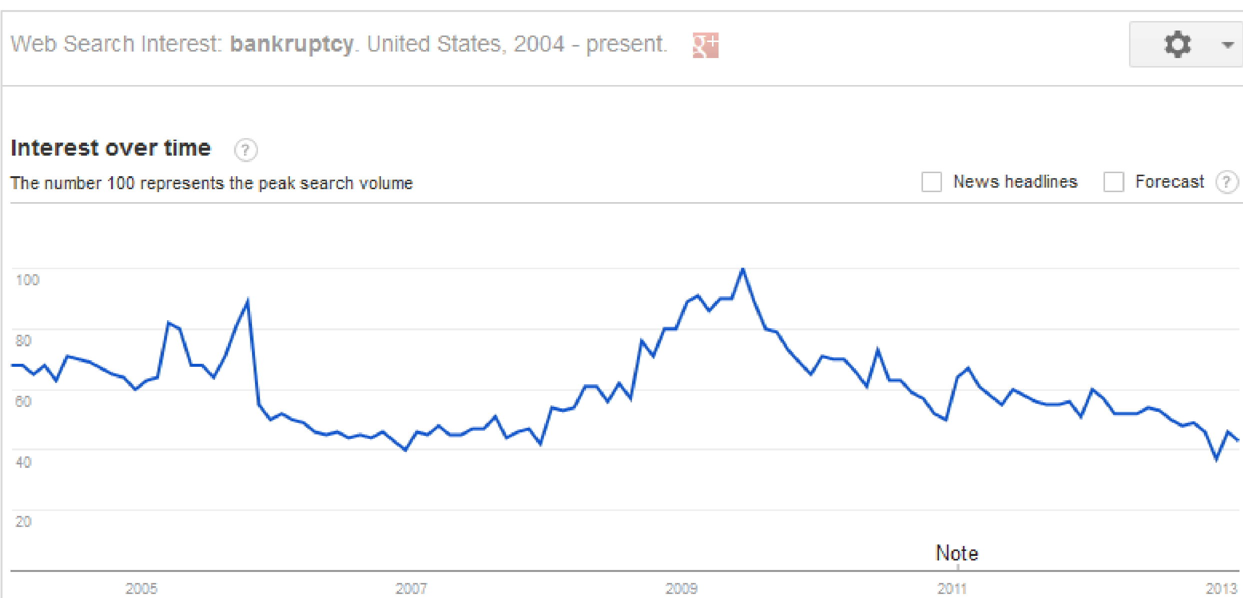


Figure 2: Search for "Recession" and Consumer Confidence

We plot the monthly log SVI for "recession" (with a minus sign) against the monthly University of Michigan Consumer Sentiment Index. The data are from 2004/01 to 2011/12. The correlation between the two series is 0.858.

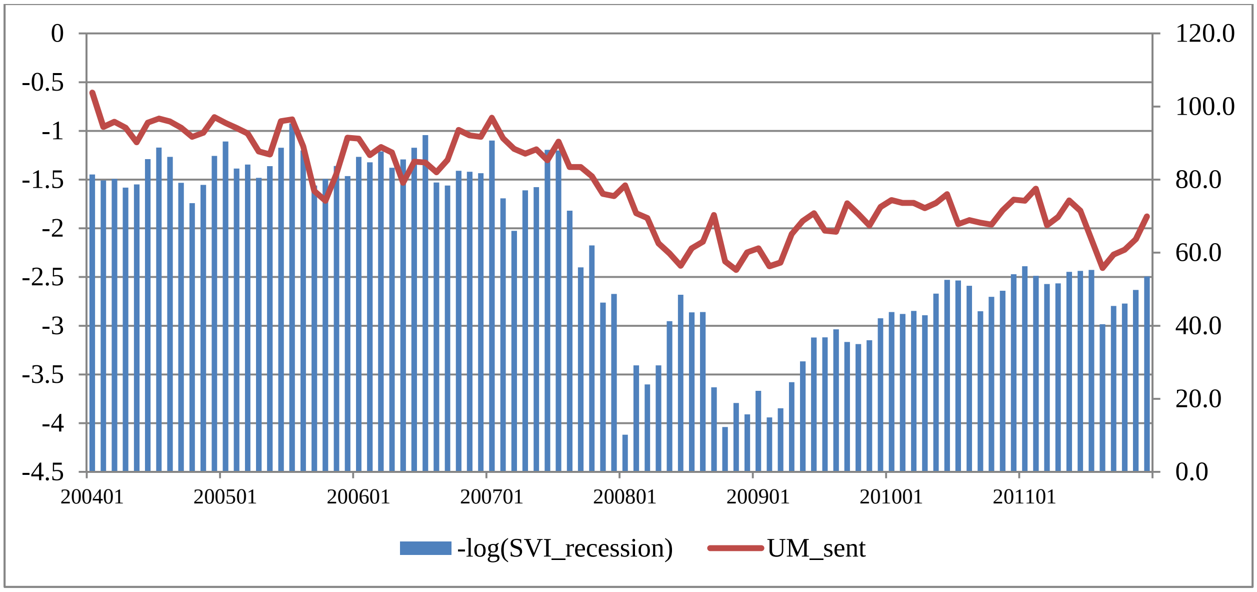
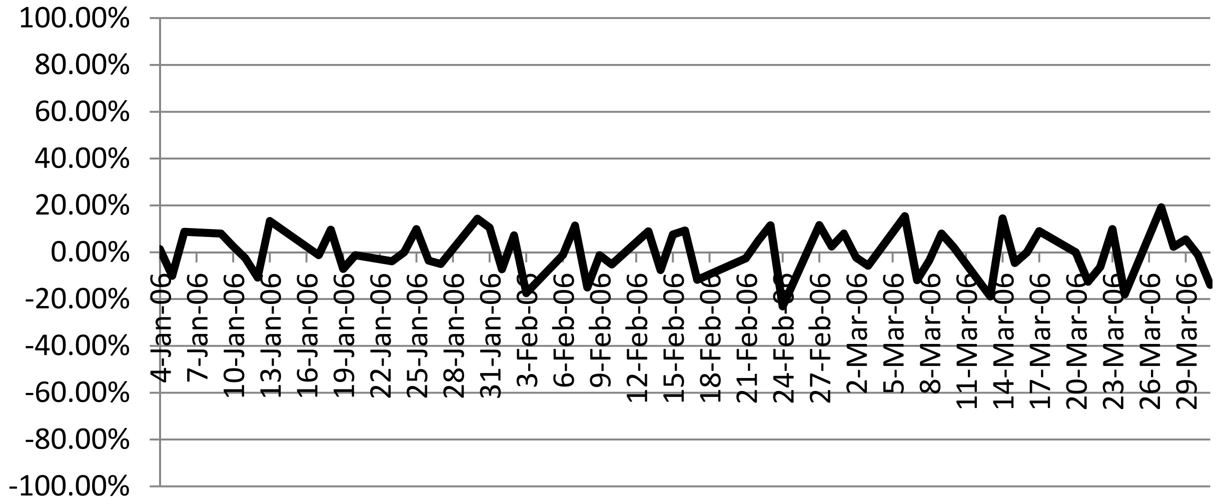


Figure 3: SVI Change Examples for "Inflation" and "Price of Gold"

We plot two examples of daily changes in SVI. The first is for the term "Inflation" over the period January 2006 – March 2006 plotted in the top panel. The second is for the term "Price of Gold" over the period October 2006 – December 2006 plotted in the bottom panel.

SVI Change for "Inflation": January 2006 – March 2006



SVI Change for "Price of Gold": October 2006 – December 2006

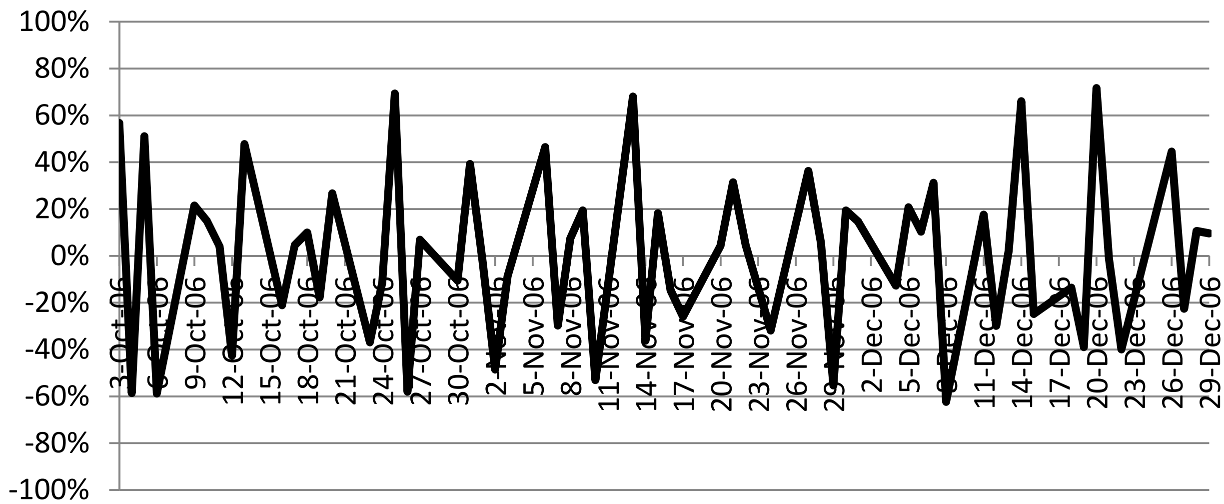


Table 1: FEARS Terms from the Full Sample

This table reports the 30 search terms derived from words of economic sentiment in the Harvard and Lasswell dictionaries (see the description in Section 2.1) which have had the largest negative correlation with the market. The terms are ordered from most negative (GOLD PRICES) to least negative (SOCIAL SECURITY OFFICE).

	Search Term	T-Statistic
1	GOLD PRICES	-6.04
2	RECESSION	-5.60
3	GOLD PRICE	-4.81
4	DEPRESSION	-4.56
5	GREAT DEPRESSION	-4.15
6	GOLD	-3.98
7	ECONOMY	-3.52
8	PRICE OF GOLD	-3.23
9	THE DEPRESSION	-3.20
10	CRISIS	-2.93
11	FRUGAL	-2.87
12	GDP	-2.85
13	CHARITY	-2.63
14	BANKRUPTCY	-2.50
15	UNEMPLOYMENT	-2.46
16	INFLATION RATE	-2.32
17	BANKRUPT	-2.28
18	THE GREAT DEPRESSION	-2.17
19	CAR DONATE	-2.11
20	CAPITALIZATION	-2.10
21	EXPENSE	-1.97
22	DONATION	-1.89
23	SAVINGS	-1.82
24	SOCIAL SECURITY CARD	-1.71
25	THE CRISIS	-1.65
26	DEFAULT	-1.63
27	BENEFITS	-1.56
28	UNEMPLOYED	-1.55
29	POVERTY	-1.52
30	SOCIAL SECURITY OFFICE	-1.51

Table 2: FEARS and S&P 500 Index Returns

This table relates S&P 500 index daily returns to FEARS. The dependent variables are contemporaneous returns (column (1)), future S&P 500 index daily returns in the next five days (columns (2), (4), (5), (6) and (7), respectively), and future S&P 500 index return over the first two days (column (5)). The independent variable is the FEARS index. The set of control variables include lagged returns up to five lags, changes in a news-based measure of economic policy uncertainty (EPU), the CBOE volatility index (VIX), and changes in the Aruoba-Diebold-Scotti (ADS) business conditions index. The standard errors are bootstrapped standard errors. *, **, and *** denote significance at the 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1, t+2]	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS	-0.00562***	0.00196*	0.00214**	0.00412***	-0.000794	-0.000915	0.00103
	(0.00134)	(0.00103)	(0.00112)	(0.00140)	(0.000946)	(0.000976)	(0.00101)
VIX	-0.000187***	1.73e-05	-4.10e-06	9.31e-06	2.24e-07	-6.89e-07	-1.02e-05
	(6.53e-05)	(6.23e-05)	(6.21e-05)	(8.30e-05)	(6.46e-05)	(6.53e-05)	(5.87e-05)
EPU	4.90e-06	-1.35e-05*	1.20e-05	-1.67e-06	8.29e-06	-1.07e-05	2.59e-06
	(7.06e-06)	(7.24e-06)	(7.64e-06)	(1.03e-05)	(8.10e-06)	(7.34e-06)	(7.11e-06)
ADS	-0.0232	-0.0152	-0.0176	-0.0322	-0.0101	-0.00530	-0.0162
	(0.0305)	(0.0337)	(0.0330)	(0.0432)	(0.0321)	(0.0348)	(0.0351)
Ret(t)		-0.123***	-0.0612	-0.183***	0.0429	-0.0263	-0.0417
		(0.0384)	(0.0505)	(0.0634)	(0.0413)	(0.0504)	(0.0487)
Ret(t-1)	-0.160***	-0.0744	0.0386	-0.0374	-0.00681	-0.0530	0.0175
	(0.0370)	(0.0544)	(0.0408)	(0.0624)	(0.0489)	(0.0515)	(0.0497)
Ret(t-2)	-0.0907*	0.0127	-0.0241	-0.0112	-0.0532	-0.00903	-0.0356
	(0.0542)	(0.0403)	(0.0487)	(0.0633)	(0.0498)	(0.0459)	(0.0497)
Ret(t-3)	0.00416	-0.0148	-0.0547	-0.0673	0.00380	-0.0320	0.0147
	(0.0418)	(0.0487)	(0.0494)	(0.0644)	(0.0501)	(0.0474)	(0.0417)
Ret(t-4)	-0.0319	-0.0497	0.00261	-0.0483	-0.0270	0.0143	-0.0116
	(0.0455)	(0.0534)	(0.0471)	(0.0568)	(0.0482)	(0.0420)	(0.0493)
Ret(t-5)	-0.0533	-0.00464	-0.0398	-0.0408	0.0219	-0.0146	0.0367
	(0.0498)	(0.0451)	(0.0491)	(0.0661)	(0.0439)	(0.0481)	(0.0462)
Constant	0.00418***	-0.000134	0.000244	0.000170	0.000162	0.000255	0.000402
	(0.00119)	(0.00115)	(0.00116)	(0.00155)	(0.00120)	(0.00122)	(0.00109)
Observations	1,861	1,860	1,859	1,859	1,858	1,857	1,856
Adjusted R^2	0.064	0.026	0.011	0.027	0.003	0.001	0.001

Table 3: FEARS and Returns to Other Asset Classes

This table relates several alternative index daily returns to FEARS. The dependent variables are contemporaneous returns (column (1) and column (5)) and future returns (columns (2) to (4), and columns (6) to (8)) while the independent variables are the FEARS index and a set of control variables (unreported) which include lagged returns up to five lags, changes in a news-based measure of economic policy uncertainty (EPU), the CBOE volatility index (VIX), and changes in the Aruoba-Diebold-Scotti (ADS) business conditions index. The test assets in Panels A include CRSP equally-weighted and value-weighted portfolio daily returns. Panel B includes S&P Exchange Traded Fund (SPY) daily returns, Nasdaq Exchange Traded Fund (QQQQ) daily returns, Russell 1000 Exchange Traded Fund (IWB) daily returns, and Russell 2000 Exchange Traded Fund (IWM) daily returns. Panel C include CRSP 10-year constant maturity Treasury portfolio daily returns. Bootstrapped standard errors are in parentheses. *, **, and *** denote the coefficient estimates are significant at ten, five and one percent significance level respectively.

Panel A: FEARS and CRSP equally-weighted and value-weighted index returns

	CRSP EW Index Returns				CRSP VW Index Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1, t+2]	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1, t+2]
FEARS	-0.00551***	0.00193*	0.00184*	0.00379***	-0.00556***	0.00206**	0.00208*	0.00416***
	(0.00128)	(0.00102)	(0.000980)	(0.00125)	(0.00132)	(0.00105)	(0.00113)	(0.00137)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,861	1,860	1,859	1,859	1,861	1,860	1,859	1,859
Adjusted R^2	0.038	0.005	0.005	0.005	0.055	0.017	0.009	0.018

Panel B: FEARS and selected exchange traded funds (ETFs) returns

	SPY ETF Returns				QQQQ ETF Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1, t+2]	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1, t+2]
FEARS	-0.00559***	0.00210**	0.00171	0.00382***	-0.00497***	0.00194*	0.00182	0.00374**
	(0.00138)	(0.00104)	(0.00113)	(0.00136)	(0.00144)	(0.00106)	(0.00114)	(0.00154)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,861	1,860	1,859	1,859	1,855	1,853	1,852	1,851
Adjusted R^2	0.061	0.025	0.013	0.026	0.033	0.008	0.003	0.008

	IWB ETF Returns				IWM ETF Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1, t+2]	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1, t+2]
FEARS	-0.00537***	0.00207*	0.00180	0.00390***	-0.00550***	0.00280**	0.00214	0.00497***
	(0.00128)	(0.00106)	(0.00112)	(0.00136)	(0.00180)	(0.00140)	(0.00142)	(0.00183)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,861	1,860	1,859	1,859	1,861	1,860	1,859	1,859
Adjusted R^2	0.055	0.018	0.009	0.018	0.052	0.016	0.004	0.020

Panel C: FEARS and treasury returns

	(1)	(2)	(3)	(4)
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1, t+2]
FEARS	0.00119***	-0.000547*	-0.000512	-0.00106**
	(0.000386)	(0.000319)	(0.000340)	(0.000500)
Constant	Yes	Yes	Yes	Yes
Observations	1,846	1,845	1,844	1,844
Adjusted R^2	0.021	0.007	0.008	0.013

Table 4: FEARS and Limits to Arbitrage

This table links FEARS to daily high-minus-low return spreads on portfolios constructed by sorting on stock characteristics related to limits to arbitrage. In panel A, these portfolios are constructed by single sorts on either the CAPM beta, total volatility, downside beta, or downside volatility. In Panel B, we remove the effect from beta by conducting independent double sorts (e.g., we compute high-volatility-minus-low-volatility return spreads using only stocks with similar betas). In each regression, the dependent variables are contemporaneous returns (columns with odd numbers) and next-two-day returns (columns with even numbers) while the main independent variable is the FEARS index. The set of control variables (unreported) include lagged returns up to five lags, changes in a new-based measure of economic policy uncertainty (EPU), the CBOE volatility index (VIX), and changes in the Aruoba-Diebold-Scotti (ADS) business conditions index. The CAPM beta is computed following Scholes and Williams (1977) to account for the non-synchronicity in daily returns. Downside beta and downside volatility are computed following Ang, Chen, and Xing (2006). Bootstrapped standard errors are in parentheses. *, ** and *** denote the coefficient estimates are significant at ten, five and one percent significance levels respectively.

Panel A: Single-sorted Portfolio Return Spreads

	Beta		Total Volatility		Downside Beta		Downside Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ret(t)	Ret[t+1, t+2]	Ret(t)	Ret[t+1, t+2]	Ret(t)	Ret[t+1, t+2]	Ret(t)	Ret[t+1, t+2]
FEARS	-0.00658***	0.00624***	-0.00401***	0.00371***	-0.0112***	0.00665***	-0.00940***	0.00585**
	(0.00218)	(0.00222)	(0.00126)	(0.00138)	(0.00225)	(0.00233)	(0.00245)	(0.00262)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,861	1,859	1,861	1,859	1,861	1,859	1,861	1,859
Adjusted R^2	0.024	0.009	0.047	0.058	0.042	0.011	0.040	0.017

Panel B: Beta-neutral double-sorted Portfolio Return Spreads

	Total Volatility		Downside Beta		Downside Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
	Ret(t)	Ret[t+1, t+2]	Ret(t)	Ret[t+1, t+2]	Ret(t)	Ret[t+1, t+2]
FEARS	-0.00443***	0.00276**	-0.00691***	0.00514***	-0.00347***	0.00193**
	(0.00127)	(0.00120)	(0.00192)	(0.00158)	(0.00096)	(0.00094)
Controls	Yes	Yes	Yes	Yes	YES	YES
Observations	1,861	1,859	1,861	1,859	1,861	1,859
Adjusted R^2	0.063	0.030	0.050	0.009	0.069	0.036

Table 5: Robustness Checks

This table reports results from various robustness checks. The dependent variables are contemporaneous and future S&P 500 index daily returns All specification include a set of controls, including lagged returns up to five lags, changes in a new-based measure of economic policy uncertainty (EPU), the CBOE volatility index (VIX), and changes in the Aruoba-Diebold-Scotti (ADS) business conditions index. Panel A considers robustness with respect to the construction of the FEARS index, including estimates when the top 25 terms are used (columns 1 and 2), the top 35 terms are used (columns 3 and 4) and without winsorization (columns 5 and 6). Panel B considers additional controls, including a media-based sentiment measure as in Tetlock (2007), return decile fixed effects, turnover and holiday controls. Holiday controls constitute dummy variables before and after each NYSE holiday. Panel C considers subsets of the data. Columns 1 and 2 consider the remaining sample when all macro announcements (Savor and Wilson (2012)) have been removed; and columns 3 and 4 consider the sample period after June 1, 2006 when Google Trends data became publicly available. Panel D considers tradability and reports results based on various exchange traded funds' open-to-close adjusted-returns on day (t+2). The set of exchange traded funds include the S&P Exchange Traded Fund (SPY), the Nasdaq Exchange Traded Fund (QQQQ), the Russell 1000 Exchange Traded Fund (IWB), and the Russell 2000 Exchange Traded Fund (IWM). *, **, and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A: Construction

	Top 25		Top 35		No Winsorization	
	(1)	(2)	(3)	(4)	(5)	(6)
	Ret(t)	Ret[t+1, t+2]	Ret(t)	Ret[t+1, t+2]	Ret(t)	Ret[t+1, t+2]
FEARS	-0.00538***	0.00384***	-0.00553***	0.00432***	-0.00578***	0.00437***
	-0.00129	-0.00135	-0.00138	-0.00145	-0.0014	-0.00139
Controls	Yes	Yes	Yes	Yes	YES	YES
Observations	1,861	1,859	1,861	1,859	1,861	1,859
Adjusted R^2	0.064	0.026	0.062	0.027	0.067	0.028

Panel B: Additional Controls

	Media		Decile Return Fixed Effects		Holidays		Turnover	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ret(t)	Ret[t+1, t+2]	Ret(t)	Ret[t+1, t+2]	Ret(t)	Ret[t+1, t+2]	Ret(t)	Ret[t+1, t+2]
FEARS	-0.00585***	0.00454***	-0.00193**	0.00411***	-0.00575***	0.00426***	-0.00554***	0.00424***
	(0.00135)	(0.00133)	(0.00087)	(0.00142)	(0.00137)	(0.00142)	(0.00141)	(0.00145)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1613	1613	1861	1859	1861	1859	1861	1859
Adjusted R^2	0.072	0.035	0.793	0.028	0.063	0.026	0.065	0.029

Panel C: Subsamples

	No Macro Announcements		After June 2006	
	(1)	(2)	(3)	(4)
	Ret(t)	Ret[t+1, t+2]	Ret(t)	Ret[t+1, t+2]
FEARS	-0.00575***	0.00326**	-0.00810***	0.00576***
	(0.00138)	(0.00146)	-0.00189	-0.00223
Controls	Yes	Yes	Yes	Yes
Observations	1,558	1,556	1,386	1,384
Adjusted R^2	0.062	0.032	0.077	0.029

Panel D: Tradability

	(1)	(2)	(3)	(4)
	SPY	QQQQ	IWB	IWM
FEARS	0.00260**	0.00260**	0.00262**	0.00352***
	(0.00102)	(0.00114)	(0.00103)	(0.00134)
Controls	Yes	Yes	Yes	Yes
Observations	1,482	1,476	1,482	1,482
Adjusted R^2	0.016	0.012	0.012	0.010

Table 6: FEARS and Volatility

This table relates FEARS to stock market volatility. In Panel A, we model the seasonal-adjusted log realized volatility and log VIX as ARFIMA(1,d,1) processes which include FEARS (or its first or second lags) and other control variables. Realized volatility is computed using SPY intraday data. Both Panel A and B are estimated using the maximum likelihood method. Panel B relates Chicago Board of Exchange (CBOE) VIX futures daily returns to FEARS. For a contract with given settlement date, its daily return is computed as the change of logarithm of daily prices. Daily returns are obtained from the nearest to maturity contract until five trading day before the nearest-to-maturity contract's settlement date. Afterward, daily returns are obtained from the second nearest to maturity contract. The control variables include changes in a news-based measure of economic policy uncertainty (EPU), and changes in the Aruoba-Diebold-Scotti (ADS) business conditions index.*, ** and *** denote the coefficient estimates are significant at ten, five and one percent significance level respectively.

Panel A: ARFIMA(1,d,1) on seasonal-adjusted log realized volatility and log VIX

	Realized Volatility on SPY			VIX		
	(1)	(2)	(3)	(4)	(5)	(6)
p	-0.137	-0.091	-0.105	0.846***	0.842***	0.842***
	(0.119)	(0.119)	(0.118)	(0.029)	(0.031)	(0.031)
q	-0.066	-0.117	-0.105	-0.528***	-0.524***	-0.523***
	(0.128)	(0.126)	(0.125)	(0.051)	(0.053)	(0.053)
d	0.483***	0.484***	0.484***	0.493***	0.494***	0.494***
	(0.019)	(0.018)	(0.018)	(0.010)	(0.009)	(0.009)
FEARS	0.217***			0.160***		
	(0.045)			(0.003)		
FEARS, 1st lag		-0.036			0.003	
		(0.045)			(0.003)	
FEARS, 2nd lag			-0.033			-0.002
			(0.045)			(0.003)
Controls	YES	YES	YES	YES	YES	YES
Observations	1861	1860	1859	1861	1860	1859
Log Likelihood	-2118.4	-2128.9	-2128.2	2326.0	2313.0	2311.4

Panel B: Returns on VIX futures contract

	(1)	(2)	(3)	(4)
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1, t+2]
FEARS	0.0123***	-0.00381	-0.00497*	-0.00882**
	(0.00308)	(0.00250)	(0.00266)	(0.00350)
Controls	Yes	Yes	Yes	Yes
Observations	1,861	1,860	1,859	1,859
Adjusted R^2	0.012	0.000	-0.001	0.000

Table 7: Sentiment and Fund Flows

This table reports the results of contemporaneous and predictive regressions. We consider two mutual fund groups specializing in equity (Panel A) and medium-term Treasury bond (Panel B). For each mutual fund group, we obtain its daily fund flow (as a percentage of TNA) from Trim Tabs. To remove the persistence in fund flow, we use a ARFIMA(1,d,1) model to extract daily flow innovations. The set of control variables include lagged returns up to five lags, changes in a news-based measure of economic policy uncertainty (EPU), the CBOE volatility index (VIX), and changes in the Aruoba-Diebold-Scotti (ADS) business conditions index. Bootstrapped standard errors are in parentheses. *, ** and *** denote the coefficient estimates are significant at ten, five and one percent significance level respectively.

Panel A: Equity Fund Flow

	Flow (t)	Flow (t+1)	Flow (t+2)	Flow (t+3)	Flow (t+4)
	(1)	(2)	(3)	(4)	(5)
FEARS	-3.61e-05	-6.24e-05	-7.98e-05**	-7.87e-05*	-7.64e-05*
	(5.01e-05)	(4.85e-05)	(4.06e-05)	(4.39e-05)	(4.16e-05)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,319	1,318	1,317	1,316	1,315
Adjusted R^2	0.084	0.096	0.108	0.079	0.044

Panel B: Bond Fund Flow

	Flow (t)	Flow (t+1)	Flow (t+2)	Flow (t+3)	Flow (t+4)
	(1)	(2)	(3)	(4)	(5)
FEARS	0.000157	8.21e-05	0.000168	0.000236**	5.95e-05
	(0.000204)	(1.78e-05)	(0.000109)	(0.000109)	(9.83e-05)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,319	1,318	1,317	1,316	1,315
Adjusted R^2	0.015	0.013	0.017	0.013	0.016