

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

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

First Draft: September 2, 2009

This Draft: June 4, 2010

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 2008, 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, Ralph Koijen, Bob Jennings, Owen Lamont, Paul Schultz, Andrei Shleifer, Paul Tetlock, Dick Thaler, Yu Yuan and seminar participants at University of Notre Dame and State of Indiana Annual Conference and the 2010 NBER Behavioral Economics 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, Kenan-Flagler Business School, University of North Carolina at Chapel Hill. E-mail: joseph_engelberg@kenan-flagler.unc.edu; Tel: (919) 962-6889.

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

“Most of the time common stocks are subject to irrational and excessive price fluctuations in both directions as the consequence of the ingrained tendency of most people to speculate or gamble... to give way to hope, fear and greed.”

— Benjamin Graham, *The Intelligent Investors*.

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 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. Consistent with sentiment theories, we find FEARS predict return reversals: although increases in FEARS correspond with low returns today, they predict high returns (reversal) tomorrow. Moreover, increases in FEARS predict increases in asset-class volatility and mutual fund flow out of equity funds.

The appeal of our search-based sentiment measure is more transparent when compared with

¹A particularly interesting thread of literature examines exogenous and plausible sentiment changing non-economical events such as sports game’s outcomes (i.e., “sport sentiment”) (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.

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), mutual fund flows, among others (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 higher 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 (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. Economic fundamentals change over time, which clouds precise interpretation of empirical findings relating investor sentiments to asset prices. With a high-frequency sentiment measure, one can carry out sharper empirical tests that isolate the longer-term impact of economic fundamentals.² 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 about job loss. Moreover, 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.

²To 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.

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 Figure 1 plots SVI for “credit card debt” and “recession” respectively. The plots conform with intuition. For example, the SVI for “credit card debt” has been rising steadily since the middle of 2008 as consumers have 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 2004 to 2008, the two times series are highly correlated with a correlation coefficient greater than 0.8.⁴ Again, SVI on “recession” seems to lead the MCSI during the financial crisis of 2008. In contrast to the survey-based market sentiment measure, SVI also captures sentiment swings at a higher frequency. For example, Khandani and Lo (2007) analyze the quant crisis during the tumultuous week of August 6, 2007. They argue the crisis is partially related to “a climate of fear and panic, heightening the risk sensitivities of managers and investors across all markets and style categories.” The bottom Panel of Figure 2 plots the daily SVI for “recession” against the CBOE market volatility index (VIX) during the week from August 6 to August 14. Remarkably, the SVI is highly correlated with the VIX (also known as the “investor fear gauge” by practitioners). These examples illustrate the potential of search-based measures in capturing broad-based investor sentiment in real time.

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 text analytics literature in finance which focuses

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

⁴The 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.

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 (<http://www.google.com/insights/search/>) 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, 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 FEARS and market returns. Increases (decreases) in Micro and Macro FEARS correspond with low (high) returns. However, in the days following, this relationship reverses. Increases in FEARS today predicts increases in 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).

In Section 4 we consider the DSSW prediction that sentiment swings will generate excess volatility by relating daily realized volatility to the FEARS indices. Because intraday transaction data is needed for this calculation, we focus our attention on exchange-traded funds (ETFs) such as the extremely liquid SPDR S&P500 (AMEX: SPY) and the PowerShares QQQ Trust (NASDAQ: QQQQ). Volatility is well-known to be persistent and long-lived (Engel and Patton (2001) and Andersen et al. (2001)) so we model this long-range dependence through the fractional integrated autoregressive moving average model, $ARFIMA(p, d, q)$, which allows us to extract innovations in volatility. When we examine the predictive power of our FEARS indices on future volatility

innovations, we find it to be positive and significant across many ETFs. An increase in FEARS today predicts a positive realized volatility innovation tomorrow, even after controlling for other existing predictors of future volatility such as current return and turnover.

As a more direct test of the “noise trading” hypothesis, we also 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 Treasury bonds, which resemble the ETFs we have examined. We document strong persistence in fund flows and again use the *ARFIMA* model to extract daily innovations to these fund flows. We find that our FEARS index has significant incremental predictive power on future daily fund flow innovations *only among equity funds*. Specifically, an increase in the FEARS index predicts outflows from equity mutual funds but no change in flows for safer funds like bonds. These results are consistent with the well-documented flight-to-quality phenomenon in distressed times.

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 only 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

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

⁶The 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.

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 (<http://www.google.com/insights/>) 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”, “depression symptoms”, “anxiety depression”, etc. From these related searches we filter out searches unrelated to U.S. or household 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 Trends 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., *Mirco FEARS*) and concerns about business conditions (i.e., *Macro FEARS*). Table 1 lists these 27 search terms.

The SVIs of these 27 terms cover the sampling period from 2004/01 - 2008/12. Google Insights 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. The daily SVIs are therefore normalized within each quarter. In another words, SVIs in the same

⁷According 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.”

⁸The 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.

quarter are scaled by its time-series average within 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:

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

Some of the search terms have intra-week and intra-year seasonality. To eliminate seasonality from $\Delta FEARS_{j,t}$ we regress $\Delta FEARS_{j,t}$ on weekday dummies and month dummies and keep the residual. To 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 seasonally-adjusted, 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,

$$\Delta Micro_FEARS_t = \frac{1}{\Theta(S_{micro,t})} \sum_{j \in S_{micro}} \Delta Adjusted_FEARS_{j,t} \quad (2)$$

$$\Delta Macro_FEARS_t = \frac{1}{\Theta(S_{macro,t})} \sum_{j \in S_{macro}} \Delta Adjusted_FEARS_{j,t} \quad (3)$$

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 .

A Principal Component Analysis (PCA) of all 27 search terms suggests that our organization of terms into Macro and Micro FEARS is reasonable. The Principal Component Analysis (PCA) is conducted for the period from April 2004 to September 2008 as some search terms have missing SVIs during the first quarter of 2004 and the last quarter of 2008. Figure 3 plots the percentage of total variance explained by each of the 27 factors (or eigenvectors). The figure clearly points towards a strong common component. The first factor (or the eigenvector corresponding to the largest eigenvalue) explains almost 67% of the total variation across the 27 search terms. Beyond the first six factors, the remaining factors add negligible additional explanatory power.

The first six factors are not unique to rotations. To better understand the meaning of these

factors, we rotate these factors using a varimax rotation method. An appealing feature of the varimax rotation method is that each rotated factor will be highly correlated with some search terms but almost uncorrelated with all the other search terms. The resulting rotated factors can then be interpreted based on the search terms that it loads heavily on. Table 2 reports the top three search terms that each of the first six rotated factors loads on. It also reports the percentage of total variance explained by each of the rotated factors. Due to factor rotation, the total variance explained is different from those reported in Figure 3.

The first factor, which explains more than 20.2% of the total variance, loads significantly on many search terms, but most heavily on “The Depression”, “The Great Depression” and “Great Depression.” Therefore, it is clearly a depression-related factor. The second factor, which explains almost 12.4% of the total variance, loads primarily on “Job Search”, “Job Openings” and “Job Opportunity” and is therefore a job-related factor. Similarly, we can label the third, fourth, fifth and sixth factors as the bankruptcy, unemployment, debt and inflation/recession related factors, respectively. Of these factors, factors 1 and 6 essentially compose Macro FEARS because they concern depression, inflation and recession while factors 2 to 5 essentially compose Micro FEARS because they concern job loss, bankruptcy and personal debt issues.

2.2 Other Data

Our daily news data come from the Dow Jones Archive (DJA) as in Tetlock (2009). An alternative way of capturing negative sentiment, as discussed in Tetlock (2007), is to examine negative words in news articles. Following Tetlock et al. (2008), for each article in the Dow Jones Archive Database on day t , we compute the fraction of negative words. Then, we calculate the weighted average across all articles on day t where the weights are based on the number of words in each article, excluding so-called “stop words”. This gives us a broad, daily sentiment measure based on the linguistic content of media articles across all stocks on day t , $Negative_News_t$. To identify the negative words, Tetlock et al. (2008) use the Harvard IV-4 dictionary. Loughran and McDonald (2009) 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, board, foreign, vice and liability, simply describe company operations. Instead, they develop an alternative negative word list that better reflects the tone of financial text. To measure the uncertainties implied by the

media articles, we also use the Harvard IV-4 dictionary or the alternative dictionary developed by Loughran and McDonald (2009) to identify words of uncertainty and calculate $Uncertain_News_t$ in the same manner in which we calculate $Negative_News_t$. We obtain qualitatively similar results when using either the Harvard IV-4 word list or the word list of Loughran and McDonald (2009), and our results reported through out 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 (2000) 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) regard it as an alternative market sentiment measure. As an additional control, we include the VIX index as a control variable in our specifications.

Our daily mutual fund flow data are obtained from TrimTabs, Inc. A description of TrimTabs data can be found in Edelen and Warner (2001) and Greene and Hodges (2002). TrimTabs collects daily flow information for about 1000 distinct mutual funds during our sampling period from 2004 to 2008, 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”, which best resembles our Treasury-bond ETF (TLT). For each group, we compute the daily flow as the ratio between dollar flow (inflow minus outflow) and fund Total Net Assets(TNA).

Other variables are constructed from standard data sources. The price and volume related variables are obtained from CRSP. The transaction-level data on the ETFs are obtained from the New York Stock Exchange Trades and Quotes (TAQ) database. Our data cover the five-year period from January, 2004 to December, 2008.

3 FEARS and Asset Returns

One salient feature of sentiment theories is the heterogeneity of investors. In sentiment models, there are typically investors who suffer from some 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 impact on asset prices, a market friction must exist. In classical models such as DeLong et al. (1990) the key additional ingredient is the 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 3 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 class i 's return on day $t+k$, where k ranges from 0 to 5 in consecutive columns of Table 3. Control variables ($Control_{i,t}^m$) include lagged asset-class returns (up to five lags), VIX_t , $Negative_News_t$ and $Uncertain_News_t$. The main variables of interests are the Macro and Micro FEARS indices, $\Delta Macro_FEARS_t$ and $\Delta Micro_FEARS_t$ respectively.

When $k = 0$, the negative coefficient on $\Delta Macro_FEARS_t$ and $\Delta Micro_FEARS_t$ suggests a negative contemporaneous relationship between Micro and Macro FEARS and broad equity indices such as the the CRSP Value-Weighted Index (Panel A), NASDAQ 100 Index (Panel B), S&P 500 Index (Panel C) and the Russell 2000 Index (Panel D).⁹ 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 five-percent level or higher, and economically large. For example, Panel A of Table 3 shows that one

⁹Except for CRSP value-weighted index daily returns, which are obtained from CRSP database, all other index returns are obtained from the closing prices of index-related ETFs.

standard deviation increase in Macro (Micro) FEARS corresponds with a contemporaneous decline of 12 basis points (12 basis points) for the daily CRSP value-weighted indices, after controlling for the lagged returns, contemporaneous VIX, and news media sentiment.¹⁰ Similarly, a one standard deviation increase in Macro (Micro) FEARS corresponds with a contemporaneous decline of 15 basis points (11 basis points) for the S&P 500 index daily return.

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. For equity asset classes, this reversal largely occurs when $k = 1$ for $\Delta Micro_FEARS_t$, and $k = 2$ for $\Delta Macro_FEARS_t$. For example, although a standard deviation increase in Macro (Micro) FEARS corresponds with a contemporaneous *decrease* of 15 bps (11 bps) in the S&P 500 when $k = 0$, a standard deviation increase in Macro FEARS predicts an *increase* of 10 basis points in the S&P 500 at $k = 2$, and a standard deviation increase in Micro FEARS predicts an *increase* of 9 basis points in the S&P 500 at $k = 1$.

In contrast to the negative contemporaneous relationship between Micro and Macro FEARS and broad equity indices, as shown in Panel E, Table 3, the contemporaneous relationship between Macro FEARS and the Lehman Long-term (20-plus year) Treasury Bond Index is positive and statistically significant at one-percent level. A one standard deviation increase in Macro FEARS is accompanied by a 7 basis points increase in the bond index return. There is no statistically significant and economically important contemporaneous relationship between Micro FEARS and bond returns. There is some evidence of return reversal effect associated with Macro FEARS, but it is not statistically significant.

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 (Shleifer and Vishny, 1997; Stein, 2008). That is, arbitrage capital moves slowly to take advantage of the irrational beliefs of sentiment investors. Motivated by limits to arbitrage, we consider two additional sets of testing assets and explore the sentiment effect on asset prices.

The first set of testing assets are beta-sorted portfolios obtained from CRSP. CRSP computes a

¹⁰A one standard deviation change in the Macro (Micro) FEARS index corresponds to .55 (.43). 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.

Scholes-Williams beta for common stocks traded on NYSE and AMEX using daily returns within a year, then forms decile portfolios based on the Scholes-Williams beta. According to Baker, Bradley, and Wurgler (2010) high beta portfolios are prone to speculative trading of sentiment investors. Moreover, high beta stocks may be unattractive to arbitragers who face institutional constraints such as benchmarking. Because of these two forces work in the same direction for high beta stocks, it is natural to conjecture that the investor sentiment may have a larger impact among high beta stocks than among low beta stocks. The results are reported in Table 4. As shown in Panel A, sentiment has a strong negative contemporaneous relationship with the high-beta stock portfolio's daily return. A one standard deviation increase in Macro FEARS and Micro FEARS is associated with 17 basis points and 21 basis points decrease of high-beta stock portfolio returns (both regression coefficients are statistically significant at five-percent level or higher). Again, both Macro FEARS and Micro FEARS predict future return reversal effects. At $k = 2$, the reversal associated with Macro FEARS is about 18 basis points; while at $k = 1$, the return reversal associated with Micro FEARS is about 14 basis points. For the low-beta stock portfolios, as shown in Panel B, though Macro FEARS is negatively correlated with daily portfolio returns, its magnitude is smaller. A one standard deviation increase in Macro FEARS is accompanied by a decrease in contemporaneous return of 6 basis points. Though there is evidence of a return reversal effect, it is imprecisely estimated. We also consider the daily spreads between high-beta and low-beta sorted portfolios. Regressing the spreads against Macro and Micro FEARS reveals the differential impact of investor sentiment on the daily returns of the high-beta and low-beta sorted portfolios. Panel C confirms that sentiment has stronger impact on the 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 $k = 0$.

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 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.

Similar to the evidence from the high-beta and low-beta sorted portfolios, Tables 5 shows the

contemporaneous relationship between sentiment and return, as well as the reversal pattern is much stronger among stocks with high volatility. However, perhaps because the returns of high volatility portfolios are noisy, the reversal patterns are harder to estimate. Overall, this evidence provides additional support for the sentiment model of Baker and Wurgler (2006, 2007), which highlights the interaction of speculative trading and limits to arbitrage. It also provides cross-sectional evidence for sentiment-induced mispricing. For 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 create future volatility. In DSSW, risk averse arbitrageurs know that prices can diverge further away from fundamentals before they converge. As a result, they may take smaller positions when betting against mispricing. If uninformed noise traders base their trading decisions on sentiment, then extreme sentiment changes will lead to more noise trading, greater mispricing and predict excessive future volatility. To our knowledge, no prior work has used a high-frequency sentiment measure to predict market-level volatility.¹¹ In this section we examine the relationship between FEARS and daily volatility.

4.1 Constructing Realized Volatility

Recently, there have been many innovations in modeling volatility at a high frequency. With the availability of intraday transaction prices, we are able to observe volatility at a daily frequency using so-called realized volatility (RV) measures developed by Andersen, Bollerslev, Diebold, and Ebens (2001) and Andersen, Bollerslev, Diebold, and Labys (2003) among others. Following closely Andersen, Bollerslev, Diebold, and Ebens (2001), we implement the realized volatility estimation procedure. Since intraday transaction data is needed to calculate daily realized volatilities, we focus our attention on exchange-trade funds (ETFs). We examine three equity ETFs: the SPDR S&P500 (AMEX: SPY), the PowerShares QQQ Trust (NASDAQ: QQQQ), and the iShares Russell 2000

¹¹Using 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.

Index (NYSE: IWM). We also examine a Treasury ETF: iShares Barclays 20+ Year Treasury Bond (NYSE: TLT). The Treasury ETF is a useful instrument. Because its nominal cashflow is fixed, any predictability for volatility must come from the discount rate channel via real interest rates or sentiment. All five ETFs are extremely liquid. For instance, the average percentage bid-ask spread is only 0.045%, smaller than that of the largest stocks in the top size decile (average percentage bid-ask spread is 0.1%).

The liquidity associated with the ETFs allow us to measure their realized volatility accurately using intraday transaction data from TAQ. Similar to Antweiler and Frank (2004), we choose 15-minute periods when we sample the intraday returns $r_{i,t,d}^2$ which denotes the intraday return for asset i during the d -th period on day t . Asset i 's (annualized) realized volatility on day t is given by

$$v_{i,t} = 250 \sum_{d=1}^N r_{i,t,d}^2. \quad (5)$$

The time series $v_{i,t}$ is truncated at 2 of to alleviate the impact of outliers. We use the time-series demeaned natural logarithm of asset i 's realized volatility $\ln(\widehat{v_{i,t}}) = \ln(v_{i,t}) - \overline{\ln(v_{i,t})}$ as our measure of volatility. These daily normalized log realized volatilities are plotted in Figure 4. Evidently, as we enter the September of 2008 when the stock market collapsed, volatility surged across all asset classes, more so for stock ETFs than for the treasury and gold ETFs.

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

$$\Phi(L)(1-L)^d y_t = \Theta(L)\varepsilon_t \quad (6)$$

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.¹² The estimate of the autoregressive coefficient p is not significantly different from zero, so we set it to zero and

¹²We use Ox Metrics ARFIMA package to implement these estimates. Specifically, to estimate the fractional integration parameter, the estimation uses Geweke and Porter-Hudak (1983) log-periodogram method. Doornik and Ooms (2006) outline the details of the algorithm.

estimate a simple $ARFIMA(0, d, 1)$ model. After extracting the $ARFIMA(0, d, 1)$ residuals, we remove any intra-week and intra-year seasonality in volatility changes by regressing the residuals against weekday and month dummies.

The statistical estimates of ARFIMA models are presented in Table 6. Consistent with early findings in Andersen et al. (2001) and Antweiler and Frank (2004), each of the time-series of ETF realized volatilities has a strong moving-average (MA) component but no statistically significant autoregressive (AR) component. The fractional cointegration parameter values are reliably different from zero in all cases, but none of them is above 0.5. The extracted volatility innovations are plotted in Figure 5 across the six ETFs. 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 realized volatility.

Although we extract the volatility innovations by fitting the ARFIMA model to the full sample, 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 repeat our entire analysis using daily changes in log realized volatilities which do not use future information, we find similar results for our FEARS indices.

4.2 Empirical Results

After extracting the seasonally-adjusted $ARFIMA(0,d,1)$ realized volatility innovations ($\epsilon_{i,t} = (1 - L)^d \ln(v_{i,t})$), we examine the incremental predictive power of the Micro and Macro FEARS indices on volatility using the following regressions:

$$\epsilon_{i,t+k} = \beta_0 + \beta_1 \Delta Macro_FEARS_t + \beta_2 \Delta Micro_FEARS_t + \sum_m \gamma_m Control_{i,t}^m + u_{i,t+k} \quad (7)$$

Control variables($Control_{i,t}^m$) include VIX, $Negative_News_t$ and $Uncertain_News_t$, and lagged ETF 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.¹³ For these reasons,

¹³See Black (1976), Christie (1982), French, Schwert, and Stambaugh (1987), and Glosten, Jagannathan, and Runkle (1993) among others. The common explanations of asymmetric volatility are a leverage effect or a time-varying risk premium, although both are less applicable in the 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

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 FEARS and volatility after controlling for returns, VIX, *Negative_News_t* and *Uncertain_News_t*. For example, Panel A, Table 7 shows that a one standard deviation increase in $\Delta Macro_FEARS_t$ corresponds with a contemporaneous 5.6% increase in realized volatility for the Nasdaq 100. In addition, a one standard deviation increase in $\Delta Micro_FEARS_t$ corresponds with a contemporaneous 4.8% increase in realized volatility for the Nasdaq 100 index. The magnitudes are similar for the SPY, IWM and TLT exchange-traded funds. Moreover, Macro FEARS is a statistically significant predictor of future volatility among several of the asset classes. For example, a one standard deviation change in Macro FEARS today predicts a 4.6% increase in volatility tomorrow (p-value < .05). Likewise for TLT, a one standard deviation increase in Macro FEARS today predicts an 11.4% increase in realized volatility tomorrow (p-value < .01). In fact the coefficient on $\Delta Macro_FEARS_t$ for day $(t + 1)$ volatility is positive in each of the four ETFs and statistically significant at the 5% level in two of them (QQQQ and TLT). The evidence for Micro FEARS is weak: the coefficient is the opposite sign but economically and statistically insignificant in all but one specification (ETF: TLT).

The fact that Macro FEARS is correlated with and predictive of volatility even after controlling for returns suggests that the FEARS indices are able to identify the subset of events that induce volatility. For example, we know that there is a contemporaneous correlation between the FEARS indices and returns from Section 3: there is more search for negative terms on days in which the market is down. However, the fact that Macro FEARS is predictive of volatility even after controlling for returns suggests the FEARS indices help identify the subset of negative events that are particularly relevant for volatility.

stock price declines while informed trades reduce volatility following stock price increases.

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. 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 details. Because of this potential one-day reporting delay, we note that TrimTabs flow in day $t + 1$ may actually contain flow in day t . To address this problem, we run regressions of contemporaneous fund flows, fund flows 1, 2, 3, and 4 days ahead, and a fund flow average over 2 to 4 days ahead. In particular, we run the following regression:

$$flow_{i,t+k} = \beta_0 + \beta_1 \Delta Macro_FEARS_t + \beta_2 \Delta Micro_FEARS_t + \sum_m \gamma_m Control_{i,t}^m + u_{i,t+k} \quad (8)$$

where fund class i denotes includes bond and equity funds. Control variables($Control_{i,t}^m$) include VIX , $Negative_News_t$ and $Uncertain_News_t$, and five lags of market returns. The results of

these regressions are reported in Table 8.

We find that our Macro FEARS index has significant incremental predictive power on future daily fund flow innovations for equity funds but no predictive power for bond funds. A one-standard deviation increase in Macro FEARS is associated with contemporaneous equity fund outflow of 0.13. Moreover, the outflow from equity funds persist for about a week, with the average outflow of 0.20 during the 2 to 4 day window (significant at the five-percent level). There is little evidence that Micro FEARS index is associated with daily equity fund flows.

The contemporaneous relationship between Macro and Micro FEARS indices and bond fund flow, as well as the predictive power of Macro and Micro FEARS indices on future bond fund flow is not statistically significant. The average effect during the 2 to 4 day window is economically small. This could be due to the fact that sentiment investors move assets out of equity funds then hold on the cash rather than directly invest into bond funds.

Overall, given that daily mutual fund flows are likely capturing aggregate “noise” trading within these asset classes, we view the predictive power of our FEARS index on fund flows as direct supporting evidence for the “noise trading” hypothesis of DeLong et. al. (1990).

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 DeLong, Shleifer, Summers and Waldmann (1990). 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.¹⁴ 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. For example, we find that Macro FEARS today predicts volatility tomorrow across several asset classes. However, just because we see search ahead of a volatility spike 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 deviations from fundamentals.

6.2 Search as a Measure of Sentiment

Beyond endogeneity concerns, there are also other interpretations of our measure and its subsequent predictability for asset volatility. For instance, it is possible that search for terms like “recession” or “great depression” proxy for time-varying risk-aversion. In Campbell and Cochrane (1999), a low surplus consumption ratio will jointly cause risk-aversion and volatility to increase. In Kyle and Xiong (2001) when convergence traders have reduced capital as a result of losses, their risk aversion will 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.

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,

¹⁴Qui 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.”

there is little evidence that risk-aversion changes as rapidly as daily (see Brunnermeier and Nagel (2008)). Therefore, it seems less likely 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 governing the dynamics of asset returns which is in turn positively related to future asset volatility (see Veronesi (1999) among many others). The VIX index is commonly viewed as an indicator of such aggregate uncertainty but we do not find any evidence that VIX is related to return reversal. Moreover, Macro FEARS remains a strong predictor of future asset volatility even after controlling for VIX.

Finally, some readers may worry that search for FEARS terms 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 82% 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

Measuring investor sentiment is an empirical challenge. A good sentiment measure should have several desirable properties: it should be direct; it should encompass a large and relevant population of an economy and it should be verifiable by some objective measure of behavior.

In this paper, we introduced a new sentiment measure created from the search behavior of households which has these properties. By aggregating queries like “recession”, “bankruptcy” and “credit card debt” we construct Financial and Economic Attitudes Revealed by Search (FEARS) indices. In particular, we show the sentiment index constructed in this paper predicts market returns.

Our FEARS indices 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 index has strong predictive power for daily volatility. We show that the FEARS index strongly predicts next-day volatility across various asset classes during the period from 2004 to 2008, even after controlling for existing predictors of future volatilities such as return, the CBOE market volatility index (VIX) and news-based sentiment indices. This evidence is consistent with the “noise trading” hypothesis of DeLong et. al. (1990). Using daily aggregate mutual fund flows, we also provide direct evidence for “noise” trading. Increases in the Macro FEARS index predicts daily mutual fund flows out of equity funds but not out of bond funds.

Moreover, this paper underscores the usefulness of search data in financial applications. Search data has the potential to *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.
- Avramov, Doron, Tarun Chordia and Amit Goyal, 2006, The Impact of Trades on Daily Volatility, *Review of Financial Studies* 19, 1531-1565, 1241-1277.
- Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.
- Baker, Malcom, Brendan Bradley, and Jeffrey Wurgler, 2010, Benchmarks as limits to arbitrage: understanding the low volatility anomaly, Working Paper, New York University Stern School of Business and Harvard Business School.
- 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.
- Baker, Malcolm, Wurgler, Jeffrey and Yu Yuan, 2010, Global, Local, and Contagious Investor Sentiment. Working Paper, New York University Stern School of Business and Harvard Business School.
- 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: Latent 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.
- Doornik, Jurgen A., and Marius Ooms, 2004, Inference and forecasting for ARFIMA models with an application to US and UK inflation, *Studies in Nonlinear Dynamics and Econometrics* 8(2), Article 14.
- 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., Eric Ghysels and Bumjean Sohn, 2008, On the Economic Sources of Stock Market Volatility, *Working Paper*, New York University.
- 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.
- Geweke, John, and Susan Porter-Hudak, 1983, The Estimation and Application of Long Memory Time Series Models, *Journal of Time Series Analysis* 4(4), 221-238.
- 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, *Journal 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.
- Jones, Charles, Gautam Kaul, and Marc Lipson, 1994, Transactions, Volume and Volatility, *Review of Financial Studies* 7, 631-651.
- Kaplanski, Guy, and Haim Levy, 2010, Sentiment and stock prices: The case of aviation disaster, *Journal of Financial Economics* 95, 174-201.
- Kyle, Albert, and Wei Xiong, 2001, Contagion as a Wealth Effect, *Journal of Finance* 56, 1401-1440.
- Khandani, Amir and Andrew W. Lo, 2008, What Happened to the Quants in August 2007? *Working Paper*, MIT.
- 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, 2009, When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks, *Journal of Finance* forthcoming.
- Lemmon, Michael L., and Evgenia V. Portniaguina, 2006, Consumer Confidence and Asset Prices: Some Empirical Evidence, *Review of Financial Studies* 19 (4), 1499-1529.
- Qiu, Lily and Ivo Welch, 2006, Investor Sentiment Measures, *Working Paper*, Brown University.
- 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.

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 Trends Search

The figures represent the graphical outputs for Google Trends' search terms. The top panel plots weekly aggregate search frequency (SVI) for "credit card debt." SVI for "credit card debt" is the weekly search volume for "credit card debt" scaled by the average search volume of "credit card debt. Bottom Panel plots similar SVI for "recession."

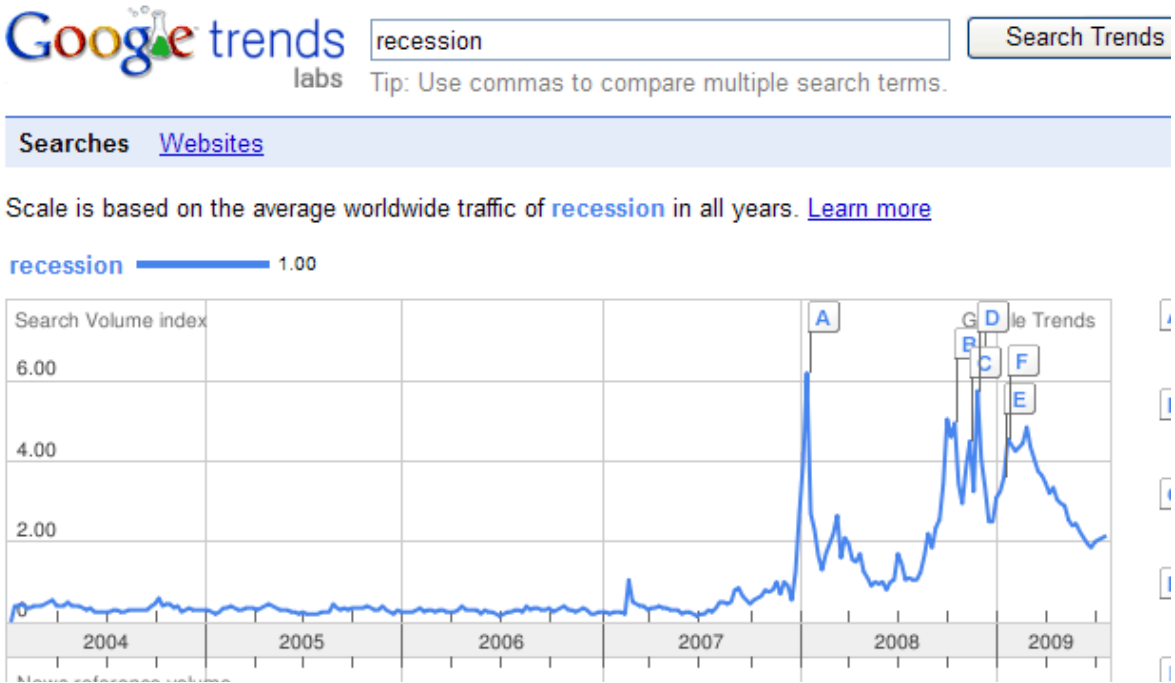


Figure 2: SVI on “recession” and Other Variables

Top panel plots the monthly log SVI for “recession” (with a minus sign) against the monthly University of Michigan Consumer Sentiment Index. Bottom Panel plots the daily SVI for "recession" against the daily CBOE market volatility index (VIX) during the week from August 6 to August 14 in 2007.

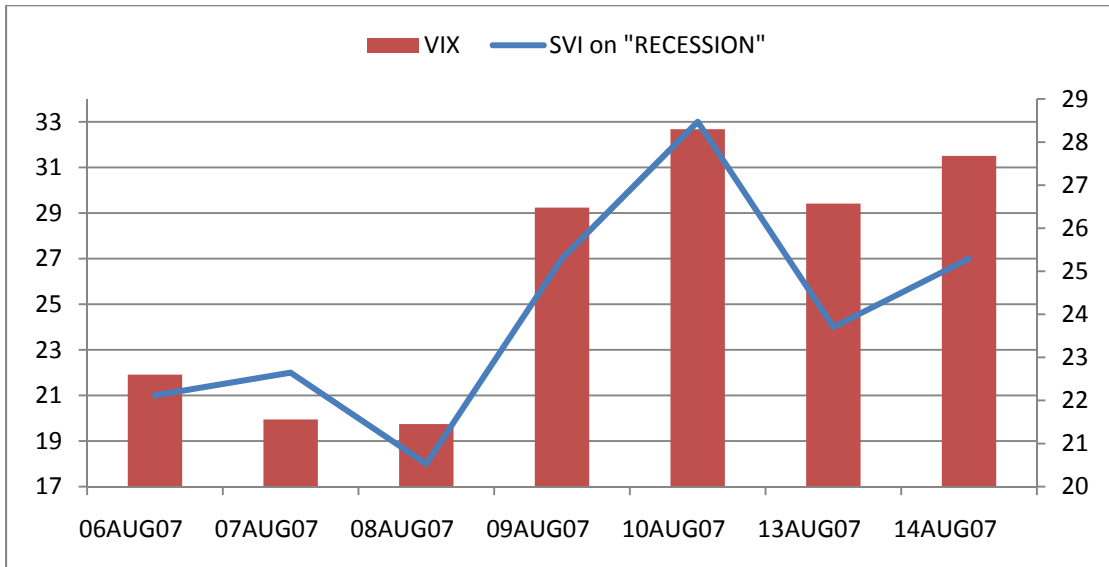
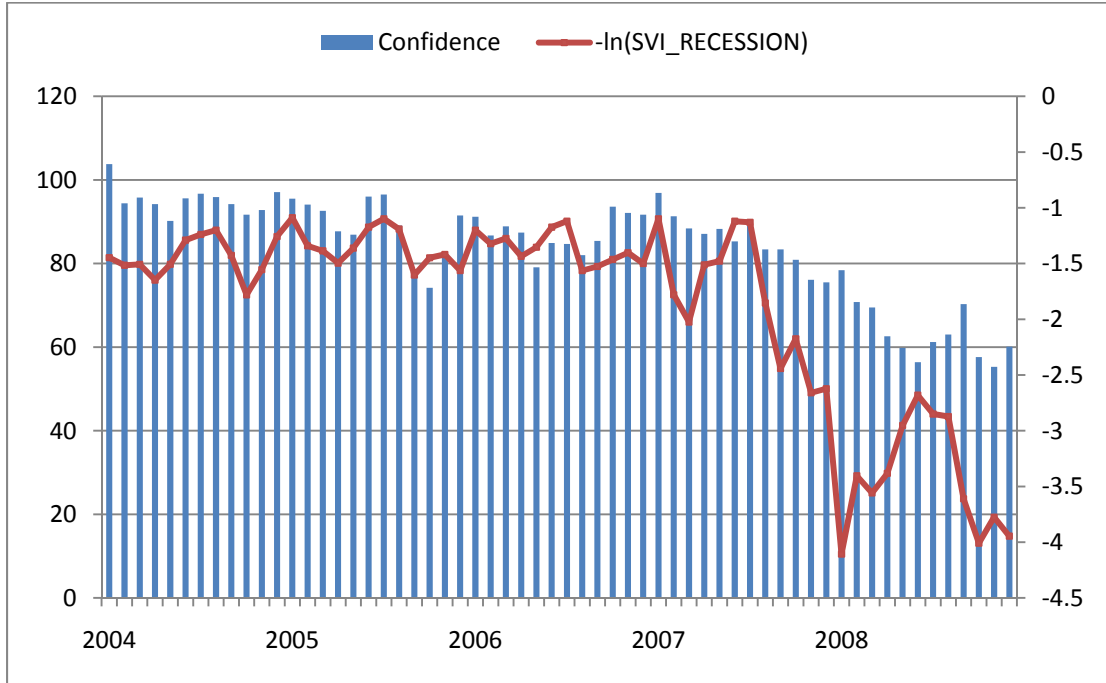


Figure 3: Percentage of Variance Explained by Each Factor

We apply Principal Component Analysis (PCA) to the cross-section of daily SVI changes on 27 search terms. The figure plots the percentage of total variance explained by each of the 27 factors.

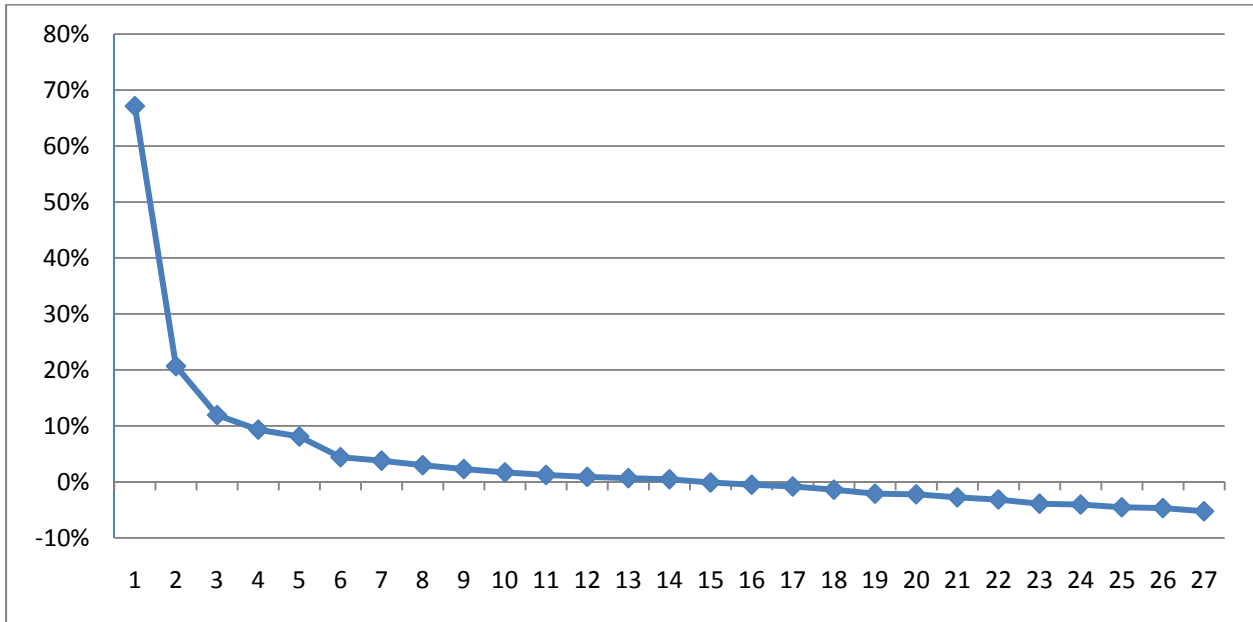


Figure 4: Normalized Daily Log Realized Volatilities across ETFs

This figure plots the daily normalized log realized volatilities. The four ETFs are: (1) SPDR S&P500 (AMEX: SPY), (2) PowerShares QQQ Trust (NASDAQ: QQQQ), (3) iShare Russell 2000 Index (NYSE: IWM) and (4) iShares Barclays 20+ Year Treasury Bond (NYSE: TLT).

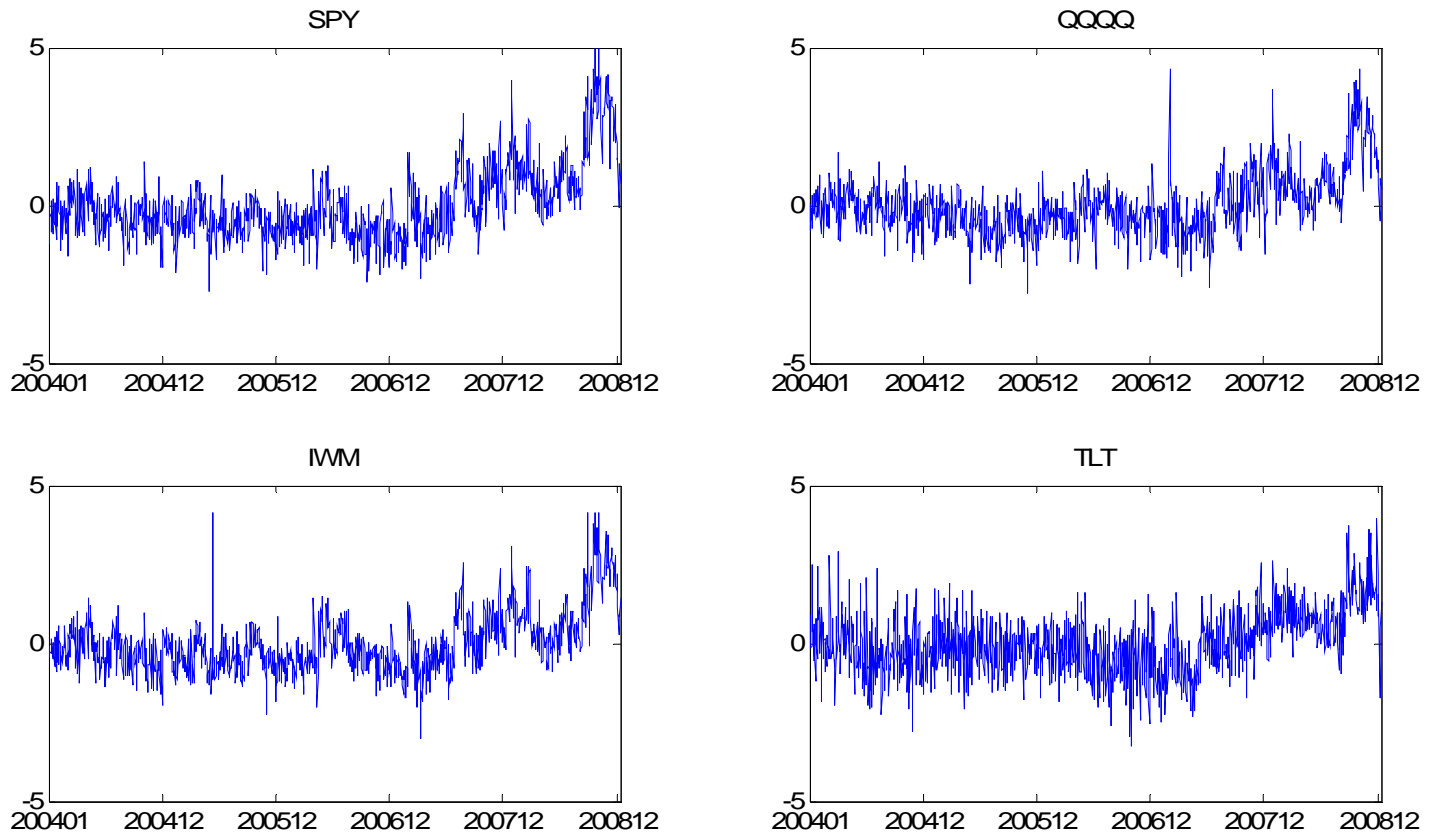


Figure 5: ARFIMA(0,d,1) Daily Realized Volatilities Innovations across ETFs

This figure plots the daily ARFIMA(0,d,1) innovations on the log normalized realized volatilities. The parameter estimates for d can be found in Table 3. The four ETFs are: (1) SPDR S&P500 (AMEX: SPY), (2) PowerShares QQQ Trust (NASDAQ: QQQQ), (3) iShare Russell 2000 Index (NYSE: IWM) and (4) iShares Barclays 20+ Year Treasury Bond (NYSE: TLT).

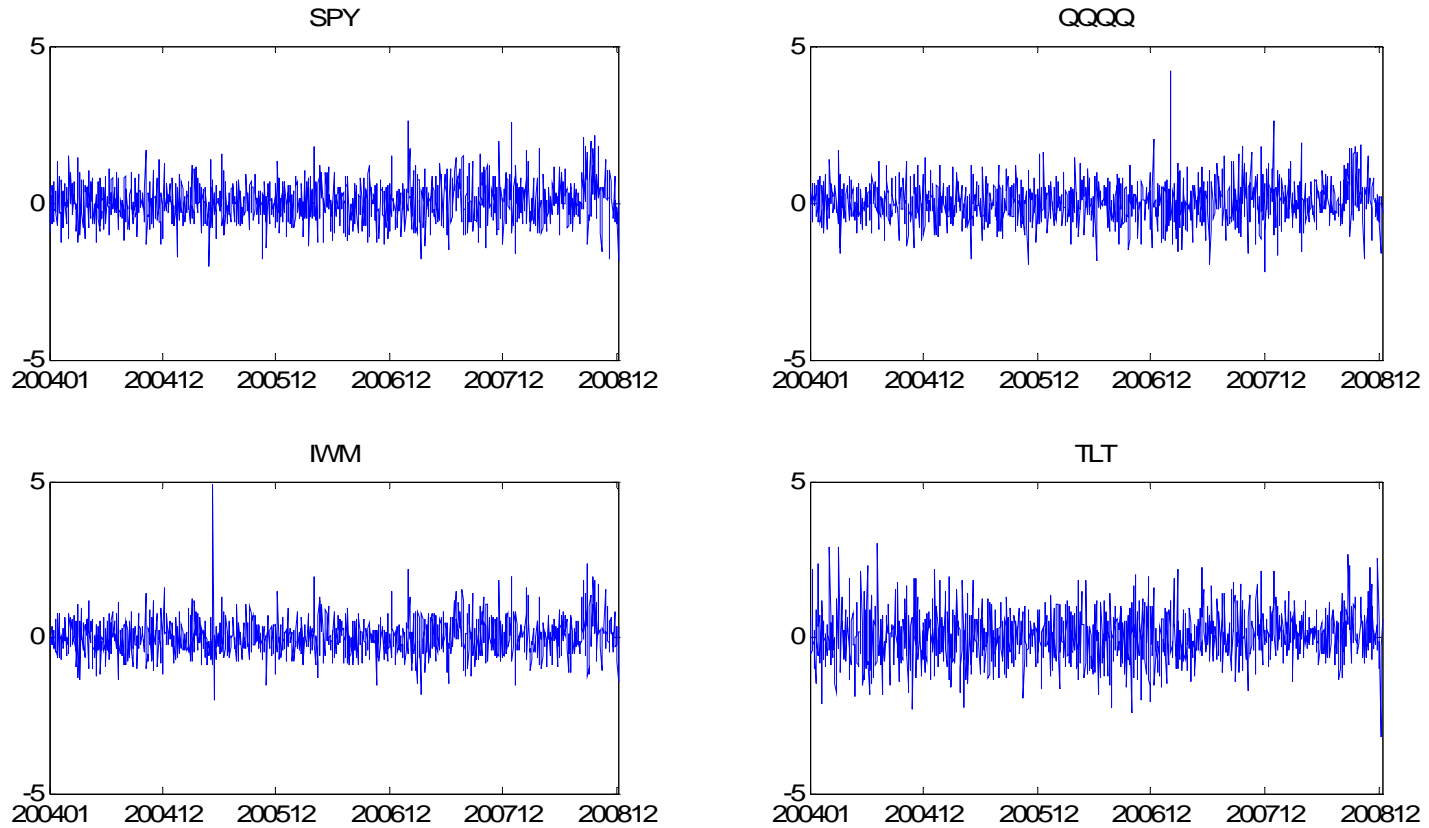


Table 1: Search Terms used in FEARS Index

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

Table 2: Factor Analysis

We apply Principal Component Analysis (PCA) to the cross-section of daily SVI changes on 27 search terms. We choose the number of factors to be six and rotate the first six factors using the varimax method. For each of six rotated factors, we then report the top three search terms it loads on. We also report the percentage of total variance explained by each of the factor.

	Factor 1	Factor 2	Factor 3
Search Term 1	The Depression	Job Search	Bankruptcy
Search Term 2	The Great Depression	Job Openings	Bankruptcy Court
Search Term 3	Great Depression	Job Opportunity	Job Bank
% of variance explained	20.2%	12.4%	12.2%

	Factor 4	Factor 5	Factor 6
Search Term 1	Unemployment Office	Credit Debt	Inflation
Search Term 2	Unemployment Insurance	Credit Card Debt	Inflation Rate
Search Term 3	Unemployment Benefits	Debt Consolidation	Recession
% of variance explained	7.3%	10.9%	9.7%

Table 3: Investor Sentiment and Returns

This table shows OLS regression results. The dependent variables are contemporaneous returns and future returns while the independent variables are the Macro and Micro FEARS indices. The set of control variables include lagged returns up to five lags, a negative news sentiment measure, an uncertainty news sentiment measure (based on the Harvard IV-4 dictionary list of negative and uncertainty words), and the CBOE volatility index (VIX). The standard errors are robust to heteroskedasticity and autocorrelations with five lags. The test assets in Panels A, B, C, D, and E are CRSP value-weighted, SPY, QQQQ, TLT and IWM daily returns respectively. Panel A displays the coefficients on all of the control variables and the remaining panels omit them for brevity. *, **, and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A: Sentiment and CRSP value-weighted returns

	(1)	(2)	(3)	(4)	(5)	(6)
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS: Macro (t)	-0.00222** (0.00100)	-0.000559 (0.000863)	0.00208** (0.000890)	-7.28e-05 (0.000764)	-0.000985 (0.000849)	-0.000433 (0.000884)
FEARS: Micro (t)	-0.00280*** (0.00107)	0.00194** (0.000889)	-0.000272 (0.00103)	0.000244 (0.000819)	0.000510 (0.000981)	-0.000371 (0.000983)
VIX (t)	-0.00217** (0.000855)	-0.000246 (0.000764)	-0.000357 (0.000730)	-0.000324 (0.000680)	-0.000362 (0.000699)	-0.000307 (0.000682)
Negative News (t)	-0.130 (0.0895)	-0.0652 (0.0860)	0.0562 (0.0796)	-0.0283 (0.0898)	0.0617 (0.0853)	0.0232 (0.0870)
Uncertainty News (t)	-0.353 (0.299)	0.328 (0.276)	-0.195 (0.315)	0.279 (0.309)	-0.194 (0.286)	-0.219 (0.349)
Ret(t)		-0.0904 (0.0578)	-0.138* (0.0729)	0.0864* (0.0505)	-0.0964 (0.0603)	-0.0639 (0.0617)
Ret(t-1)	-0.131** (0.0533)	-0.144* (0.0766)	0.0812 (0.0550)	-0.0671 (0.0619)	-0.0618 (0.0645)	0.0444 (0.0791)
Ret(t-2)	-0.171** (0.0736)	0.0526 (0.0531)	-0.115* (0.0592)	-0.0675 (0.0650)	0.00444 (0.0766)	-0.0502 (0.0661)
Ret(t-3)	0.0376 (0.0540)	-0.100* (0.0603)	-0.0471 (0.0622)	0.0192 (0.0739)	-0.0361 (0.0630)	0.0394 (0.0616)
Ret(t-4)	-0.103* (0.0570)	-0.0429 (0.0727)	-0.00178 (0.0708)	-0.0265 (0.0649)	0.0281 (0.0654)	0.00808 (0.0698)
Ret(t-5)	-0.0561 (0.0697)	-0.000149 (0.0660)	-0.0393 (0.0603)	0.0320 (0.0640)	0.00301 (0.0704)	0.0367 (0.0648)
Constant	-0.00107 (0.000665)	-0.000163 (0.000609)	-0.000203 (0.000578)	-0.000176 (0.000527)	-0.000219 (0.000545)	-0.000177 (0.000544)
Observations	1239	1239	1239	1239	1239	1239
Adjusted R-squared	0.099	0.038	0.041	0.014	0.007	0.002

Panel B: Sentiment and QQQQ Daily Returns

	QQQQ Daily Return					
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS: Macro (t)	-0.00172* (0.00105)	-0.00129 (0.000914)	0.00247*** (0.000957)	-0.000106 (0.000878)	-0.00159* (0.000902)	-0.000367 (0.000971)
FEARS: Micro (t)	-0.00270*** (0.00104)	0.00214** (0.00100)	-0.000232 (0.00107)	-5.20e-05 (0.00105)	0.000948 (0.00109)	-0.00112 (0.00130)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1228	1226	1225	1224	1223	1222
Adjusted R-squared	0.060	0.024	0.022	0.008	0.005	-0.002

Panel C: Sentiment and SPY Daily Returns

	SPY Daily Return					
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS: Macro (t)	-0.00276*** (0.00102)	-0.000748 (0.000845)	0.00177** (0.000865)	0.000410 (0.000757)	-0.00132 (0.000807)	-1.57e-05 (0.000881)
FEARS: Micro (t)	-0.00245** (0.00102)	0.00210** (0.000970)	-0.000204 (0.000958)	-0.000538 (0.000943)	0.000678 (0.000940)	-0.00114 (0.00112)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1234	1233	1232	1231	1230	1229
Adjusted R-squared	0.108	0.052	0.037	0.009	0.018	0.014

Panel D: Sentiment and IWM Daily Returns

	IWM Daily Returns					
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS: Macro (t)	-0.00212* (0.00109)	-0.000900 (0.00109)	0.00227** (0.00110)	-0.000702 (0.001000)	-0.000836 (0.000997)	-0.000328 (0.00109)
FEARS: Micro (t)	-0.00355*** (0.00123)	0.00326*** (0.00121)	-5.03e-05 (0.00122)	-0.000234 (0.00118)	-0.000284 (0.00121)	-0.000771 (0.00138)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1234	1233	1232	1231	1230	1229
Adjusted R-squared	0.069	0.025	0.014	0.009	0.010	0.004

Panel E: Sentiment and TLT Daily Returns

	TLT Daily Return					
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS: Macro (t)	0.00123*** (0.000468)	-6.69e-05 (0.000436)	-0.000343 (0.000425)	-3.20e-05 (0.000406)	4.16e-05 (0.000435)	-0.000197 (0.000406)
FEARS: Micro (t)	0.000133 (0.000600)	-0.000670 (0.000528)	0.000170 (0.000543)	0.000195 (0.000545)	-0.000482 (0.000581)	7.91e-05 (0.000503)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1234	1233	1232	1231	1230	1229
Adjusted R-squared	0.026	0.006	0.008	0.012	0.014	0.013

Table 4: Sentiment and Beta-Sorted Portfolio Returns

This table shows OLS regression results. The dependent variables are contemporaneous returns and future returns while the independent variables are the Macro and Micro FEARS indices. The set of control variables include lagged returns up to five lags, negative news sentiment measure, uncertainty news sentiment measure (based on Harvard H-4 dictionary list of negative and uncertainty words list), and CBOE volatility index (VIX). The standard errors are robust to heteroskedasticity and autocorrelations. The test assets in Panels A, B and C are high beta portfolio daily returns, low beta portfolio daily returns, and return spreads between high and low beta portfolio, respectively. *, **, and *** denote the coefficient estimates are significant at ten, five and one percent significance level respectively.

Panel A: Sentiment and High Beta Portfolio Daily Returns

	High Beta Portfolio Daily Returns					
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS: Macro (t)	-0.00303** (0.00144)	-5.66e-05 (0.00138)	0.00319** (0.00135)	-0.000419 (0.00122)	-0.00102 (0.00126)	-0.000824 (0.00136)
FEARS: Micro (t)	-0.00492*** (0.00160)	0.00320** (0.00160)	-0.000152 (0.00152)	0.000826 (0.00176)	0.000279 (0.00174)	0.000568 (0.00198)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1239	1239	1239	1239	1239	1239
Adjusted R-squared	0.060	0.013	0.014	0.006	0.003	0.003

Panel B: Sentiment and Low Beta Portfolio Daily Returns

	Low Beta Portfolio Daily Returns					
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS: Macro (t)	-0.00112** (0.000440)	0.000326 (0.000312)	9.31e-05 (0.000305)	-1.51e-05 (0.000280)	-0.000360 (0.000302)	-0.000513* (0.000287)
FEARS: Micro (t)	-0.000588 (0.000397)	1.52e-05 (0.000441)	0.000840** (0.000408)	0.000127 (0.000576)	0.000610 (0.000557)	0.000159 (0.000497)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1239	1239	1239	1239	1239	1239
Adjusted R-squared	0.085	0.059	0.013	0.010	0.007	-0.000

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

	High Beta Portfolio - Low Beta Portfolio Daily Return Spreads					
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS: Macro (t)	-0.00210* (0.00124)	-0.000137 (0.00127)	0.00313** (0.00128)	-0.000406 (0.00116)	-0.000543 (0.00119)	-0.000279 (0.00130)
FEARS: Micro (t)	-0.00449*** (0.00142)	0.00305** (0.00139)	-0.000814 (0.00137)	0.000514 (0.00151)	-0.000249 (0.00148)	0.000338 (0.00172)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1239	1239	1239	1239	1239	1239
Adjusted R-squared	0.047	0.012	0.018	0.011	0.009	0.008

Table 5: Sentiment and Volatility-Sorted Portfolio Returns

This table shows OLS regression results. The dependent variables are contemporaneous returns and future returns while the independent variables are the Macro and Micro FEARS indices. The set of control variables include lagged returns up to five lags, negative news sentiment measure, uncertainty news sentiment measure (based on Harvard H-4 dictionary list of negative and uncertainty words list), and CBOE volatility index (VIX). The standard errors are robust to heteroskedasticity and autocorrelations. The test assets in Panels A, B and C are high return volatility portfolio daily returns, low return volatility portfolio daily returns, and return spreads between high and low return volatility portfolio, respectively. *, ** and *** denote the coefficient estimates are significant at ten, five and one percent significance level respectively.

Panel A: Sentiment and High Volatility Portfolio Daily Returns

	High Volatility Sorted Portfolio Daily Returns					
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS: Macro (t)	-0.00228** (0.000994)	0.000258 (0.000890)	0.00160* (0.000884)	0.000305 (0.000815)	-0.000843 (0.000803)	-0.00109 (0.000875)
FEARS: Micro (t)	-0.00367*** (0.00105)	0.00127 (0.00106)	0.000466 (0.00108)	0.00136 (0.00142)	0.000484 (0.00132)	0.000684 (0.00157)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1239	1239	1239	1239	1239	1239
Adjusted R-squared	0.096	0.041	0.009	0.006	0.001	0.004

Panel B: Sentiment and Low Volatility Portfolio Daily Returns

	Low Volatility Sorted Portfolio Daily Returns					
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS: Macro (t)	-0.00159** (0.000699)	-1.57e-05 (0.000298)	0.000231 (0.000339)	9.25e-05 (0.000300)	-0.000330 (0.000353)	-0.000215 (0.000321)
FEARS: Micro (t)	-0.000258 (0.000536)	0.000244 (0.000420)	0.000422 (0.000449)	-7.58e-05 (0.000502)	0.000372 (0.000515)	0.000175 (0.000465)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1239	1239	1239	1239	1239	1239
Adjusted R-squared	0.107	0.083	0.021	0.026	0.022	0.013

Panel C: Sentiment and High minus Low Volatility Portfolio Daily Return Spreads

	High Volatility Sorted Portfolio - Low Volatility Sorted Portfolio Daily Return Spreads					
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret(t+3)	Ret(t+4)	Ret(t+5)
FEARS: Macro (t)	-0.000581 (0.000683)	0.000287 (0.000772)	0.00106 (0.000686)	0.000233 (0.000692)	-0.000182 (0.000707)	-0.000884 (0.000756)
FEARS: Micro (t)	-0.00376*** (0.000830)	0.00128 (0.000829)	0.000516 (0.000845)	0.00124 (0.00111)	-3.67e-05 (0.00100)	0.000436 (0.00133)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1239	1239	1239	1239	1239	1239
Adjusted R-squared	0.109	0.071	0.026	0.016	0.012	0.016

Table 6: ARFIMA(0,d,1) Estimation

This table reports the estimates of fitting ARFIMA(0,d,1) model to the normalized log daily realized volatilities on the six ETFs. d refers to the fractional integration. Standard errors associated with the estimates are in italics. A software package called Ox Metrics ARFIMA is used in the estimation. The six ETFs are: (1) SPDR S&P500 (AMEX: SPY), (2) PowerShares QQQ Trust (NASDAQ: QQQQ), (3) iShare Russell 2000 Index (NYSE: IWM), and (4) iShares Barclays 20+ Year Treasury Bond (NYSE: TLT).

	QQQQ	SPY	IWM	TLT
d	0.476	0.494	0.492	0.454
Std.Error	<i>0.03</i>	<i>0.01</i>	<i>0.01</i>	<i>0.04</i>
MA(1)	-0.179	-0.150	-0.167	-0.386
Std.Error	<i>0.04</i>	<i>0.03</i>	<i>0.03</i>	<i>0.06</i>

Table 7: Sentiment and Realized Volatility

This table shows OLS estimates of the coefficients on FEARS macro index and micro index on FEARS macro index and micro index on contemporaneous realized volatility innovations and future realized volatility innovations for different indices. Realized volatility innovations are calculated by fitting ARFIMA(0,d,1) model to the normalized log daily realized volatilities on the five ETFs and then adjusting for intra-week and intra-year seasonality. The set of control variables include lagged returns up to five lags, negative news sentiment measure, uncertainty news sentiment measure (based on Harvard H-4 dictionary list of negative and uncertainty words list), and CBOE volatility index (VIX). The standard errors are robust to heteroskedasticity and autocorrelations. The test assets in Panels A, B and C are high return volatility portfolio daily returns, low return volatility portfolio daily returns, and return spreads between high and low return volatility portfolio, respectively. *, ** and *** denote the coefficient estimates are significant at ten, five and one percent significance level respectively.

Panel A: Sentiment and QQQQ Volatility

	(1)	(2)	(3)	(4)	(5)	(6)
	Vol(t)	Vol(t+1)	Vol(t+2)	Vol(t+3)	Vol(t+4)	Vol(t+5)
FEARS: Macro (t)	0.102*** (0.0364)	0.0842** (0.0360)	0.0859* (0.0496)	-0.00388 (0.0364)	-0.0178 (0.0377)	0.0253 (0.0338)
FEARS: Micro (t)	0.111** (0.0475)	-0.0106 (0.0427)	-0.0532 (0.0532)	-0.0451 (0.0445)	0.0119 (0.0417)	0.0201 (0.0470)
VIX (t)	0.00381** (0.00160)	0.00326** (0.00160)	0.00288* (0.00162)	0.00269 (0.00172)	0.00295* (0.00174)	0.00257 (0.00183)
Negative News (t)	1.400 (3.502)	5.757 (3.584)	-4.192 (3.724)	-3.276 (3.903)	1.019 (3.941)	-0.374 (4.092)
Uncertainty News (t)	-12.83 (13.32)	5.531 (14.85)	-18.49 (17.04)	1.855 (14.77)	-9.520 (14.89)	2.090 (16.97)
Ret(t)	-4.574*** (1.417)	-10.01*** (1.507)	-5.281*** (1.208)	-2.402* (1.332)	-2.560* (1.381)	0.702 (1.191)
Ret(t-1)	-10.25*** (1.448)	-5.777*** (1.146)	-2.531** (1.286)	-2.891** (1.386)	0.319 (1.198)	0.121 (1.386)
Ret(t-2)	-6.913*** (1.203)	-3.622*** (1.064)	-3.366*** (1.298)	0.0777 (1.195)	-0.125 (1.369)	-2.592** (1.233)
Ret(t-3)	-3.262*** (1.085)	-2.889** (1.274)	0.360 (1.197)	0.0932 (1.355)	-2.465** (1.254)	-0.652 (1.218)
Ret(t-4)	-3.293*** (1.205)	-0.204 (1.183)	-0.356 (1.247)	-2.700** (1.283)	-0.618 (1.198)	0.679 (1.413)
Ret(t-5)	-0.309 (1.181)	-0.178 (1.211)	-2.741** (1.316)	-0.617 (1.181)	0.900 (1.431)	-1.733 (1.173)
Constant	-0.0675** (0.0325)	-0.0570* (0.0328)	-0.0478 (0.0337)	-0.0431 (0.0349)	-0.0481 (0.0350)	-0.0402 (0.0363)
Observations	1,228	1,227	1,226	1,225	1,224	1,223
Adjusted R-squared	0.122	0.090	0.030	0.008	0.004	0.001

Panel B: Sentiment and SPY Volatility

	SPY Volatility					
	Vol(t)	Vol(t+1)	Vol(t+2)	Vol(t+3)	Vol(t+4)	Vol(t+5)
FEARS: Macro (t)	0.126*** (0.0333)	0.0559 (0.0360)	0.00909 (0.0360)	-0.0112 (0.0342)	-0.00164 (0.0338)	0.0359 (0.0340)
FEARS: Micro (t)	0.0973** (0.0422)	-0.00861 (0.0418)	-0.0789* (0.0434)	0.0123 (0.0421)	0.00227 (0.0455)	-0.0192 (0.0462)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1,234	1,233	1,232	1,231	1,230	1,229
Adjusted R-squared	0.146	0.090	0.028	0.004	0.000	0.001

Panel C: Sentiment and IWM Volatility

	IWM Volatility					
	Vol(t)	Vol(t+1)	Vol(t+2)	Vol(t+3)	Vol(t+4)	Vol(t+5)
FEARS: Macro (t)	0.0918*** (0.0315)	0.0297 (0.0321)	0.0421 (0.0338)	0.00428 (0.0340)	-0.00573 (0.0307)	0.0267 (0.0346)
FEARS: Micro (t)	0.0853** (0.0403)	-0.0288 (0.0398)	-0.0681* (0.0397)	-0.0191 (0.0472)	0.0537 (0.0445)	-0.0365 (0.0469)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1,234	1,233	1,232	1,231	1,230	1,229
Adjusted R-squared	0.127	0.093	0.028	0.005	0.004	0.000

Panel D: Sentiment and TLT Volatility

	TLT Volatility					
	Vol(t)	Vol(t+1)	Vol(t+2)	Vol(t+3)	Vol(t+4)	Vol(t+5)
FEARS: Macro (t)	0.109** (0.0457)	0.208*** (0.0502)	-0.0618 (0.0487)	-0.00586 (0.0444)	-0.0477 (0.0472)	-0.0111 (0.0448)
FEARS: Micro (t)	0.144** (0.0627)	-0.137** (0.0642)	-0.0136 (0.0569)	-0.0256 (0.0605)	0.0787 (0.0577)	0.0557 (0.0558)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1,234	1,233	1,232	1,231	1,230	1,229
Adjusted R-squared	0.025	0.023	0.007	0.005	0.004	0.001

Table 8: Sentiment and Fund Flows

This table reports the results of contemporaneous and predictive regressions. We consider two mutual fund groups specializing in medium-term Treasury bond (MTB) and equity (Equity). For each mutual fund group, we obtain its daily fund flow (as a percentage of TNA multiplied by 10000) 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, uncertainty news sentiment measure (based on Harvard H-4 dictionary list of negative and uncertainty words list), and CBOE volatility index (VIX). The standard errors are robust to heteroskedasticity and autocorrelations. The test assets in Panels A, B and C are high return volatility portfolio daily returns, low return volatility portfolio daily returns, and return spreads between high and low return volatility portfolio, respectively. *, ** and *** denote the coefficient estimates are significant at ten, five and one percent significance level respectively.

Panel A: Equity Fund Flow

	Equity Fund Flow					
	Flow(t)	Flow(t+1)	Flow(t+2)	Flow(t+3)	Flow(t+4)	Average Flow(t+2 to t+4)
FEARS: Macro (t)	-0.237 (0.303)	-0.458* (0.243)	-0.257 (0.254)	-0.587** (0.259)	-0.162 (0.275)	-0.366** (0.179)
FEARS: Micro (t)	0.182 (0.417)	0.026 (0.346)	-0.161 (0.301)	0.069 (0.315)	-0.257 (0.395)	-0.051 (0.232)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1,230	1,229	1,228	1,227	1,226	1,225
Adjusted R-squared	0.079	0.097	0.102	0.071	0.040	0.154

Panel B: Bond Fund Flow

	Bond Fund Flow					
	Flow(t)	Flow(t+1)	Flow(t+2)	Flow(t+3)	Flow(t+4)	Average Flow(t+2 to t+4)
FEARS: Macro (t)	0.072 (0.472)	-0.275 (0.474)	-0.188 (0.459)	0.089 (0.466)	-0.824* (0.470)	-0.286 (0.231)
FEARS: Micro (t)	0.096 (0.584)	1.11e-05 (0.549)	2.74e-05 (0.538)	-0.049 (0.549)	0.307 (0.540)	0.137 (0.285)
Control Variables	Included	Included	Included	Included	Included	Included
Observations	1,230	1,229	1,228	1,227	1,226	1,225
Adjusted R-squared	0.027	0.025	0.010	0.006	0.005	0.051