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

Zhi Da[†], Joseph Engelberg[‡] and Pengjie Gao[§]

First Draft: September 2, 2009
This Draft: December 14, 2011

Abstract

We use the daily internet search volume from millions of households to reveal market-level sentiment in real time. By aggregating the volume of queries related to household concerns (e.g. "recession", "credit card debt" and "bankruptcy"), we construct Financial and Economic Attitudes Revealed by Search (FEARS) indices as new measures of investor sentiment. Between 2004 and 2011, we find increases in FEARS lead to return reversals: although FEARS are associated with low returns today they predict high returns tomorrow. In the cross-section of stocks, the reversal effect is strongest among stocks which are attractive to noise traders and hard to arbitrage. FEARS also predict excess volatility and daily mutual fund flow. When FEARS are high, investors are more likely to pull money out of equity mutual funds but not out of bond funds. Taken together, the results are broadly consistent with theories of investor sentiment.

*We thank Nick Barberis, Shane Corwin, Jennifer Conrad, David Hirshleifer, Bob Jennings, Shimon Kogan, Ralph Koijen, Owen Lamont, Paul Schultz, Andrei Shleifer, Paul Tetlock, Dick Thaler, Yu Yuan and seminar participants at University of Notre Dame, State of Indiana Annual Conference, the 2010 NBER Behavioral Economics meeting and the WFA 2010 meeting for helpful comments and discussions. We are grateful to Conrad Gann at TrimTabs, Inc. for his assistance with the daily mutual fund data used in this study. Jianfeng Zhu provided valuable research assistance. We are responsible for remaining errors.

[†]Finance Department, Mendoza College of Business, University of Notre Dame. E-mail: zda@nd.edu; Tel: (574) 631-0354.

[‡]Finance Department, Rady School of Management, University of California at San Diego. E-mail: jengelberg@ucsd.edu; Tel: (858) 822-7912.

[§]Finance Department, Mendoza College of Business, University of Notre Dame. E-mail: pgao@nd.edu; Tel: (574) 631-8048.

1 Introduction

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

In this paper we propose a possible answer: investor sentiment can be directly measured through the internet search behavior of households. We aggregate the volume of internet search queries such as "recession", "bankruptcy" and "inflation" from millions of US households to construct Financial and Economic Attitudes Revealed by Search (FEARS) indices. We then quantify the effects of FEARS on asset prices, volatility and fund flows. We find that macro-related FEARS predict return reversals in market-level returns: 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 predict increases in implied volatility and mutual fund flow out of equity funds.

[1] A particularly interesting thread of literature examines exogenous and plausible sentiment changing non-economical events such as sports game's outcomes (i.e., "sport sentiment" as in Edmans, Garcia, and Norli (2007)), aviation disasters (Kaplanski and Levy (2010)), weather conditions (Hirshleifer and Shumway (2003)), seasonal affective disorder (SAD, Kamstra, Kramer and Levi (2003)), and associates these sentiment-changing events with asset 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, IPO first-day returns, IPO volume, option implied volatilities (VIX) or mutual fund flows (see, Baker and Wurgler (2007) for a recent and 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 → outputs with an output measure?"

Under the second approach, empiricists use survey-based indices such as the University of Michigan Consumer Sentiment Index, the UBS/GALLUP Index for Investor Optimism, or investment newsletters (Brown and Cliff (2004), Lemmon and Portniaguina (2006), and Qiu and Welch (2006)). Compared to survey-based measures of investor sentiment, the search-based sentiment measure we propose has several advantages. First, search-based sentiment measures are available in real time.[2] Survey measures are often available monthly or quarterly. In fact, we will show that our daily FEARS indices 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 insurance" *reveals* concern

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

about job loss. Finally, some economists have been skeptical about answers in survey data which are not "cross-verif(ied) with data on actual (not self-reported) behavior observed by objective external measurement" (Lamont in Vissing-Jorgensen (2003)). Search behavior is an example of such objective, external verification.

Google, the largest search engine in the world, makes public the Search Volume Index (SVI) of search terms via its product Google Insights for Search (http://www.google.com/insights/search//).[3] When a user inputs a search term into Google Insights, 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 "credit card debt" and "recession" respectively. The plots conform with intuition. For example, the SVI for "credit card debt" began rising steadily through the credit crisis as consumers become increasingly concerned about their credit card debt loads. 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 NBER announced in December 2008 that the U.S. had been in a recession since December of 2007.

At the monthly frequency, SVI correlates well with alternative measures of market sentiment. For example, the top panel of Figure 2 plots the monthly log SVI for "recession" (with a minus sign since higher SVI on "recession" signals pessimism) against the monthly University of Michigan Consumer Sentiment Index (MCSI) which asks households about their economic outlook. During our sampling period from January 2004 to March 2011, the two times series are highly correlated with a correlation coefficient of 0.875.[4] When we use the log change in SVI on "recession" this month to predict next month log change in the Michigan Consumer Sentiment Index, we find an

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

[4] The University of Michigan Consumer Sentiment Index (MCSI) is based on survey that solicits consumers' view on the general economy over the near term and the long term and their own financial situation. Consistent with this methodology, we find that monthly SVIs on terms related to general economy condition such as "credit card debt," "job," and "unemployment" are also highly correlated with MCSI.

increase in SVI to significantly predict a decrease in future Sentiment Index (t-value = 2.63). This predictive result suggests that SVI, revealing household sentiment in real time, leads survey-based sentiment measure by at least a month.

The key to the construction of our FEARS indices is the identification of relevant sentiment-revealing search terms. To identify search terms in a way that is as objective as possible, we proceed in the following way. First, we follow the textual analytic literature in finance which focuses on negative words. Tetlock (2007) and Tetlock et al. (2008) demonstrate that negative words seem to be most informative about sentiment. We construct a list of "primitive" words by taking words which are jointly classified as "negative" and "economic" words according to the Harvard IV-4 dictionary. Second, we search each "primitive" word and download the associated top ten related search terms (provided by Google) in Google Insights in order to see how these negative, economic words are used by searchers. Finally, we eliminate non-economic search terms and search terms with too few valid SVIs. This procedure results in our final list of 27 search terms.

To convert the SVI of the 27 terms into reasonable indices, we calculate daily log differences, winsorize, remove intra-week and intra-year seasonality and standardize each time series (as in Baker and Wurgler (2006)). We then sort the 27 terms into two groups and calculate the daily, average SVI change in each group to form our indices. The first group of search terms relates to micro, household-level concerns such as "credit card debt" and "unemployment insurance" which we refer to as the Micro FEARS Index. The second group of search terms relates to macro, economy-wide concerns such as "recession" or "inflation" which we refer to as the Macro FEARS Index.

We then relate our FEARS indices to asset prices. In Section 3, we find a negative contemporaneous correlation between Macro FEARS and stock market returns. Increases (decreases) in Macro FEARS correspond with low (high) returns. However, in the days following, this relationship reverses. Increases in Macro FEARS today predicts increases in stock market returns in the following days, which is consistent with sentiment-induced temporary mispricing. Moreover, this reversal is strongest among stocks with high beta and high volatility, 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 Macro FEARS (i.e. increases in FEARS correspond with high bond returns) consistent with the notion of flight-to-safety. Again, this relationship reverses in the following days.

In Section 4 we consider the DSSW prediction that sentiment swings will generate excess volatility. We find a significant positive contemporaneous correlation between the Macro FEARS index and the change in VIX. When we examine the predictive power of Macro FEARS index for future VIX changes, we again find a reversal pattern: the increase in Macro FEARS today predicts a negative VIX change days later, even after controlling for other predictors of VIX. This reversal pattern is consistent with the notion that the initial increase in VIX contains a component due to negative sentiment. As volatility displays seasonal patterns and is well-known to be persistent and long-lived (Engel and Patton (2001) and Andersen et al. (2001, 2003)), we also model this long-range dependence through the fractional integrated autoregressive moving average model, $ARFIMA(0, d, q)$, which allows us to extract innovations in seasonal-adjusted VIX. We find the same result when we replace the simple change in VIX with the innovation computed from the $ARFIMA(0, d, q)$ model.

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

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

Treasury bonds. We document strong persistence in fund flows and again use the $ARFIMA$ model to extract daily innovations to these fund flows. We find that Macro FEARS predicts daily fund flow innovations *only among equity funds*. Specifically, an increase in the FEARS index predicts outflows from equity mutual funds but no detectable outflow in bond funds.

2 Data and Methodology

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

2.1 Construction of FEARS Indices

Our objective is to build a list of search terms that reveal sentiment towards economic conditions. Following the insight in Tetlock (2007) and Tetlock et al. (2008) that the use of negative words best capture sentiment, we begin with the Harvard IV-4 list of "negative" words. Because we are interested in sentiment towards the economy, we only consider the subset of negative words that are also classified as "economic" words (e.g. "recession", "bankruptcy", "corrupt", etc.) This results in 40 unique words.[6]

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 (including permutations like "debt" as well as "debtor") into Google Insights for Search which, among other things, returns ten "top searches" related to each primitive word.[7] For example, a search for "depression" results in related searches "the depression", "great depression", "the great depression",

[6]The list of words includes bankrupt, bankruptcy, beggar, blackmail, bribe, bum, commoner, corrupt, cost, costliness, costly, debtor, default, depression, destitute, extravagant, fine, fire, gamble, hole, hustle, hustler, inflation, jobless, laid, lay, liquidate, miser, owe, poor, recession, squander, tariff, underworld, uneconomical, unemployed, unprofitable, vagabond, vagrant and waste.

[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."

"depression symptoms", "anxiety depression", etc. From these related searches we filter out searches unrelated to economics. For example, "laid" generates a related search called "laid off" as well as a related search called "laid back." We keep only the former. We also only keep primitive words which had related search terms that are economic terms in order to filter out noisy primitive words (which may have an economic meaning but whose common usage does not relate to economics). For example, "vagabond" generates only related terms like "vagabond inn" and "vagabond Miami" which are not economic terms. This suggests that "vagabond" itself is not a common-use economic term. After this process we are left with 56 terms.[8]

Finally, we eliminate terms that are searched infrequently. In particular, we eliminate search terms that have at least two years of missing data according to Google Insights when the search data are restricted to the U.S. Our final list is composed of 27 search terms that can be broadly sorted into household-level concerns (i.e., *Micro FEARS*) and concerns about business conditions (i.e., *Macro FEARS*). Table 1 lists these 27 search terms.

We download the SVI for each of these 27 terms over our sampling period of 2004/01 - 20011/3 from Google Insights. Google Insights allows users to restrict SVI results to specific countries (e.g. search volume for "recession" from Polish households). Because the dependent variables of interest in this paper are related to U.S. indices, we restrict the SVI results to the U.S. Thus, the measures we construct represent the sentiment of American households. Google Insights also provide SVIs on a daily basis when you download them for a time window less than or equal to a quarter. We thus download the daily SVI time series from Google Insights one quarter at a time.

[8] The list of words includes bankruptcy, going bankrupt, bankruptcy court, chapter 7 bankruptcy, chapter 7, filing bankruptcy, file bankruptcy, bankruptcy information, chapter 13 bankruptcy, chapter 13, after bankruptcy, bankruptcy attorney, bankruptcy lawyer, cost of living, credit debt, debt consolidation, credit card debt, national debt, debt relief, debt collection, debt settlement, the depression, great depression, economic depression, the great depression, inflation, inflation rate, inflation calculator, us inflation, inflation rates, rate of inflation, inflation index, jobless claims, jobless rate, job search, job openings, new job, job opportunities, job application, job bank, unemployment benefits, unemployment rate, unemployment office, unemployment insurance, laid off, lay off, owe money, loans poor credit, recession, the recession, us recession, recession over, recession depression, economic recession, recession end and is recession over.

Thus, the daily SVIs in a particular quarter are therefore scaled by the time series maximum SVI in that quarter. While this normalization does not affect us in computing daily SVI change within a quarter, it does create a problem when we compute SVI change over consecutive quarters. For this reason, we are not able to compute the daily SVI on the first trading day of a quarter. For other days, we can define the daily change in search term j as:

$$\Delta FEARS_{j,t} = \ln(SVI_{j,t}) - \ln(SVI_{j,t-1}). \quad (1)$$

2.1.1 Extreme Values, Seasonality and Heteroskedasticity

Figure 3 plots the daily log changes for two FEARS terms: "Inflation" and "Unemployment benefits." The figures demonstrate several important features of the search data. The first is seasonality: SVI change rises during the beginning of the week (e.g., Monday and Tuesday) and falls throughout the week which generates the repeated 5-day hump-shaped pattern depicted in Figure 3. Moreover there is considerable variance differences across terms. SVI change for "Inflation" and "Unemployment benefits" are plotted on the same scale so that the heteroskedasticity is apparent. In fact, the standard deviation of SVI change for "Unemployment benefits" is nearly three greater than that of "Inflation." Finally, the SVI change for "Unemployment benefits" indicates the presence of some extreme values that are driven by search patterns around the holidays.

To mitigate any concerns about outliers and to address the issues of seasonality and heteroskedasticity 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 $\Delta FEARS_{j,t}$ we regress $\Delta FEARS_{j,t}$ on weekday dummies and month dummies and keep the residual. Finally, to address heteroskedasticity and make each times series comparable, we standardize each of the 27 time series by scaling each by the time-series standard deviation as in Baker and Wurgler

(2006). This leaves us with a winsorized, seasonally-adjusted and standardized daily change in search volume, $\Delta Adjusted\_FEARS_{j,t}$. To compute our Micro and Macro FEARS indices, we simply average across the set of micro-related search terms, S_{micro}, and the set of macro-related search terms, S_{macro}, identified in Table 1,

$$\Delta Micro\_FEARS_t = \frac{1}{\Theta\left(S_{micro,t}\right)} \sum_{j \in S_{micro}} \Delta Adjusted\_FEARS_{j,t} \tag{2}$$

$$\Delta Macro\_FEARS_t = \frac{1}{\Theta\left(S_{macro,t}\right)} \sum_{j \in S_{macro}} \Delta Adjusted\_FEARS_{j,t} \tag{3}$$

where $\Theta()$ is a count function counting how many valid terms are in the set of micro- or macro-related search terms on day t.

2.2 Other Data

Our daily 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 Harvard IV-4 dictionary. Loughran and McDonald (2011) argue that some negative words in the Harvard dictionary 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 the Harvard IV-4 word list or the word list of Loughran and McDonald (2011), and our results reported throughout the paper are based on the Harvard IV-4 word list.

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

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 two highly liquid index ETFs: the SPDR S&P500 (AMEX: SPY), and the PowerShares QQQ Trust (NASDAQ: QQQQ). Finally, we obtain Treasury portfolio returns from the CRSP 10-year constant maturity Treasury file.

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 1000 distinct mutual funds which represent approximately 20% of the universe of US-based mutual funds according to Greene and Hodges (2002). TrimTabs aggregates the daily flows for groups of mutual funds categorized using fund objectives from Morningstar. For our study, we focus on the daily flow of two groups of mutual funds. The first group (Equity) specializes in equity. The second group (MTB) specializes in "Intermediate Treasury Bonds." For each group, we compute the daily flow as the ratio between dollar flow (inflow minus outflow) and fund Total Net Assets (TNA). The data we received from TrimTabs covers the five-year period from January, 2004 to December, 2008.

3 FEARS and Asset Returns

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

3.1 FEARS and Average Returns

One salient feature of sentiment theories is the heterogeneity of investors. In sentiment models, there is typically one class of investors who suffer from a bias, such as extrapolative expectations about future cash flows. These sentiment investors exhibit pessimistic sentiment when their beliefs about future cash flows are exceedingly low and they exhibit optimistic sentiment when their beliefs are about future cash flow realizations are exceedingly high.

However, the presence of sentiment investors does not necessarily mean there will be consequences for asset prices. In order for sentiment investors to have an affect on asset prices, market frictions must exist. In classical models such as DSSW the key additional ingredient is a downward sloping demand curve for risky assets faced by both sentiment investors and rational investors. In states of the world when sentiment investors are overly pessimistic, they sell risky assets to rational investors. Since demand curves are downward sloping, their sales can temporarily depress stock prices and generate negative returns. Because their biased beliefs are stationary, on average such beliefs are corrected the following period. Therefore, asset prices exhibit a short-term reversal.

Table 2 provides evidence of such return reversals. It reports the results from the following specification:

$$return_{i,t+k} = \beta_0 + \beta_1 \Delta Macro\_FEARS_t + \beta_2 \Delta Micro\_FEARS_t + \sum_m \gamma_m Control_{i,t}^m + u_{i,t+k}. \quad (4)$$

In regression (4), $return_{i,t+k}$ denotes asset i's return on day $t+k$, where k ranges from 0 to 2 in consecutive columns of Table 2. We also consider two-day cumulative returns, $return_{i,(t+1,t+2)}$, to gain a perspective on the cumulative effects of return reversals. In addition, we consider longer horizons, ranging from $k=3$ to $k=5$. Since none of the regressors are statistically significant and point estimates are economically negligible, we do not report them. Control variables ($Control_{i,t}^{m}$) include lagged asset-class returns (up to five lags), VIX_t, and $Negative\_News_t$. The main variables of interests are the Macro and Micro FEARS indices, $\Delta Macro\_FEARS_t$ and $\Delta Micro\_FEARS_t$, respectively. We calculate bootstrapped standard errors and our statistical inference is conservative.[9]

We first report our results using the raw FEARS data in Panel A. That is, we do not take out any seasonality in search volume, standardization, and winsorization (i.e., "unadjusted FEARS"). In Panel B, we report results using the adjusted Macro and Micro FEARS indices ("adjusted FEARS"), where issues of seasonality, heteroskedasticity and extreme values have been addressed.

When $k=0$, the negative coefficient on $\Delta Macro\_FEARS_t$ and $\Delta Micro\_FEARS_t$ suggests a negative contemporaneous relationship between Macro and Micro FEARS and a broad equity index, the Standard and Poor's 500 Index, although only Macro FEARS is statistically significant. In general, adjusted FEARS and unadjusted FEARS perform very similar in the tests relating Macro FEARS indices to contemporaneous returns. Days in which there were sharp declines in the equity indices there were also sharp increases in search for terms like "recession", "bankruptcy", "inflation" and so on. The correlation of FEARS and asset returns is statistically significant at the one-percent level or higher, and economically large. For example, Panel B of Table 2 shows that one standard deviation increase in adjusted Macro FEARS corresponds with a contemporaneous decline of 14 basis points for the daily Standard and Poor's 500 index, after controlling for lagged

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

returns, contemporaneous VIX, and news media sentiment.[10,11]

Much of this effect, however, is temporary. In the following days the positive and significant coefficient on $\Delta Macro\_FEARS_t$ and $\Delta Micro\_FEARS$ suggests increases in FEARS predict *higher* returns. This reversal largely occurs when $k = 1$ for $\Delta Micro\_FEARS_t$, and $k = 2$ for $\Delta Macro\_FEARS_t$. Again, only Macro FEARS is statistically significantly when examining reversals.

The adjusted FEARS and unadjusted FEARS perform very similarly in the tests relating Macro and Micro FEARS indices to future return reversals, though adjusted FEARS index performs better in terms of statistical significance. This difference is largely driven by seasonality in FEARS which creates significant variation in FEARS that is unrelated to returns. Thus, when the seasonality is removed we see a clearer picture of the covariance between returns and FEARS.[12] Both standardization and winsorization do not alter our results in discernible ways. In fact, without winsorization, we obtain even stronger results when detecting return reversals. In the tests that follow, we focus on the adjusted FEARS indices.

As shown in Panel B, a standard deviation increase in Macro FEARS corresponds with a contemporaneous *decrease* of 14 basis points in the S&P 500 when $k = 0$, a standard deviation increase in Macro FEARS predicts an *increase* of 2 basis points in the S&P 500 at $k = 1$, and a standard deviation increase in Macro FEARS predicts an *increase* of 8 basis points in the S&P 500 at $k = 2$ (significant at the 5% level).[13] The net impact of a standard deviation increase in

[10] A one standard deviation change in the Macro (Micro) FEARS index corresponds to 0.46 (0.34). Recall that while each individual search term has been standardized so that it's standard deviation is one by construction, the average across search terms will not have a standard deviation of one given correlation among search terms.

[11] It is also worth pointing out that, in the earlier draft of the paper, for a shorter sample period between January 2004 and December 2008, we obtain a very similar estimate of 15 basis points for a one-standard-deviation change in Macro FEARS index values.

[12] We are grateful to our discussant, Owen Lamont, for suggesting we deseasonalize the FEARS indices.

[13] While daily returns are measured from market close on day t to market close on day $t+1$, daily SVIs are measured over the 24 hours on day t. As a result, the return on day $t+1$ may reflect both the negative sentiment after market close on day t and the reversal during trading hours on day $t+1$, which is likely why we often detect significant reversal only on day $t+2$.

Macro FEARS predicts an *increase* of 10 basis points in the S&P 500 between $k = 1$ and $k = 2$ (significant at the 5% level).

Table 3 reports results using different test assets. Panels A through C focus on different equity portfolios while Panel D focuses on Treasury securities. The test assets are the CRSP equally-weighted portfolio (Panel A), the S&P 500 Index exchange traded fund (Panel B), the NASDAQ 100 exchange traded fund (Panel C), and the CRSP 10-year constant maturity Treasury portfolio. Across all assets, a contemporaneous increase in Macro FEARS is always associated with a contemporaneous decrease of equity returns, and a contemporaneous increase of Treasury security returns. Moreover, an increase in Macro FEARS today (i.e., $k = 0$) always predicts a return reversal of equities in the coming two days (i.e., $k = 1$ and $k = 2$), and a return reversal of Treasury securities on the second day (i.e., $k = 2$). The effect of Macro FEARS on equities is typically larger in both initial and future returns compared to Treasury securities. A standard deviation increase in Macro FEARS corresponds with a contemporaneous *decrease* of 11 to 14 basis points among equities at $k = 0$ (significant at the 1% significance), and a standard deviation increase in Macro FEARS predicts an increase of 8 to 10 basis points at $k = 2$ (significant at the 5% level). In contrast, a standard deviation increase in Macro FEARS corresponds with a contemporaneous *increase* of 2.99 basis points for Treasury securities at $k = 0$ (significant at the 5% level), and a standard deviation decrease in Macro FEARS predicts a decrease of 3 basis points at $k = 2$ (significant at the 5% level). Overall, Tables 3 and Table 3 illustrate that the FEARS indices, in particular, the Macro FEARS index, is strongly associated with contemporaneous returns and predicts future return reversals.

3.2 FEARS and Limits to Arbitrage

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

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

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

Panels A and Panel B from Table 4 confirm the hypothesis. As shown in Panel A, sentiment has a more negative contemporaneous relationship with high-beta stocks. For example, a one standard deviation increase in Macro FEARS is associated with a 13.51 basis points decrease in the return spread between the high-beta and low-beta stock portfolio (statistically significant at the

5% level). Again, Macro FEARS also predicts future return reversal effects. At $k = 2$, the reversal of the return spread associated with Macro FEARS is about 13.79 basis points. Thus sentiment has stronger impact on high-beta stocks than low-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 $k = 0$.

Certain assets are also particularly prone to the so-called "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 during when investor sentiment is high, we anticipate a portfolio of stocks with high downside risk should underperform a portfolio of stocks with relatively low downside risk. Following Ang, Chen, and Xing (2006), we consider two measures of "downside risk." The first measure is "downside beta", which was first introduced by Bawa and Lindenberg (1977). Specifically, at the end of each month, we estimate the "downside beta" (i.e., β_i^-) for individual stocks as follows,

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

using past one-year of daily returns.

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

$$\sigma_i^- = \sqrt{var\left(r_i | r_m < \mu_m\right)}, \tag{6}$$

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

As an analog 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 next month. The return spreads between the returns of the high "downside beta" and low "downside beta" stock portfolios are the test assets in Panel C of Table 4. Similarly, Panel D relates FEARS and return spreads between the high "downside sigma" and low "downside sigma" stock portfolios. Sentiment's effect on these return spreads are large. For instance, a one standard deviation increase in Macro FEARS is associated with a 16.57 basis points decrease in the return spreads between the high downside beta and low downside beta stock portfolio (statistically significant at the 5% level). Again, Macro FEARS also predicts future return reversal effects. At $k = 2$, the reversal of the return spreads associated with Macro FEARS is about 15.79 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 $k = 0$.

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.

4 FEARS and Volatility

A long strand of literature starting from Black (1986) suggests that investor sentiment and the resulting noise trading can affect both the level and the volatility of asset prices. In DSSW, risk averse arbitrageurs know that prices can diverge further away from fundamentals before they converge. As a result, they take smaller positions when betting against mispricing. 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.[14] In this section we examine the relationship between FEARS and the daily VIX index.

4.1 VIX Innovation

We start with the daily log VIX index which is plotted in the top panel of Figure 4. Evidently, as we enter September of 2008, when the stock market fell sharply, VIX surged. We first remove potential seasonal effects from log VIX by regressing it on day-of-the-week and month-of-the-year dummies. The residuals, or the seasonal-adjusted log VIX time series are plotted in the middle panel of Figure 4.

Since volatility is persistent and long-lived (Engel and Patton (2001) and Andersen et al. (2001, 2003)), we also model the long-range dependence through the fractional integrated autoregressive moving average model, $ARFIMA(p, d, q)$:

$$\Phi(L)(1-L)^d y_t = \Theta(L)\varepsilon_t \tag{7}$$

where the autoregressive coefficient is p, fractional integration parameter is $0 < d < 0.5$, and the moving-average coefficient is q. By implementing an ARFIMA model, our objective is to remove the predictable components from the volatility series and extract the innovations. The estimate of the autoregressive coefficient p is not significantly different from zero, so we set it to zero and estimate a simple $ARFIMA(0, d, 1)$ model. The extracted VIX innovations are plotted in the bottom of Figure 4. It is clear that the ARFIMA innovations are free of time trends, not autocorrelated and close to white noise. In another words, the ARFIMA model works well in extracting the innovations from the time series of VIX index.

Although we extract the volatility innovations by fitting the ARFIMA model to the full sample,

[14] Using Yahoo! message board activityas 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.

we want to emphasize that this procedure should not result in a "look-ahead bias" that leads to spurious predictive power in our Macro FEARS index. When we first conduct our analysis using daily changes in log VIX which do not use future information and we find similar results.

4.2 Empirical Results

We first examine the relation between changes in log VIX (Δvix) and our FEARS indices using the following regressions:

$$\Delta vix_{i,t+k} = \beta_0 + \beta_1 Macro\_FEARS_t + \beta_2 Micro\_FEARS_t + \sum_m \gamma_m Control_{i,t}^m + u_{i,t+k} \qquad (8)$$

Control variables($Control_{i,t}^m$) include current negative news sentiment measure, current and lagged (5 lags) Δvix and market returns. For example, it has become a stylized fact that volatility is negatively correlated with lagged returns, a phenomenon known as the asymmetric volatility effect.[15] For these reasons, we first include lagged returns (5 lags) as controls in each specification. Moreover, to the extent that low returns increase FEARS, by including them as control variables β_1 and β_2 capture the incremental predictive power of the FEARS indices that is not attributable to its correlation with returns.

The most robust finding among the volatility specifications is the contemporaneous correlation between Macro FEARS and the change in log VIX even after the inclusion of all the control variables. For example, Panel A of Table 5 shows that an increase in Macro FEARS leads to a significant increase in VIX. Specifically, a one standard deviation increase in Macro Fears corre-

[15] See Black (1976), Christie (1982), French, Schwert, and Stambaugh (1987), and Glosten, Jagannathan, and Runkle (1993) among others. Explanations for the asymmetric volatility effect include leverage effects or a time-varying risk premium, although both are less applicable in our high-frequency setting. Instead, Avramov, Chordia and Goyal (2006) find that the asymmetric volatility effect at the daily frequency can be explained by the rational expectation models of Hellwig (1980) and Wang (1994): non-informational liquidity trades increase volatility following stock price declines while informed trading reduces volatility following stock price increases.

sponds with a contemporaneous 7.54% increase in VIX. When we examine the predictive power of the Macro FEARS index on future VIX changes, we again find a reversal pattern: the increase in Macro FEARS today predicts a negative VIX change two days later, even after controlling for other existing predictors of future VIX. This reversal pattern is consistent with the notion that the initial increase in VIX contains a component due to negative sentiment.

We then replace changes in log VIX (Δvix) with the ARFIMA VIX innovations in regression equation (8). The statistical estimates of ARFIMA models are presented in Panel B of Table 5. Consistent with prior literature, log VIX has a strong moving-average (MA) component. The fractional cointegration parameter values is close to but smaller than 0.5. In Panel C of Table 5, we report the results from regressions using the VIX innovations as independent variables. The basic conclusion hardly changes. An increase in the Macro FEARS today leads to a significantly higher VIX index today but the VIX index reverts back to normal within two days.

5 FEARS and Fund Flows

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

Bollerslev and Jubinski (1999) and Fleming and Kirby (2006) provide evidence that an individual stock's daily trading volume series exhibits long-run temporary dependencies, which can be modelled using a fractionally integrated processes. Similar to observations made on the volume of individual stocks, we also find very strong persistence and long-memory components in daily fund flows. For this reason, we first demean each of the daily fund flow series, and apply the $ARFIMA(p, d, q)$ models to extract daily fund flow innovations. Our diagnostics indicate that the $ARFMA(1, d, 1)$ model fits the underlying daily fund flows well. The integration parameter values are in the neighborhood of 0.40 and p-value less than 0.1%. In addition, the moving average (MA) as well as the autoregressive (AR) terms are all statistically significant at the 1% level or higher.

There is one data issue worth pointing out. TrimTabs mutual fund flow is calculated using both publicly observable net asset value (NAV) and privately reported total asset value (NTA). Despite the obvious accuracy of NAV, the NTA information might be reported with a delay of one day for some funds. Both Edelen and Warner (2001), as well as Greene and Hodges (2002) document this issue, and analyze it in detail. Because of this potential one-day reporting delay, we note that TrimTabs flow in day $t + 1$ may actually contain flow in day t (see also Yuan (2008)). We run regressions of contemporaneous fund flows, fund flows 1, 2, 3, and 4 days ahead, and a fund flow average over 1 to 4 days ahead. In particular, we run the following regression:

$$flow_{i,t+k} = \beta_0 + \beta_1 \Delta Macro\_FEARS_t + \beta_2 \Delta Micro\_FEARS_t + \sum_m \gamma_m Control^m_{i,t} + u_{i,t+k} \quad (9)$$

where fund class i denotes includes bond and equity funds. Control variables($Control^m_{i,t}$) include VIX, and $Negative\_News_t$, and five lags of market returns. The results of these regressions are reported in Table 6.

We find that our Macro FEARS index has significant incremental predictive power on future daily fund flow innovations for equity funds but no significant relationship with bond fund flows. In the equity flow regressions the coefficient on Macro FEARS is negative on each day we consider: $t = 0, 1, 2, 3$ and 4 and is statistically significant for days t=2 (p-value $< 5\%$) t=3 (p-value $<5\%$). In contrast, in the bond flow regressions the coefficient on Macro FEARS is positive on days $t = 0, 1, 2$

and 3 although not significant. Overall, an increase in Macro FEARS predictive outflow from equity (significant) and inflow to treasury bond (insignificant) There is little evidence that Micro FEARS index is associated with daily equity or bond fund flows.

Considering equity flows, the coefficients on Macro FEARS are economically large. A one standard deviation increase in Macro FEARS is associated with contemporaneous equity fund flows of $-1.41 \times 10^{-5} (= 0.46 \times -3.07 \times 10^{-5})$. Given the average fund flows in our sample is about -5.06×10^{-5}, that is about 28% of the typical average daily flows. Similarly, if we look at the day $(t+1)$ to $(t+4)$ average flows, a one standard deviation increase in Macro FEARS is associated with an average daily equity fund flow of -2.01×10^{-5}, about 40% of the typical average daily flows.

In short, the evidence herein suggests that individual investors sell equity funds when negative sentiment is high. However, there is no significant evidence that investors are buying treasury bonds. Perhaps this is indicative of the fact that, when negative sentiment is high, individuals pull their money out of the market entirely (more so for equity funds) and simply hold cash.

6 Discussion of Alternative Interpretations

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

6.1 Endogenous Search

Some readers may be concerned that search is endogenous to macroeconomic events. For example, there must be some macro events which coordinate the large spikes in search we observe in Figure 1. This does not disqualify search as a measure of sentiment. In fact, we should expect investor sentiment to be endogenous to macroeconomic events.[16] News arrives daily - some of it will affect investor sentiment and some of it will not. To the extent that daily returns capture the (signed) news arrival of the day, we have explicitly controlled for news events in each of our specifications. Therefore, we can think of our FEARS indices as describing the amount of sentiment generated by an event.

Other readers will be concerned about reverse causality in some of our prediction models if events are anticipated. We cannot conclude that sentiment today caused volatility 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 3) mitigates such concerns. The fact that we find high FEARS today is correlated with low returns today but predicts high returns tomorrow makes reverse causality unlikely. It is implausible that investors, anticipating a high return tomorrow, would search for terms like "recession" and "inflation" today. Returns reversal following a spike in the FEARS index is more consistent with sentiment models which predict temporary deviation from fundamentals.

6.2 Search as a Measure of Sentiment

Beyond endogeneity concerns, there are also other interpretations of our measure and its subsequent predictability for asset volatility. For instance, it is possible that search for terms like "recession"

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

or “great depression” proxy for time-varying risk-aversion. In Campbell and Cochrane (1999), a low surplus consumption ratio will jointly cause risk-aversion and volatility to increase. In Kyle and Xiong (2001) when convergence traders have reduced capital as a result of losses, their risk aversion will increases (due to wealth effects) while asset volatility increases as they liquidate their positions. Both models generate a correlation between risk aversion and volatility in the time series.

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

Alternatively, search volume for negative terms 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 many others). While the VIX index is commonly viewed as an indicator of such aggregate uncertainty, we do not find any evidence that VIX is related to return reversal. Moreover, Macro FEARS remains a strong predictor of future VIX even after controlling for current VIX.

Finally, some readers may worry that search for FEARS is a neutral activity which does not reflect underlying pessimism or optimism. The argument is that households may search for terms like “inflation” or “recession” not because they are concerned about inflation or a recession but rather because they wish to gather information about inflation or recession. This claim is not supported by the evidence. First, even a cursory look at many of the FEARS components (such as “recession” or “credit card debt”) suggests they increase in bad times. For example, (negative) search volume for the term “recession” has an 87.5% correlation with the University of Michigan’s Consumer Confidence Index, suggesting most of the time households search for “recession” when they are worried about a recession. Second, recall from Section 3 that we find a contemporaneous, negative relationship between FEARS and equity returns. The days in which equity returns are low are the same days in which households search for terms in the FEARS indices.

7 Conclusion

By aggregating queries like "recession", "bankruptcy" and "credit card debt" we construct Financial and Economic Attitudes Revealed by Search (FEARS) indices. We show that macro-related FEARS predicts aggregate market returns. In particular, FEARS are correlated with low returns today but predict high returns tomorrow, a reversal pattern that is consistent with sentiment-induced temporary mispricing. Moreover, this effect is strongest among stocks that are favored by sentiment investors and are difficult to arbitrage. In addition, the sentiment indices have strong predictive power for daily volatility. We show that FEARS has a positive contemporaneous correlation with VIX which also reverses. Finally, using daily aggregate mutual fund flows, we also provide direct evidence for "noise" trading. Increases in Macro FEARS index trigger daily mutual fund flows out of equity funds but not out of bond funds. The evidence is broadly consistent with the "noise trading" hypothesis of De Long et. al. (1990).

More generally, this paper follows a new strand of the sentiment literature which proposes novel, high-frequency measures that do not rely on market outcomes like return and volume. Tetlock (2007) suggests that a journalist's tone as measured by the frequency of negative words in a *Wall Street Journal* column capture sentiment and also shows that this tone has predictability for returns. Tetlock (2007) argues that "these results have two reasonable interpretations: the media reports investor sentiment before this sentiment is fully incorporated into market prices; or the media directly influences investors' attitudes toward securities. " Although we also find predictability for returns, our results have only one reasonable interpretation because aggregate search volume does not require a journalist as intermediary. As such this paper underscores the usefulness of search data in financial applications. Search data has the potential to objectively *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, Torben, Tim Bollerslev, Francis X. Diebold and Heiko Ebens, 2001. The distribution of realized stock return volatility, *Journal of Financial Economics* 61, 43-76.

Andersen, Torben, Tim Bollerslev, Francis X. Diebold and Paul Labys, 2003, Modeling and Forecasting Realized Volatility, *Econometrica* 71, 579-625.

Antweiler, Werner and Murray Z. Frank, 2004, Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards, *Journal of Finance* 59, 1259-1294.

Ang, Andrew, Joe Chen, and Yuhang Xing, 2006, Downside Risk, *Review of Financial Studies* 19, 1191-1239.

Avramov, Doron, Tarun Chordia and Amit Goyal, 2006, The Impact of Trades on Daily Volatility, *Review of Financial Studies* 19, 1531-1565, 1241-1277.

Baker, Malcom, Brendan Bradley, and Jeffrey Wurgler, 2011, Benchmarks as limits to arbitrage: understanding the low volatility anomaly, *Financial Analysts Journal* 67, 40-54.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645-1680.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor Sentiment in the Stock Market, *Journal of Economic Perspectives* 21, 129-151.

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, Fischer, 1976, Studies of Stock Price Volatility Changes, *Proceeding of the 1976 meetings of the American Statistical Association, Business and Economical Statistics Section*, 177–181.

Black, Fischer, 1986, Noise, *Journal of Finance* 41, 529-543.

Bloomfield, Robert, Maureen O'Hara, and GIdeon Saar, 2009, How Noise Trading Affects Markets: An Experimental Analysis, *Review of Financial Studies* 22(6), 2275-2302.

Bollerslev, Tim, and Dan Jubinski, 1999, Equity Trading Volume and Volatility: Laten Information Arrivals and Common Long-Run Dependencies, *Journal of Business and Economic Statistics* 17, 9 - 21.

Brown, Stephen J., Goetzmann, William N., Hiraki, Takato, Shiraishi, Noriyoshi and Watanabe, Masahiro, 2002, Investor Sentiment in Japanese and U.S. Daily Mutual Fund Flows. Yale ICF Working Paper No. 02-09.

Brown, Gregory, and Michael Cliff, Investor Sentiment and Asset Valuation, *Journal of Business* 78(2), 405-440.

Brunnermeier, Markus, and Stefan Nagel, 2008, Do Wealth Fluctuations Generate Time-varying Risk Aversion? Micro-Evidence on Individuals' Asset Allocation, *American Economic Review* 98(3), 713-736.

Campbell, John, and John Cochrane, 1999, By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior, *Journal of Political Economy* 107 (2), 205-251.

Christie, Andrew A., 1982, The Stochastic Behavior of Common Stock Variances - Value, Leverage and Interest Rate Effects, *Journal of Financial Economics* 10, 407–432.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Noise Trader Risk in Financial Markets, *Journal of Political Economy* 98, 703-738.

Edelen, Roger and Jerold 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, Alex, Diego Garcia, and Oyvind Norli, 2007, Sports Sentiment and Stock Returns, *Journal of Finance* 62(4), 1967-1998.

Engel, Robert F., and Andrew J. Patton, 2001, What good is a volatility model? *Quantitative Finance* 1, 237-245.

Fleming, Jeff, and Chris Kirby, 2006, Long Memory in Volatility and Trading Volume, *Working Paper*, Rice University.

French, Kenneth R., William Schwert, and Robert Stambaugh, 1987, Expected Stock Returns and Volatility, *Journal of Financial Economics* 19, 3–29.

Glosten, Larry R., Ravi Jagannathan, and David E. Runkle, 1993, On the Relation Between the Expected Value and the Volatility of the Nominal Excess Returns of Stocks, J*ournal of Finance* 48, 1779–1801.

Graham, Benjamin, 1949, The Intelligent Investors, New York Harper & Brothers.

Greene, Jason T. and Charles W. Hodges, 2002, The dilution impact of daily fund flows on open-end mutual funds, *Journal of Financial Economics* 65, 131-158.

Hellwig, Martin F., 1980, On the Aggregation of Information in Competitive Markets, *Journal of Economic Theory* 22, 477–498.

Hirsheifer, David, and Tyler Shumway, 2003, Good Day Sunshine: Stock Returns and the Weather, *Journal of Finance* 58, 1009-1032.

Kamstra, Mark J., Lisa A. Kramer, and Maurice D. Levi, 2003, Winter Blues: A SAD Stock Market Cycle, *American Economic Review* 93, 324-343.

Kaplanski, Guy, and Haim Levy, 2010, Sentiment and stock prices: The case of aviation disaster, *Journal of Financial Economics* 95, 174–201.

Keynes, John M., 1936, The General Theory of Employment, Interest and Money, Macmillan Cambridge University Press.

Kyle, Albert, and Wei Xiong, 2001, Contagion as a Wealth Effect, *Journal of Finance* 56, 1401-1440.

Kogan, Leonid, Stephen A. Ross, Jiang Wang, and Mark M. Westerfield, 2006, The Price Impact and Survival of Irrational Traders, *Journal of Finance* 61(1), 195 - 229.

Kogan, Leonid, Stephen A. Ross, Jiang Wang, and Mark M. Westerfield, 2009, Market Selection, *Working Paper*, MIT.

Koski, Jennifer L., Edward M. Rice and Ali Tarhouni, 2008, Noise Trading and Volatility: Evidence from Day Trading and Message Boards, *Working Paper*, University of Washington.

Loughran, Tim, and Bill McDonald, 2011, When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks, *Journal of Finance* 66, 35-65.

Lemmon, Michael L., and Evgenia V. Portniaguina, 2006, Consumer Confidence and Asset Prices: Some Empirical Evidence, *Review of Financial Studies* 19 (4), 1499-1529.

Pontiff, Jeffrey, 1996, Costly Arbitrage: Evidence from Closed-End Funds, *Quarterly Journal of Economics* 111(4), 1135-1151.

Qiu, Lily and Ivo Welch, 2006, Investor Sentiment Measures, *Working Paper*, Brown University.

Shleifer, Andrei, and Robert W. Vishny, 1997, The Limits of Arbitrage, *Journal of Finance* 52, 35-55.

Singer, Eleanor, 2002, The Use of Incentives to Reduce Nonresponse in Household Surveys, *Working Paper*, University of Michigan.

Tetlock, Paul C., 2007, Giving Content to Investor Sentiment: The Role of Media in the Stock Market, *Journal of Finance* 62, 1139-1168.

Tetlock, Paul C., Maytal Saar-Tsechansky, and Sofus Macskassy, 2008, More Than Words: Quantifying Language to Firms' Fundamentals, *Journal of Finance* 63 (3), 1437-1467.

Veronesi, Pietro, 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 Wealth? Evidence from Expectations and Actions, *NBER Macroeconomics Annual*.

Wang, Jiang, 1994, A Model of Competitive Stock Trading Volume, *Journal of Political Economy* 102, 127–168.

Whaley, Robert E., 2001, The Investor Fear Gauge, *Journal of Portfolio Management* 26, 12-17.

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.

Figure 1: Illustrations of Google Search Volume

The figures represent the graphical outputs from Google Insight for Search. The top panel plots weekly aggregate search frequency (SVI) for "credit card debt" in the United States. SVI for "credit card debt" is the weekly search volume for "credit card debt" scaled by the maximum search volume of "credit card debt. The bottom panel plots the SVI for "recession" in the United States.

Figure 2: Search for “Recession” and Consumer Confidence

We plot the monthly log SVI for “recession” (with a minus sign) against the monthly University of Michigan Consumer Sentiment Index. The data are from 2004/01 to 2011/03. The correlation between the two series is 0.875.

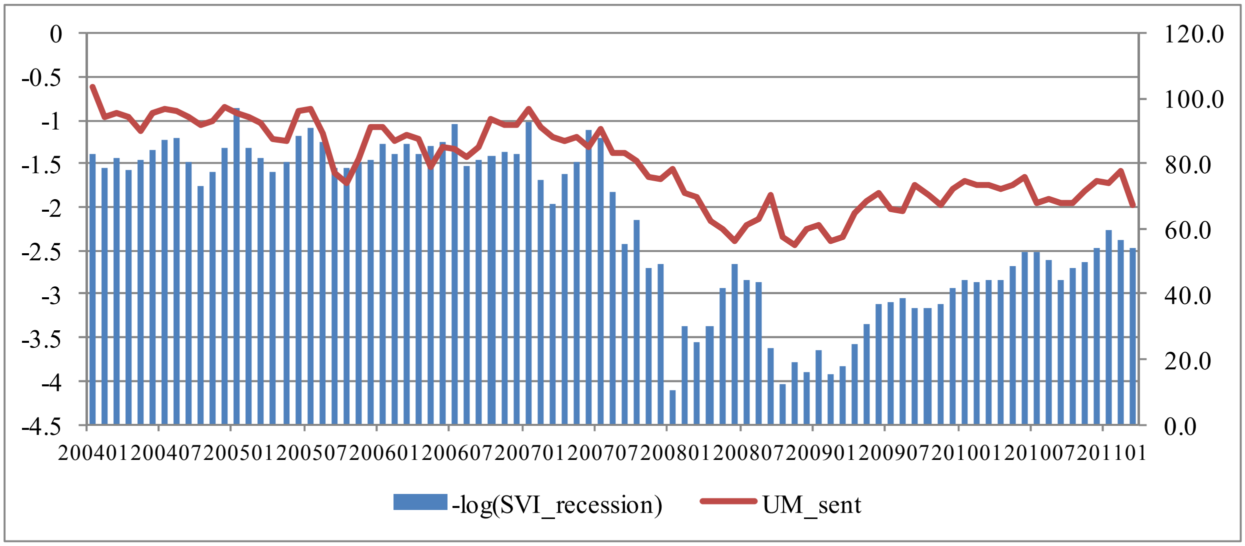
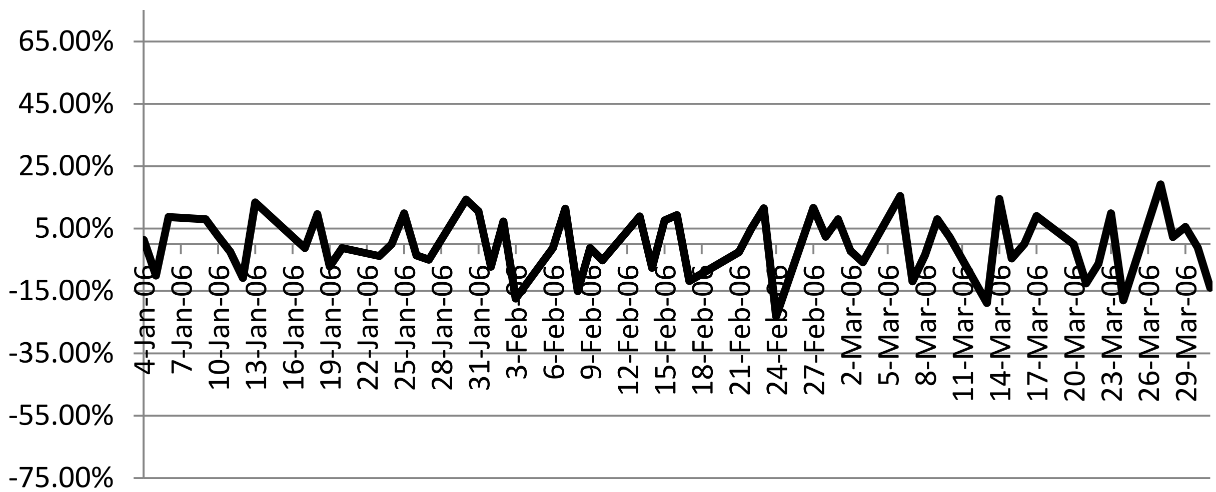


Figure 3: SVI Change Examples for "Inflation" and "Unemployment benefits"

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 "Unemployment benefits" over the period October 2004 – December 2004.

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



SVI Change for "Unemployment benefits" : October 2004 – December 2004

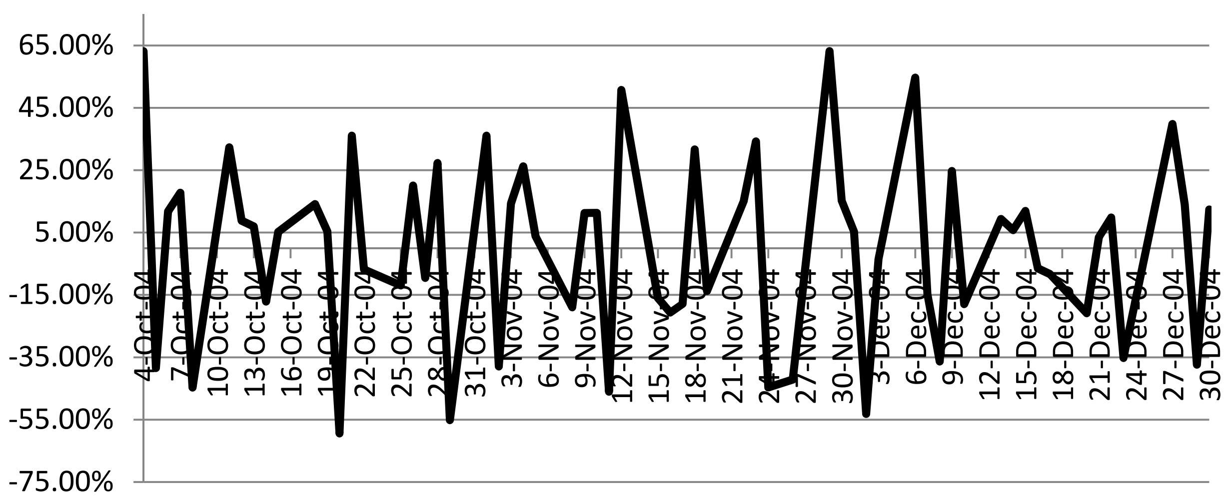


Figure 4: Log VIX, Seasonal Adjustment, and ARFIMA Innovations

The top figure plots the raw log VIX. We then remove the day-of-week and month-of-year seasonality and plot the seasonal-adjusted log VIX in the middle. Finally we feed the seasonal-adjusted log VIX to ARFIMA(0,d,1) estimation and plot the innovations in the bottom.

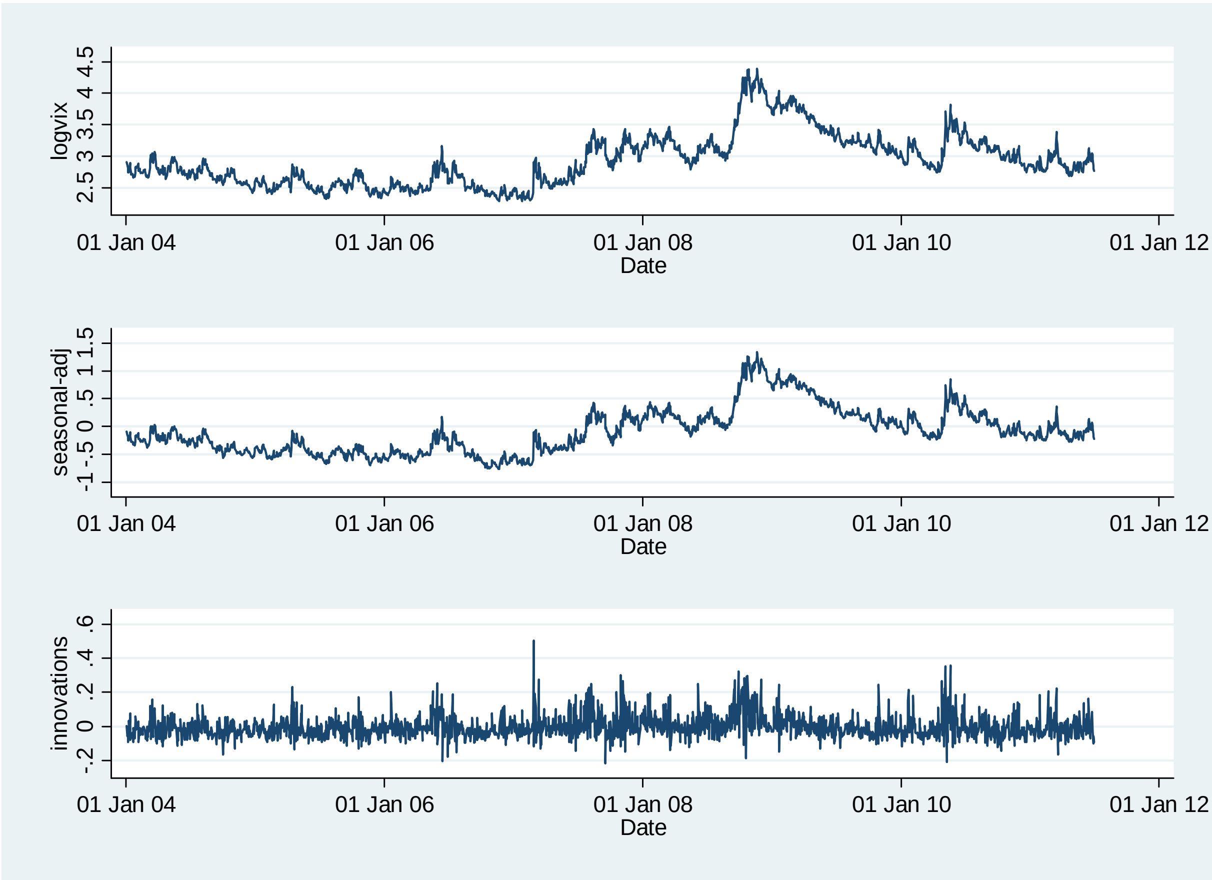


Table 1: Search Terms used in FEARS Index

This table contains the list of 27 search terms used in the construction of the Financial and Economic Attitudes Revealed by Search index, or FEARS index. They are categorized in two groups.

Micro FEARS	Macro FEARS
job search	national debt
job openings	the depression
new job	great depression
job opportunities	the great depression
job application	inflation
job bank	inflation rate
unemployment benefits	cost of living
unemployment rate	recession
unemployment office	
unemployment insurance	
debt collection	
bankruptcy	
bankruptcy court	
chapter 7	
filing bankruptcy	
chapter 13	
credit debt	
debt consolidation	
credit card debt	

Table 2: FEARS and S&P 500 Index Returns

This table relates the S&P 500 index daily returns to Macro and Micro FEARS. The dependent variables are contemporaneous returns (column (1)) and future S&P 500 index daily returns (columns (2) to (4)) while the independent variables are the Macro and Micro FEARS indices. Panel A uses the raw, unadjusted Macro and Micro FEARS indices. Panel B uses the winsorized, de-seasonalized and standardized (adjusted) Macro and Micro FEARS indices. The set of control variables include lagged returns up to five lags, a negative news sentiment measure, and the CBOE volatility index (VIX). The standard errors are bootstrapped standard errors. *, **, and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A: Raw FEARS and S&P 500 Returns

	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS	-0.0144***	0.000333	0.00602*	0.00644
	(0.00403)	(0.00365)	(0.00359)	(0.00467)
Micro FEARS	0.00544	0.00658*	-0.00528	0.00147
	(0.00444)	(0.00385)	(0.00423)	(0.00537)
VIX	-0.000182***	6.10e-06	-1.07e-05	-8.66e-06
	(6.53e-05)	(7.01e-05)	(7.18e-05)	(9.14e-05)
Pessimism	-7.53e-05	-0.000500	3.87e-05	-0.000485
	(0.000398)	(0.000442)	(0.000411)	(0.000589)
Ret(t)		-0.134***	-0.0982	-0.231***
		(0.0428)	(0.0610)	(0.0722)
Ret(t-1)	-0.157***	-0.116*	0.0667	-0.0518
	(0.0458)	(0.0653)	(0.0471)	(0.0783)
Ret(t-2)	-0.128**	0.0446	-0.0466	-0.00254
	(0.0621)	(0.0442)	(0.0611)	(0.0718)
Ret(t-3)	0.0337	-0.0343	-0.0219	-0.0547
	(0.0452)	(0.0555)	(0.0531)	(0.0742)
Ret(t-4)	-0.0447	-0.0213	-0.00138	-0.0247
	(0.0546)	(0.0559)	(0.0530)	(0.0661)
Ret(t-5)	-0.0349	-0.00235	-0.0329	-0.0313
	(0.0590)	(0.0520)	(0.0571)	(0.0767)
Constant	0.00375***	-3.51e-05	0.000278	0.000301
	(0.00114)	(0.00123)	(0.00129)	(0.00160)
Observations	1,609	1,609	1,609	1,609
Adjusted R^2	0.064	0.032	0.015	0.031

Panel B: Standardized FEARS and S&P 500 Returns

	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS	-0.00305***	0.000422	0.00185**	0.00228**
	(0.000863)	(0.000848)	(0.000839)	(0.00111)
Micro FEARS	-0.000628	0.00103	-0.00104	3.42e-05
	(0.00112)	(0.000987)	(0.00106)	(0.00134)
VIX	-0.000183***	7.90e-06	-1.08e-05	-6.83e-06
	(6.60e-05)	(7.05e-05)	(6.81e-05)	(9.22e-05)
Pessimism	-3.81e-05	-0.000498	1.80e-05	-0.000504
	(0.000415)	(0.000445)	(0.000404)	(0.000596)
Ret(t)		-0.133***	-0.0972	-0.229***
		(0.0410)	(0.0595)	(0.0733)
Ret(t-1)	-0.159***	-0.116*	0.0676	-0.0507
	(0.0445)	(0.0650)	(0.0452)	(0.0719)
Ret(t-2)	-0.127**	0.0437	-0.0476	-0.00456
	(0.0618)	(0.0475)	(0.0580)	(0.0700)
Ret(t-3)	0.0349	-0.0345	-0.0232	-0.0562
	(0.0451)	(0.0568)	(0.0583)	(0.0802)
Ret(t-4)	-0.0465	-0.0194	-0.00176	-0.0232
	(0.0544)	(0.0602)	(0.0575)	(0.0674)
Ret(t-5)	-0.0386	-0.000419	-0.0312	-0.0276
	(0.0567)	(0.0537)	(0.0580)	(0.0744)
Constant	0.00379***	-7.38e-05	0.000279	0.000263
	(0.00116)	(0.00123)	(0.00120)	(0.00163)
Observations	1,609	1,609	1,609	1,609
Adjusted R^2	0.063	0.030	0.017	0.032

Table 3: FEARS and Returns to Other Asset Classes

This table relates several alternative index daily returns to Macro and Micro FEARS. The dependent variables are contemporaneous returns (column (1)) and future returns (columns (2) to (4)) while the independent variables are the Macro and Micro FEARS indices. The set of control variables (unreported) include lagged returns up to five lags, negative news sentiment, and the CBOE volatility index (VIX). The test assets in Panels A, B, C and D are CRSP equally-weighted portfolio daily returns, S&P Exchange Traded Fund (SPY) daily returns, Nasdaq Exchange Traded Fund (QQQQ), and CRSP 10-year constant maturity Treasury portfolio daily returns respectively. The standard errors are computed using bootstrap method. *, **, and *** denote the coefficient estimates are significant at ten, five and one percent significance level respectively.

Panel A: CRSP Equally-Weighted Portfolio Return

	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS	-0.00234***	0.000542	0.00165**	0.00221*
	(0.000804)	(0.000789)	(0.000728)	(0.00114)
Micro FEARS	-0.000839	0.000550	-0.000996	-0.000428
	(0.00111)	(0.000972)	(0.00101)	(0.00143)
Controls	YES	YES	YES	YES
Observations	1,609	1,609	1,609	1,609
Adjusted R^2	0.027	0.004	0.004	0.001

Panel B: S&P Exchange Traded Fund (ETF) Return

	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS	-0.00305***	0.000380	0.00176**	0.00214**
	(0.000839)	(0.000863)	(0.000805)	(0.00108)
Micro FEARS	-0.000368	0.000747	-0.000834	-4.60e-05
	(0.00105)	(0.00103)	(0.000999)	(0.00143)
Controls	YES	YES	YES	YES
Observations	1,609	1,609	1,609	1,609
Adjusted R^2	0.060	0.027	0.020	0.030

Panel C: Nasdaq Exchange Traded Fund (ETF) Return

	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS	-0.00286***	0.000369	0.00216**	0.00254**
	(0.000873)	(0.000921)	(0.000893)	(0.00123)
Micro FEARS	0.000355	0.000461	-0.00150	-0.00102
	(0.00118)	(0.00117)	(0.00117)	(0.00147)
Controls	YES	YES	YES	YES
Observations	1,609	1,609	1,609	1,609
Adjusted R^2	0.031	0.011	0.010	0.010

Panel D: 10-year constant to maturity Treasury portfolio return

	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS	0.0655**	0.0101	-0.0658**	-0.0377
	(0.0298)	(0.0268)	(0.0298)	(0.0422)
Micro FEARS	-0.0400	-0.105***	0.0815**	-0.00294
	(0.0389)	(0.0364)	(0.0351)	(0.0553)
Controls	YES	YES	YES	YES
Observations	1,598	1,598	1,598	1,598
Adjusted R^2	0.013	0.011	0.012	0.004

Table 4: FEARS and Limits to Arbitrage

This table relates several volatility sorted portfolio returns to Macro and Micro FEARS. The dependent variables in Panels A are daily return spreads created by longing high-beta stocks and shorting low-beta stocks. The dependent variables in Panels B are daily return spreads created by longing high-volatility stocks and shorting low-volatility stocks. The dependent variables in Panels C are daily return spreads created by longing high-downside-beta stocks and shorting low-downside-beta stocks. The dependent variables in Panels D are daily return spreads created by longing high-downside-volatility stocks and shorting low-downside-volatility stocks. In each panel, the dependent variables are contemporaneous returns (column (1)) and future returns (columns (2) to (4)) while the independent variables are the Macro and Micro FEARS indices. The set of control variables include lagged returns up to five lags, the negative news sentiment measure, and CBOE volatility index (VIX). The standard errors are computed using the bootstrap method. *, ** and *** denote the coefficient estimates are significant at ten, five and one percent significance level respectively.

Panel A: Sentiment and high-minus-low Beta Portfolio Daily Return Spreads

	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS	-0.00296**	0.000769	0.00302**	0.00379**
	(0.00132)	(0.00132)	(0.00124)	(0.00178)
Micro FEARS	-0.00133	0.00190	-0.00307*	-0.00125
	(0.00170)	(0.00171)	(0.00169)	(0.00232)
Controls	YES	YES	YES	YES
Observations	1,609	1,608	1,607	1,607
Adjusted R^2	0.005	0.001	0.004	0.004

Panel B: Sentiment and High minus Low "Total Volatility (Total Sigma)" Portfolio Daily Return Spreads

	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS	-0.00128	0.00121	0.00135*	0.00259**
	(0.000824)	(0.000810)	(0.000821)	(0.00125)
Micro FEARS	-0.00141	0.000426	-0.00144	-0.00103
	(0.00113)	(0.00116)	(0.00112)	(0.00183)
Controls	YES	YES	YES	YES
Observations	1,609	1,608	1,607	1,607
Adjusted R^2	0.044	0.039	0.022	0.053

Panel C: Sentiment and High minus Low "Downside Beta" Portfolio Daily Return Spreads

	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS	-0.00363**	-0.000962	0.00346**	0.00255
	(0.00152)	(0.00178)	(0.00160)	(0.00239)
Micro FEARS	-0.00446*	0.00462**	-0.00127	0.00358
	(0.00230)	(0.00221)	(0.00204)	(0.00287)
Controls	YES	YES	YES	YES
Observations	1,609	1,608	1,607	1,607
Adjusted R^2	0.025	0.017	0.019	0.012

Panel D: Sentiment and High minus Low "Downside Volatility (Downside Sigma)" Portfolio Daily Return Spreads

	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS	-0.00121***	-0.000126	0.000596*	0.000476
	(0.000398)	(0.000366)	(0.000357)	(0.000568)
Micro FEARS	-0.000769*	0.000639	-0.000343	0.000307
	(0.000444)	(0.000482)	(0.000465)	(0.000709)
Controls	YES	YES	YES	YES
Observations	1,609	1,608	1,607	1,607
Adjusted R^2	0.046	0.027	0.032	0.005

Table 5: FEARS and Volatility

This table relates Macro and Micro FEARS to change of the market-level volatility and ARFIMA-model filtered change of market-level volatility. In Panel A, the dependent variables are the contemporaneous VIX change (column (1)), and future VIX changes (columns (2) to (4)). The set of control variables include lagged VIX change up to five lags, the negative news sentiment measure, and market returns (column (1)) or lagged market returns (columns (2) to (4)). Panel B reports the estimates of an ARFIMA(0,d,1) model to the log daily VIX changes. Panel C is similar to Panel A, except the dependent variables are the contemporaneous ARFIMA-model filtered changes of log VIX (column (1)), and ARFIMA-model filtered future changes of log VIX (columns (2) to (4)). The standard errors are computed using the bootstrap method. *, ** and *** denote the coefficient estimates are significant at ten, five and one percent significance level respectively.

Panel A: VIX Changes, unadjusted

	ΔVIX(t)	ΔVIX(t+1)	ΔVIX(t+2)	ΔVIX(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS (t)	0.164***	0.0832	-0.207*	-0.124
	(0.0585)	(0.130)	(0.123)	(0.160)
Micro FEARS (t)	0.0929	-0.141	0.0155	-0.126
	(0.0825)	(0.165)	(0.144)	(0.198)
Controls	Included	Included	Included	Included
Observations	1,609	1,609	1,609	1,609
Adjusted R^2	0.662	0.059	0.035	0.069

Panel B: ARFIMA Estimation

	d	MA(1)
Estimates	0.499***	0.400***
Standard Errors	(0.004)	(0.015)

Panel C: VIX Changes, AFIMA-model adjusted

	ΔVIX(t)	ΔVIX(t+1)	ΔVIX(t+2)	ΔVIX(t+1, t+2)
	(1)	(2)	(3)	(4)
Macro FEARS (t)	0.00567**	0.000982	-0.00814**	-0.00716
	(0.00269)	(0.00444)	(0.00385)	(0.00545)
Micro FEARS (t)	0.00272	-0.00697	0.00171	-0.00526
	(0.00370)	(0.00557)	(0.00472)	(0.00720)
Controls	Included	Included	Included	Included
Observations	1,609	1,609	1,609	1,609
Adjusted R^2	0.558	0.126	0.129	0.211

Table 6: FEARS and Fund Flows

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

Panel A: Equity Fund Flow

	Flow (t)	Flow (t+1)	Flow (t+2)	Flow (t+3)	Flow (t+4)	Flow (t+5)
	(1)	(2)	(3)	(4)	(5)	(6)
Macro FEARS (t)	-3.07e-05	-1.16e-05	-6.24e-05**	-6.25e-05**	-3.85e-05	7.28e-06
	(3.26e-05)	(3.31e-05)	(3.17e-05)	(2.92e-05)	(3.38e-05)	(3.27e-05)
Micro FEARS (t)	4.09e-05	-5.01e-05	2.76e-05	-5.70e-06	-9.31e-06	-4.37e-05
	(4.58e-05)	(3.88e-05)	(4.05e-05)	(3.80e-05)	(4.33e-05)	(4.34e-05)
Controls	Included	Included	Included	Included	Included	Included
Observations	1,441	1,440	1,439	1,438	1,437	1,436
Adjusted R-squared	0.092	0.138	0.168	0.106	0.059	0.043

Panel B: Bond Fund Flow

	Flow (t)	Flow (t+1)	Flow (t+2)	Flow (t+3)	Flow (t+4)	Flow (t+5)
	(1)	(2)	(3)	(4)	(5)	(6)
Macro FEARS (t)	3.19e-05	7.22e-05	8.59e-05	9.28e-05	-2.92e-05	-3.58e-05
	(0.000102)	(7.86e-05)	(7.07e-05)	(7.71e-05)	(6.57e-05)	(6.93e-05)
Micro FEARS (t)	0.000154	-3.75e-05	5.10e-05	9.54e-05	-1.77e-05	5.05e-06
	(0.000125)	(8.33e-05)	(0.000132)	(7.59e-05)	(7.95e-05)	(8.30e-05)
Controls	Included	Included	Included	Included	Included	Included
Observations	1,441	1,440	1,439	1,438	1,437	1,436
Adjusted R-squared	0.020	0.017	0.021	0.014	0.016	0.018