The Sum of All FEARS Investor Sentiment and Asset Prices

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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 (i) predict short-term return reversals, (ii) predict temporary increases in volatility, and (iii) predict mutual fund flows out of equity funds and into bond funds. Taken together, the results are broadly consistent with theories of investor sentiment. (*JEL* G10)

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; DSSW hereafter) 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. Although 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

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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."

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 U.S. 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. Such trading patterns and price reversals can also come from liquidity shocks, as modeled in Campbell, Grossman and Wang (1993; CGW hereafter). In this case, high-frequency investor sentiment, as measured by FEARS, turns out to be a powerful trigger of liquidity shocks that affect prices.

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, initial public offering (IPO) first-day returns, IPO volume, option implied volatilities (VIX), or mutual fund flows (see Baker and Wurgler (2007) for a comprehensive survey 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 $\rightarrow$ 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 (2005), Lemmon and Portniaguina (2006), and Qiu and Welch (2006)). Compared with 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

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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), and seasonal affective disorder (SAD; Kamstra, Kramer, and Levi 2003), and shows these sentiment-changing events cause changes in asset prices.

2 To date, high-frequency analysis of investor sentiment is found only 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.

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 that are not "cross-verif(ied) with data on actual (not self-reported) behavior observed by objective external measurement" (Lamont, quoted 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 the terms "recession" and "bankruptcy," respectively. The plots conform with intuition. For example, the SVI for "recession" began rising in the middle of 2007 and then increased dramatically beginning in 2008. All of this was well before the National Bureau of Economic Research (NBER) announced in December 2008 that the United States 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 States 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 because 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 time 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 that an increase in SVI predicts a decrease in the MCSI (t-value = 2.56). This predictive result suggests that SVI, revealing household

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

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

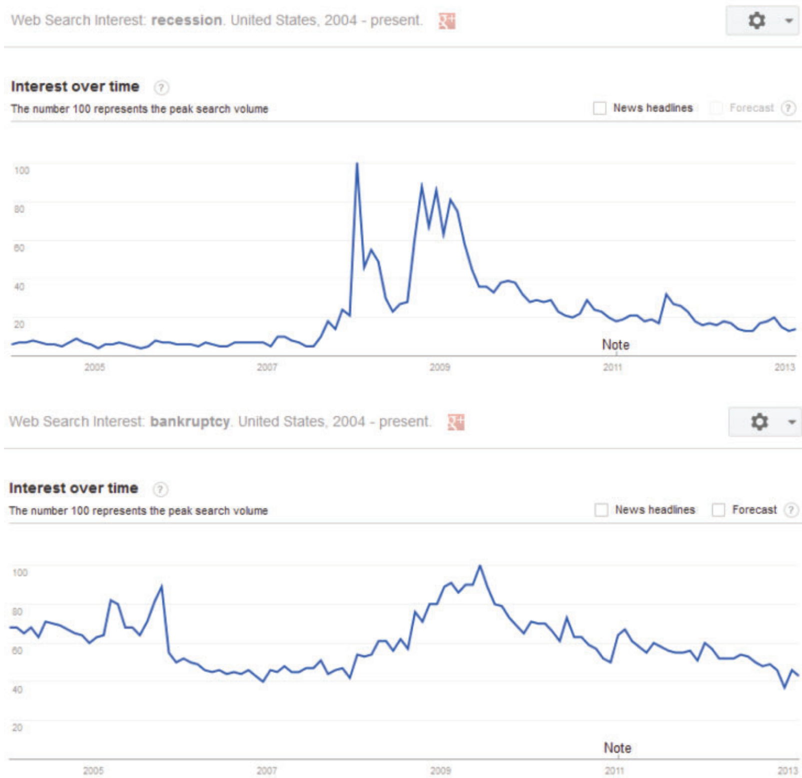

Figure 1
Illustrations of Google search volume
The figures represent the graphical output of weekly aggregate search frequency (SVI) from Google Trends (http://www.google.com/trends/). The top (bottom) panel plots weekly SVI for "recession" ("bankruptcy") in the United States. Plotted SVI is weekly search volume scaled by the maximum over the time period.

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 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

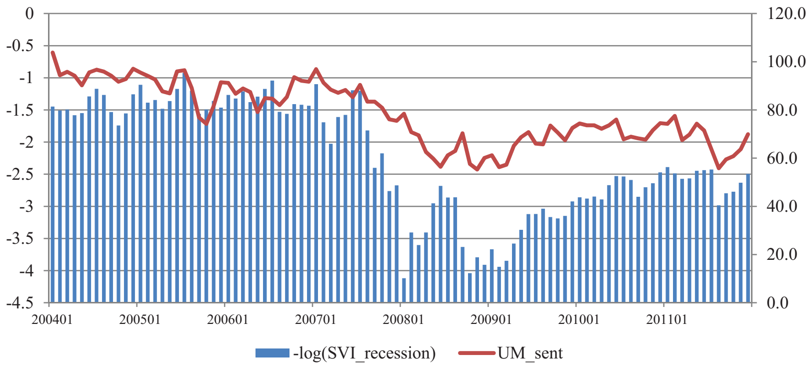

Figure 2
Search for "recession" and consumer confidence
We plot the monthly log SVI for "recession" (with a minus sign) against the monthly University of Michigan Consumer Sentiment Index. The data are from January 2004 to December 2011. The correlation between the two series is 0.858.

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 the period between January 1, 2004, and December 31, 2010. Only the search terms that 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 thirty 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 2, 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 between 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 3 we consider the prediction that high-frequency sentiment swings will generate excess volatility in the short term. We find a significant positive contemporaneous correlation between our FEARS index and daily market volatility measured as either realized volatility on the S&P 500 exchange traded fund (ETF) return or the Chicago Board of Exchange (CBOE) market volatility index (VIX). As volatility displays seasonal patterns and is well known to be persistent and long-lived (Engel and Patton 2001; Andersen, Bollerslev, Diebold and Ebens 2001; Andersen, Bollerslev, Diebold, and Labys 2003), we account for this long-range dependence through the fractional integrated autoregressive moving average (ARFIMA) model, $ARFIMA(1,d,1)$. In addition, parallel to our earlier analysis, we also examine the daily returns on a tradable volatility-based asset, the CBOE VIX futures contract. 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 that 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 4. Because 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 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.

1. 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.

1.1 Construction of FEARS index

Our objective is to build a list of search terms that reveal sentiment toward 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, Saar-Tsechansky, and Macskassy 2008). These dictionaries place words into various categories such as "positive," "negative," "weak," "strong," and so on. Because we are interested in household sentiment toward the economy, we select the set of words that are "economic"

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

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 the 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.

Next we remove terms with insufficient data. Of our 1,245 terms, only 622 have at least 1,000 observations of daily data.[8] Finally, we remove terms that are not clearly related to economics or finance. For example, a search for "depression" results in the 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 relate 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 January 2004 to December 2011 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 United States. Thus, the measures we construct represent the sentiment of American households. W 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)

[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."

[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 that the correlations are usually above 97%.

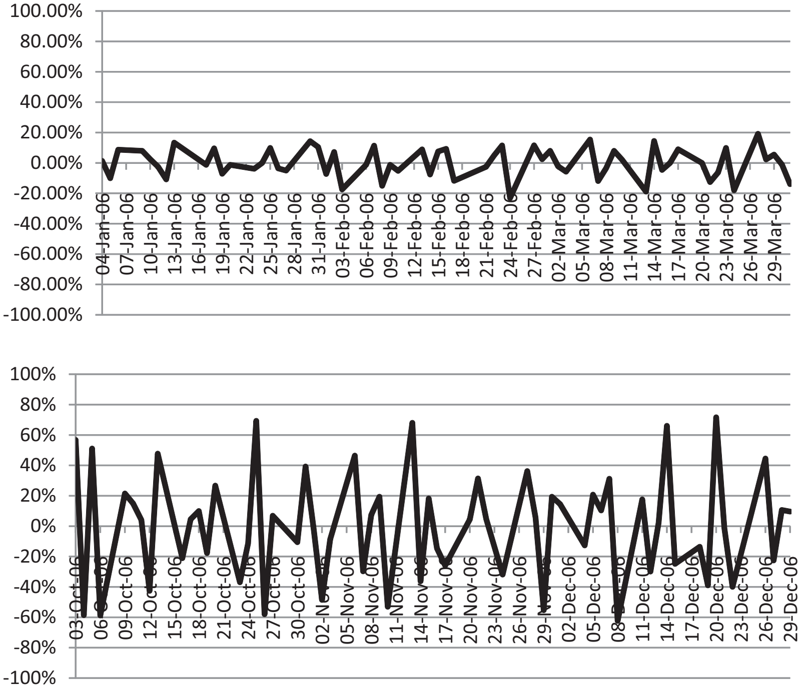

Figure 3
SVI change examples for "inflation" and "price of gold"
We plot two examples of daily changes in SVI. The first is for the term "Inflation" over the period January 2006–March 2006 plotted in the top panel. The second is for the term "Price of Gold" over the period October 2006–December 2006 plotted in the bottom panel.

and falls throughout the week, which generates the repeated five-day hump-shaped pattern depicted in Figure 3. Moreover, there is considerable variance differences across terms. SVI 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 that 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 that 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 zero terms with a t-statistic on $\Delta ASVI$ above 2.5 but fourteen terms with a t-statistic below -2.5. These terms include "recession," "great depression," "gold price," and "crisis." As in Tetlock (2007) it appears that negative terms in English language are most useful for identifying sentiment. For this reason, we use only the terms that 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 that had a t-statistic rank of i from the period January 2004 through the most recent six-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 thirty most negative terms and use these terms to form our FEARS index for the period from July 1, 2009, to December 31, 2009. $FEARS$ on day t during this period is simply the average $\Delta ASVI$ of these thirty terms on day t. Given our relatively short sample period, we choose an expanding rolling window to maximize the statistical power of the selection. We choose a cutoff of thrity as it is often considered to be the minimum number of observations needed to diversify away idiosyncratic noise. Robustness to alternative cutoff choices (e.g., top twenty-five or top thirty-five) is shown in Table 5. Finally, due to the need for an initial window of at least six months, our FEARS index starts in July 2004.

There are several advantages to 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 et al. (2009) also 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

Table 1
FEARS terms from the full sample

	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

This table reports the 30 search terms derived from words of economic sentiment in the Harvard and Lasswell dictionaries (see the description in Section 1.1) that have had the largest negative correlation with the market. The terms are ordered from most negative (GOLD PRICES) to least negative (SOCIAL SECURITY OFFICE).

relationship between searches for "gold" and market returns, consistent with the evidence in Baur and Lucey (2010), who argue that gold represents a "safe haven" 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 thirty terms over our entire sample (January 2004–December 2011). The terms that historically have the largest daily correlation with the market include "gold prices" (t-statistic = −6.04), "recession" (t-statistic = −5.60), "gold price" (t-statistic = −4.81), "depression" (t-statistic = −4.56), and "great depression" (t-statistic = −4.15).

1.2 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&P 500 (NYSEARCA: SPY), the PowerShares QQQ Trust (NASDAQ: QQQQ), the

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 ten-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 to be 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 conditions 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 Scotti (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 gross domestic product (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 the ADS index indicates progressively worse-than-average conditions. We also obtain the dates of important macroeconomic announcements about consumer price index (CPI), producer price index (PPI), unemployment rates, or 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 U.S. newspaper articles achieved by the NewsBank Access World News database with at least one term from each of the following three categories of terms: (i) "economic" or "economy"; (ii) "uncertain" or "uncertainty"; and (iii) "legislation," "deficit," "regulation," "congress," "Federal Reserve," or "White House." Baker, Bloom, and Davis (2013) provide evidence that the news-based measure of EPU seems to capture perceived economic policy uncertainty.

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[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.

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* "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 that represent approximately 20% of the universe of U.S.-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 covers the five-year period from July 2004 to October 2009.

2. 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.

2.1 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 that are not reflected by fundamentals and, in the presence of limits to arbitrage, push prices away from fundamental 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:

$$return_{i,t+k}=\beta_0+\beta_1 FEARS_t+\sum_m \gamma_m Control_{i,t}^m+u_{i,t+k}. \tag{3}$$

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 indices 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 standard-deviation increase in FEARS corresponds with a contemporaneous decline of 19 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 that compose the FEARS index were selected based 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 ensuing days, the positive and significant coefficient on $FEARS$ suggests that increases in FEARS predict higher returns. As evident in columns 2 to 4, these reversals are significant on both the first and the second days ($k=1$ and 2).[14] Specifically, a standard-deviation increase in FEARS predicts an increase of 7.1 basis points in the S&P 500 at $k=1$ (significant at the 5% level), and an *increase* of 7.3 basis points at $k=2$ (significant at the 10% level). The cumulative impact of a standard-deviation increase in FEARS predicts a cumulative increase of 14.4 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 are statistically significant and point estimates are economically negligible,

[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, and thus only strengthen our conclusions.

[13] A one-standard-deviation change in the FEARS index corresponds to 0.3549. Recall that while each individual search term has been standardized so that its standard deviation is one by construction, the average across search terms will not have a standard deviation of one given correlation among search terms.

[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 do not find one, which suggests that the effect from this mismatch in measurement of intervals is small. Moreover, FEARS on day t predict returns on day t+2 where there is no overlap of measurement intervals.

Table 2
FEARS and S&P 500 index returns

	(1) Ret(t)	(2) Ret(t+1)	(3) Ret(t+2)	(4) Ret[t+1, t+2]	(5) Ret(t+3)	(6) Ret(t+4)	(7) Ret(t+5)
FEARS	−0.00532***	0.00200**	0.00207*	0.00409***	−0.000620	−0.000800	0.00104
	(0.00130)	(0.000966)	(0.00113)	(0.00137)	(0.000937)	(0.000943)	(0.00100)
VIX	−0.000187***	1.80e–05	1.50e–07	1.43e–05	−6.07e–06	−7.02e–06	−8.61e–06
	(6.31e–05)	(6.38e–05)	(6.36e–05)	(8.29e–05)	(6.28e–05)	(6.41e–05)	(6.04e–05)
EPU	4.73e–06	−1.33e–05*	1.20e–05	−1.42e–06	8.69e–06	−8.94e–06	2.68e–06
	(7.11e–06)	(7.45e–06)	(7.65e–06)	(9.27e–06)	(7.70e–06)	(7.92e–06)	(6.78e–06)
ADS	−0.0253	−0.0208	−0.0194	−0.0394	−0.0168	−0.0174	−0.0164
	(0.0298)	(0.0310)	(0.0315)	(0.0439)	(0.0319)	(0.0341)	(0.0361)
Ret(t)		−0.121***	−0.0600	−0.179***	0.0365	−0.0252	−0.0484
		(0.0376)	(0.0521)	(0.0595)	(0.0418)	(0.0495)	(0.0488)
Ret(t–1)	−0.155***	−0.0780	0.0370	−0.0424	−0.0165	−0.0597	0.0110
	(0.0378)	(0.0546)	(0.0403)	(0.0600)	(0.0488)	(0.0521)	(0.0484)
Ret(t–2)	−0.0896*	0.0167	−0.0210	−0.00436	−0.0496	0.00443	−0.0365
	(0.0541)	(0.0408)	(0.0465)	(0.0565)	(0.0485)	(0.0458)	(0.0500)
Ret(t–3)	0.00358	−0.0163	−0.0537	−0.0679	0.00338	−0.0323	0.0134
	(0.0394)	(0.0480)	(0.0481)	(0.0638)	(0.0497)	(0.0473)	(0.0425)
Ret(t–4)	−0.0318	−0.0507	0.00377	−0.0482	−0.0308	0.0102	−0.0109
	(0.0473)	(0.0474)	(0.0452)	(0.0564)	(0.0496)	(0.0426)	(0.0496)
Ret(t–5)	−0.0532	−0.00361	−0.0369	−0.0368	0.0184	−0.0182	0.0394
	(0.0462)	(0.0446)	(0.0503)	(0.0712)	(0.0426)	(0.0496)	(0.0458)
Constant	0.00424***	−0.000170	0.000167	5.48e–05	0.000299	0.000351	0.000361
	(0.00116)	(0.00117)	(0.00116)	(0.00153)	(0.00116)	(0.00119)	(0.00112)
Observations	1,891	1,890	1,889	1,889	1,888	1,887	1,886
Adjusted R^2	0.060	0.027	0.011	0.027	0.003	0.002	0.002

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% levels, respectively.

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 ten-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 security 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 with Treasury securities. A standard-deviation increase in

FEARS corresponds with a contemporaneous decrease of 18 to 19 basis points among equities at $k=0$ (significant at the 1% level), and a reversal of 14 to 15 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 a complete reversal over the next two days (significant at the 1% level). Also, because 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.

Of course, such a short-term reversal can also be caused by a liquidity shock as in Campbell, Grossman and Wang (1993; GSW hereafter). As Baker and Stein (2004) point out, as sentiment and liquidity are intertwined, the difference between a sentiment-based story as in DSSW and a liquidity-based story as in GSW boils down how we view liquidity shocks and noise traders. Tetlock (2007) even goes so far as to say that "the difference between DSSW and CGW is philosophical rather than economic." Our results remain interesting even under the liquidity interpretation, as they suggest high-frequency investor sentiment, as measured by our FEARS, can be a powerful trigger of a liquidity shock.

Overall, Tables 2 and 3 illustrate that our FEARS index is strongly associated with contemporaneous returns and predicts future short-term return reversals.

2.2 FEARS and limits to arbitrage

As highlighted in Baker and Wurgler (2006, 2007), there are several additional channels that 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 arbitrageurs 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

Table 3
FEARS and returns to other asset classes

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

	CRSP EW Index Returns				CRSP VW Index Returns			
	(1) Ret(t)	(2) Ret(t+1)	(3) Ret(t+2)	(4) Ret[t+1,t+2]	(5) Ret(t)	(6) Ret(t+1)	(7) Ret(t+2)	(8) Ret[t+1,t+2]
FEARS	–0.00519***	0.00195**	0.00185*	0.00381***	–0.00526***	0.00211**	0.00201*	0.00413***
	(0.00128)	(0.000949)	(0.000999)	(0.00133)	(0.00130)	(0.000981)	(0.00113)	(0.00139)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,891	1,890	1,889	1,889	1,891	1,890	1,889	1,889
Adjusted R^2	0.035	0.005	0.005	0.006	0.052	0.018	0.009	0.019

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

	SPY ETF Returns				QQQQ ETF Returns			
	(1) Ret(t)	(2) Ret(t+1)	(3) Ret(t+2)	(4) Ret[t+1,t+2]	(5) Ret(t)	(6) Ret(t+1)	(7) Ret(t+2)	(8) Ret[t+1,t+2]
FEARS	–0.00527***	0.00213**	0.00164	0.00378***	–0.00457***	0.00214**	0.00173	0.00385***
	(0.00136)	(0.000971)	(0.00111)	(0.00136)	(0.00133)	(0.00106)	(0.00116)	(0.00149)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,891	1,890	1,889	1,889	1,885	1,883	1,882	1,881
Adjusted R^2	0.058	0.026	0.012	0.026	0.030	0.009	0.002	0.008

	IWB ETF Returns				IWM ETF Returns			
	(1) Ret(t)	(2) Ret(t+1)	(3) Ret(t+2)	(4) Ret[t+1,t+2]	(5) Ret(t)	(6) Ret(t+1)	(7) Ret(t+2)	(8) Ret[t+1,t+2]
FEARS	–0.00506***	0.00214**	0.00174	0.00390***	–0.00529***	0.00272**	0.00196	0.00472***
	(0.00128)	(0.000960)	(0.00111)	(0.00137)	(0.00162)	(0.00124)	(0.00145)	(0.00178)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,891	1,890	1,889	1,889	1,891	1,890	1,889	1,889
Adjusted R^2	0.052	0.019	0.009	0.019	0.041	0.014	0.005	0.015

Panel C: FEARS and Treasury returns

	(1) Ret(t)	(2) Ret(t+1)	(3) Ret(t+2)	(4) Ret[t+1,t+2]
FEARS	0.00112***	–0.000540*	–0.000624**	–0.00117***
	(0.000378)	(0.000324)	(0.000307)	(0.000426)
Constant	Yes	Yes	Yes	Yes
Observations	1,876	1,875	1,874	1,874
Adjusted R^2	0.020	0.007	0.008	0.013

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 Panel 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 includes CRSP 10-year constant maturity Treasury portfolio daily returns. Bootstrapped standard errors are in parentheses. *, **, and *** denote the coefficient estimates are significant at 10%, 5%, and 1% significance levels, respectively.

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.

Panel A from Table 4 confirms 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 22-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 that 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,

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

using the past year of daily returns.

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

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

and it is also estimated using the past 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 the 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 the 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

Table 4
FEARS and limits to arbitrage

Panel A: Single-sorted portfolio return spreads

	Beta		Total Volatility		Downside Beta		Downside Volatility	
	(1) Ret(t)	(2) Ret[t+1, t+2]	(3) Ret(t)	(4) Ret[t+1, t+2]	(5) Ret(t)	(6) Ret[t+1, t+2]	(7) Ret(t)	(8) Ret[t+1, t+2]
FEARS	–0.00620***	0.00641***	–0.0036***	0.00397***	–0.0106***	0.00716***	–0.00904***	0.00623**
	(0.00199)	(0.00226)	(0.00131)	(0.00146)	(0.00233)	(0.00243)	(0.00228)	(0.00251)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,891	1,889	1,891	1,889	1,891	1,889	1,891	1,889
Adjusted R^2	0.023	0.010	0.046	0.059	0.039	0.012	0.038	0.017

Panel B: Beta-neutral double-sorted portfolio return spreads

	Total Volatility		Downside Beta		Downside Volatility	
	(1) Ret(t)	(2) Ret[t+1, t+2]	(3) Ret(t)	(4) Ret[t+1, t+2]	(5) Ret(t)	(6) Ret[t+1, t+2]
FEARS	–0.00414***	0.00320***	–0.00614***	0.00474***	–0.00374***	0.00234**
	(0.00103)	(0.00119)	(0.00151)	(0.00148)	(0.000837)	(0.00102)
Controls	Yes	Yes	Yes	Yes	YES	YES
Observations	1,891	1,891	1,891	1,891	1,891	1,891
Adjusted R^2	0.088	0.055	0.052	0.013	0.092	0.065

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, these portfolios are constructed by single sorts on either the CAPM beta, the total volatility, the downside beta, or the downside volatility. In Panel B, we remove the effect from the beta using double sorts. For example, we conduct independent double sorts on beta and total volatility. We then compute high-volatility-minus-low-volatility return spreads using only stocks with similar betas. In each regression, the dependent variables are contemporaneous returns (column 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 10%, 5% and 1% significance levels, respectively.

spreads between the high "downside sigma" and low "downside sigma" stock portfolios. The effect of sentiment on these return spreads is large. For instance, a one-standard-deviation increase in FEARS is associated with a decrease of 37 basis points 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 25 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. Because 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 "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 twelve-month daily returns. To ensure that 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 22-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 17 basis points (statistically significant at the 1% level)—or about 77.3% ($=17/22$) of reversal of initial 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.

2.3 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 thirty 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 twenty-five search terms and top thirty-five search terms. Comparing the results in Table 5, Panel A, with those in Table 2, we find that 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 report the results 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* "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, shows that in this shorter sample our results are robustness to the inclusion of it as an additional control.

Another potential concern regarding our results is that FEARS could simply proxy for extreme market returns, which are more likely to revert in the future. Although 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

Table 5
Robustness checks

Panel A: Construction

	Top 25		Top 35		No Winsorization	
	(1) Ret(t)	(2) Ret[t+1, t+2]	(3) Ret(t)	(4) Ret[t+1, t+2]	(5) Ret(t)	(6) Ret[t+1, t+2]
FEARS	–0.00513***	0.00374***	–0.00523***	0.00428***	–0.00578***	0.00437***
	(0.00124)	(0.00132)	(0.00133)	(0.00141)	(0.00146)	(0.00149)
Controls	Yes	Yes	Yes	Yes	YES	YES
Observations	1,891	1,889	1,891	1,889	1,861	1,859
Adjusted R^2	0.061	0.026	0.059	0.027	0.067	0.028

Panel B: Additional controls

	Media		Decile Return Fixed Effects		Holidays		Turnover	
	(1) Ret(t)	(2) Ret[t+1, t+2]	(3) Ret(t)	(4) Ret[t+1, t+2]	(5) Ret(t)	(6) Ret[t+1, t+2]	(7) Ret(t)	(8) Ret[t+1, t+2]
FEARS	–0.00564***	0.00448***	–0.00190**	0.00400***	–0.00533***	0.00409***	–0.00525***	0.00419***
	(0.00133)	(0.00148)	(0.000797)	(0.00134)	(0.00130)	(0.00137)	(0.00129)	(0.00137)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,639	1,639	1,891	1,889	1,891	1,889	1,891	1,889
Adjusted R^2	0.068	0.034	0.794	0.029	0.060	0.026	0.061	0.029

Panel C: Subsamples

	No Macro Announcements		After June 2006	
	(1) Ret(t)	(2) Ret[t+1, t+2]	(3) Ret(t)	(4) Ret[t+1, t+2]
FEARS	–0.00539***	0.00325**	–0.00759***	0.00563***
	(0.00144)	(0.00139)	(0.00202)	(0.00192)
Controls	Yes	Yes	Yes	Yes
Observations	1,586	1,584	1,408	1,406
Adjusted R^2	0.058	0.032	0.073	0.029

Panel D: Tradability

	(1) SPY	(2) QQQQ	(3) IWB	(4) IWM
FEARS	0.00262***	0.00265**	0.00268***	0.00273**
	(0.00101)	(0.00115)	(0.00101)	(0.00133)
Controls	Yes	Yes	Yes	Yes
Observations	1,508	1,502	1,508	1,508
Adjusted R^2	0.016	0.011	0.013	0.007

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 thrown out, 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% levels, respectively.

is some evidence of holiday-related return phenomenon (see Ariel 1990, for example), columns 5 and 6 of Panel B remove 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 spikes in both search volume and liquidity trades, pushing prices temporarily away from fundamentals (1993). 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&P 500 index as a control variable in columns 7 and 8 of Panel B.[15] 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 although 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 we find larger effects among hard-to-arbitrage stocks in Section 2.2. 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 23, will typically be released sometime during the evening of Thursday, January 24. Moreover, Google only made this data publicly available in June 2006.

Panels C and D demonstrate 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 23 (observable by the evening of Thursday, January 24) to predict the open-to-close returns on Friday, January 25. 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 confirm the strong and significant reversals across all four ETFs. The regression coefficients are only slightly smaller compared with those in Table 3, Panel B, reflecting the fact

[15] In untabulated results we also find that controlling for signed turnover — that is, the interaction of turnover on day t with the return on day t, does not change the reversal results on days t+1 and t+2.

that we are using open-to-close returns rather than the standard close-to-close returns.

3. 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.[16] 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, Bollerslev, Diebold and Ebens (2001). Since intraday transaction data are needed to calculate daily realized volatilities, we focus our attention on the SPDR S&P 500 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, the minimum tick size. Similar to Antweiler and Frank (2004), we choose fifteen-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). Because volatility is persistent and long-lived (Engel and Patton (2001); Andersen, Bollerslev, Diebold and Ebens 2001; Andersen, Bollerslev, Diebold, and Labys 2003), we also model the long-range dependence through the fractional integrated autoregressive moving average model, $ARFIMA(1,d,1)$:

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

[16] 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.

Table 6
FEARS and volatility

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	−0.060	−0.019	−0.104	0.844***	0.838***	0.838***
	(0.133)	(0.117)	(0.124)	(0.028)	(0.030)	(0.030)
q	−0.136	−0.204	−0.194	−0.520***	−0.513***	−0.513***
	(0.140)	(0.121)	(0.129)	(0.049)	(0.051)	(0.051)
d	0.484***	0.486***	0.486***	0.493***	0.494***	0.494***
	(0.019)	(0.017)	(0.017)	(0.010)	(0.009)	(0.009)
FEARS	0.233***			0.168***		
	(0.044)			(0.003)		
FEARS, 1st lag		−0.047			−0.000	
		(0.044)			(0.003)	
FEARS, 2nd lag			−0.013			−0.002
			(0.044)			(0.003)
Controls	YES	YES	YES	YES	YES	YES
Observations	1891	1890	1889	1891	1890	1889
Log Likelihood	−2146.1	−2158.5	−2158.0	2384.0	2368.5	2367.4

Panel B: Returns on VIX futures contract

	(1) Ret(t)	(2) Ret(t+1)	(3) Ret(t+2)	(4) Ret[t+1, t+2]
FEARS	0.0119***	−0.00303	−0.00493*	−0.00798**
	(0.00326)	(0.00266)	(0.00271)	(0.00368)
Controls	Yes	Yes	Yes	Yes
Observations	1,886	1,885	1,884	1,884
Adjusted R^2	0.011	0.001	−0.001	0.001

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 that 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, or $R_t = \log(\frac{P_t}{P_{t-1}})$. 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 10%, 5%, and 1% significance levels, respectively.

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 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 has only 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 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.[17] We then use our FEARS index to predict these daily VIX futures returns using the same regression specifications in Equation (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 42-basis-points increase in VIX futures return. In the next two trading days, we again find a reversal pattern. By the end of the second trading day, we observe a total reversal of 28 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 that 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.

[17] 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.

4. 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. Because 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, Goetzmann, Hiraki, Shiraishi, and Watanabe 2002 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 process. 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 (2002) 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 one to four days ahead. In particular, we run the following regression:

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

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 $t+1$ (p-value $< 10\%$), $t+2$ (p-value $< 5\%$) and $t+3$ (p-value $< 10\%$). The results suggest that investors start to withdraw from equity mutual funds the day during the spike in FEARS (recall that the outflow on $t+1$ may actually contain outflow in day t

Table 7
Sentiment and fund flows

Panel A: Equity fund flow

	Flow (t) (1)	Flow (t+1) (2)	Flow (t+2) (3)	Flow (t+3) (4)	Flow (t+4) (5)
FEARS	1.04e–05	–8.62e–05*	–8.95e–05**	–7.60e–05*	–6.49e–05
	(5.18e–05)	(4.82e–05)	(3.89e–05)	(4.29e–05)	(4.25e–05)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,339	1,338	1,337	1,336	1,335
Adjusted R^2	0.081	0.096	0.11	0.081	0.046

Panel B: Bond fund flow

	Flow (t) (1)	Flow (t+1) (2)	Flow (t+2) (3)	Flow (t+3) (4)	Flow (t+4) (5)
FEARS	0.000174	8.31e–05	0.000165	0.000231**	6.57e–05
	(0.000224)	(1.58e–05)	(0.000108)	(0.000108)	(9.47e–05)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,339	1,338	1,337	1,336	1,335
Adjusted R^2	0.014	0.013	0.017	0.013	0.016

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 bonds (Panel B). For each mutual fund group, we obtain its daily fund flow (as a percentage of TNA) from TrimTabs. 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 10%, 5%, and 1% significance levels, respectively.

due to a reporting delay in the TrimTabs data), and such an outflow persists for the next two days. 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. Taken together, the evidence highlights a flight to safety where investors are shifting their investments from equity funds to bond funds after a spike in FEARS.

Considering equity flows, the coefficients on FEARS are economically large. For example, an one standard-deviation increase in FEARS is associated with significant equity outflows of $-3.13\ \times 10^{-5}(=0.35\times -8.95\times 10^{-5})$ on $t=2$. Given the average equity fund flow of -5.06×10^{-5}, this is about 62% of the typical daily flows. Similarly, a one-standard-deviation increase in FEARS is associated with significant bond inflows of 8.1×10^{-5} on $t=3$, which is slightly larger than the average daily bond flow (7.49×10^{-5}).

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

5. 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 (2005), 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.

5.1 Endogenous search

Some readers may be concerned that search is endogenous to macroeconomic events. For example, there must be some macro events that 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.[18] 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 causes return tomorrow in 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 2) likely mitigates such concerns. The fact that we find high FEARS today are correlated with low returns today but predict 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.

5.2 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 increase (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.

[18] Qui and Welch (2006), p. 32, 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."

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 2. 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 that 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 Sentiment Index, suggesting most of the time households search for "recession" when they are worried about a recession. Second, recall from Section 2 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.

6. Conclusion

By aggregating queries like "recession," "bankruptcy," and "depression," we construct a Financial and Economic Attitudes Revealed by Search (FEARS) index. We show that the FEARS index predicts aggregate market returns. In particular, the FEARS index is correlated with low returns today but predicts 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 it is also correlated with VIX futures returns. Finally, using daily aggregate mutual fund flows, we also provide direct evidence for "noise" trading. Increases in the 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 that 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 the results have two reasonable interpretations: the media reports investor sentiment before it is fully incorporated into market prices, or the media directly influences investors' attitudes toward stocks. 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.

References

Andersen, T., T. Bollerslev, F. X. Diebold and H. Ebens. (2001). The distribution of realized stock return volatility. *Journal of Financial Economics* 61:43–76.

Andersen, T., T. Bollerslev, F. X. Diebold, and P. Labys. (2003). Modeling and forecasting realized volatility. *Econometrica* 71:579–625.

Ang, A., J. Chen, and Y. Xing. (2006). Downside risk. *Review of Financial Studies* 19:1191–239.

Antweiler, W., and M. Z. Frank. (2004). Is all that talk just noise? The information content of Internet stock message boards. *Journal of Finance* 59:1259–94.

Ariel, R. A. (1990). High stock returns before holidays: Existence and evidence on possible causes. *Journal of Finance* 45:1611–26.

Aruoba, S. B., F. X. Diebold, and C. Scotti. (2009). Real-time measurement of business conditions. *Journal of Business & Economic Statistics* 27:417–27.

Baker, S. R., N. Bloom, and S. J. Davis. (2013). Measuring economic policy uncertainty. Working Paper, Stanford University.

Baker, M., B. Bradley, and J. Wurgler. (2011). Benchmarks as limits to arbitrage: Understanding the low volatility anomaly. *Financial Analysts Journal* 67: 40–54.

Baker, M., and J. Stein. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets* 7:271–99.

Baker, M., and J. Wurgler. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance* 61:1645–80.

———. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives* 21:129–51.

Baur, D. G., and B. M. Lucey. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds, and gold. *Financial Review* 45:217–29.

Bawa, V. S. and E. B. Lindenberg. (1977). Capital market equilibrium in a mean-lower partial moment framework. *Journal of Financial Economics* 5:189–200.

Black, F. (1986). Noise. *Journal of Finance* 41:529–43.

Bloomfield, R., M. O'Hara, and G. Saar. (2009). How noise trading affects markets: an experimental analysis. *Review of Financial Studies* 22:2275–302.

Bollerslev, T., and D. Jubinski. (1999). Equity trading volume and volatility: Latent information arrivals and common long-run dependencies. *Journal of Business and Economic Statistics* 17:9–21.

Brown, G., and M. Cliff. (2005). Investor sentiment and asset valuation. *Journal of Business* 78(2):405–40.

Brown, S. J., W. N. Goetzmann, William N., T. Hiraki, N. Shiraishi, and M. Watanabe. (2002). Investor sentiment in Japanese and U.S. daily mutual fund flows. Yale ICF Working Paper No. 02-09.

Brunnermeier, M., and S. Nagel. (2008). Do wealth fluctuations generate time-varying risk aversion? Micro-evidence on individuals' asset allocation. *American Economic Review* 98(3):713-36.

Campbell, J., and J. Cochrane, (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy* 107 (2):205–51.

Campbell, J., S. Grossman and J. Wang. (1993). Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics* 108(4):905–39.

Da, Z., P. Gao, and J. Engelberg. (2011). In search of attention. *Journal of Finance* 66:1461–99.

De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. (1990). Noise trader risk in financial markets. *Journal of Political Economy* 98:703–38.

Edelen, R., and J. Warner. (2002). Aggregate price effects of institutional trading: a study of mutual fund flows and market returns. *Journal of Financial Economics* 59:195–221.

Edmans, A., D. Garcia, and O. Norli. (2007). Sports sentiment and stock returns. *Journal of Finance* 62(4):1967–98.

Engel, R. F., and A. J. Patton. (2001). What good is a volatility model? *Quantitative Finance* 1:237–45.

Fleming, J., and C. Kirby. (2006). Long memory in volatility and trading volume. Working Paper. Rice University.

Greene, J. T., and C. W. Hodges. (2002). The dilution impact of daily fund flows on open-end mutual funds. *Journal of Financial Economics* 65:131–58.

Hellwig, Martin F. (1980). On the Aggregation of Information in Competitive Markets, *Journal of Economic Theory* 22, 477–98.

Hirsheifer, D., and T. Shumway. (2003). Good day sunshine: Stock returns and the weather. *Journal of Finance* 58:1009–1032.

Kamstra, M. J., L. A. Kramer, and M. D. Levi. (2003). Winter blues: A SAD stock market cycle. *American Economic Review* 93:324–43.

Kaplanski, G., and H. Levy. (2010). Sentiment and stock prices: The case of aviation disaster. *Journal of Financial Economics* 95:174–201.

Keynes, J. M. (1936). *The general theory of employment, interest and money*. London: Macmillan.

Kogan, L., S. A. Ross, J. Wang, and M. M. Westerfield. (2006). The price impact and survival of irrational traders. *Journal of Finance* 61(1):195–229.

Kogan, S., D. Levin, B. Routledge, J. Sagi and N. Smith. (2009). Predicting risk from financial reports with regression. Proceedings of the North American Association for Computational Linguistics Human Language Technologies Conference.

Kogan, L., S. A. Ross, J. Wang, and M. M. Westerfield. (2009). Market selection. Working Paper, MIT.

Koski, J. L., E. M. Rice and A. Tarhouni. (2008). Noise trading and volatility: Evidence from day trading and message boards. Working Paper, University of Washington.

Kyle, A., and W. Xiong. (2001). Contagion as a wealth effect. *Journal of Finance* 56:1401–40.

Lemmon, M. L., and E. V. Portniaguina. (2006). Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies* 19(4):1499–529.

Loughran, T., and B. McDonald. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance* 66:35–65.

Pontiff, J. (1996). Costly arbitrage: Evidence from closed-end funds. *Quarterly Journal of Economics* 111(4):1135–51.

Qiu, L., and I. Welch. (2006). Investor sentiment measures. Working Paper, Brown University.

Savor, P., and M. Wilson. (2013). How much do investors care about macroeconomic risk? Evidence from scheduled economic announcements. *Journal of Financial and Quantitative Analysis* 48:343–75.

Scholes, M., and J. Williams. (1977). Estimating betas from nonsynchronous data. *Journal of Financial Economics* 5:309–27.

Shleifer, A., and R. W. Vishny. (1997). The limits of arbitrage. *Journal of Finance* 52:35–55.

Singer, E. (2002). The use of incentives to reduce nonresponse in household surveys. Working Paper, University of Michigan.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance* 62:1139–68.

Tetlock, P. C., M. Saar-Tsechansky, and S. Macskassy. (2008). More than words: Quantifying language to firms' fundamentals. *Journal of Finance* 63(3):1437–67.

Veronesi, P. (1999). Stock market overreaction to bad news in good times: A rational expectations equilibrium model. *Review of Financial Studies* 12:975–1007.

Vissing-Jorgensen, A. (2003). Perspectives on behavioral finance: Does "irrationality" disappear with dealth? Evidence from expectations and actions. *NBER Macroeconomics Annual*.

Whaley, R. E. (2001). The investor fear gauge. *Journal of Portfolio Management* 26:12–7.

Wurgler, J., and E. Zhuravskaya. (2002). Does arbitrage flatten demand curves for stocks? *Journal of Business* 75:583–608.

Yuan, Yu. (2008). Attention and trading. Working Paper, University of Iowa.