# The Sum of All FEARS: Investor Sentiment, Noise Trading and Aggregate Volatility*

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**Abstract**

We use internet search volume from millions of households to measure market-level sentiment in real time. By aggregating the volume of queries related to household financial decisions and concerns (e.g. "recession" or "inflation"), we construct a Financial and Economic Attitudes Revealed by Search (FEARS) index. We show that the FEARS index strongly predicts next-day volatility across various asset classes during the period 2004 - 2008, even after controlling for existing predictors of future volatility such as return, trading volume, the CBOE market volatility index (VIX) and a news-based sentiment index. Our results support the prediction of the "noise trader" model of De Long et. al. (1990) that extreme sentiment generates volatility in financial markets. The FEARS index also predicts daily mutual fund flow across various asset classes, consistent with the notion of a "flight-to-quality" in distressed times.

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"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

Since the seminal work of De Long, Shleifer, Summers and Waldmann (1990) - hereafter DSSW - financial economists have been increasingly interested in 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; Kogan, Ross, Wang and Westerfield, 2009), there is a growing consensus that noise traders can induce large price movements and excess volatility in the short-run (see Barberis, Shleifer, and Vishny (1998), Tetlock (2007) and Edmans, Garcia and Norli (2007) among others). 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).

When testing noise traders' affect on asset prices, empiricists face a formidable challenge: we do not observe investor sentiment. To deal with this problem, empiricists have taken two approaches. 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 (e.g., Baker and Wurgler (2007)). 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 → outputs with an output measure?" Under the second approach, empiricists use investor surveys such as the American Association of Individual Investors survey, the Michigan Survey's Index of Consumer Sentiment, Conference Board Survey Consumer/CEO Confidence Survey, or UBS/GALLUP Index for Investor Optimism (Brown and Cliff (2004), Lem-

mon and Portniaguina (2006), and Qiu and Welch (2006)). While this approach is direct, these measures are low-frequency, taken from relatively small samples and come with the usual caveats that accompany survey data.

In this paper, we introduce a novel, direct and high-frequency measure of investor sentiment taken from the internet search queries of millions of households. By aggregating the volume of search for terms related to household financial decisions and economic concerns, we construct a Financial and Economic Attitudes Revealed by Search (FEARS) index. The search behavior of millions of households has the potential to reveal attitudes in real time. For example, when investors are concerned about job loss, they search for "unemployment office" or "job search"; when they are in financial distress they search for "filing bankruptcy" or "debt consolidation"; and when they are uncertain about general economic conditions, they search for "recession" or "inflation."[1] Consistent with the prediction of the DSSW model, we show that the FEARS index strongly predicts next-day volatility across various asset classes even after controlling for existing predictors of future volatility. We also find that the FEARS index predicts daily fund flows away from equities and into fixed income and metal (e.g., gold) funds consistent with a flight-to-quality in bad times. To the best of our knowledge our paper is the first to show how a direct measure of investor sentiment affects the volatility and fund flow of broad asset classes.[2]

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.[3] Second, search-based measures *reveal* rather than *elicit* attitudes. 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

[1] In fact, Treasury Secretary Larry Summers recently indicated that consumer views towards business conditions have improved because fewer people now search for the term "economic depression." See http://www.politico.com/news/stories/0709/25083.html.

[2] There is, however, some empirical evidence that relates sentiment and idiosyncratic volatility. 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.

[3] 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.

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. Second, most surveys require interviewers to contact respondents in order to ask a series of questions, a process that is both time consuming and expensive. Hence, most consumer confidence surveys are based on samples of less than a thousand households and available at the monthly or yearly frequency. In contrast, search volume is aggregated in real-time based on the behavior of millions of households. It is also is freely available from Google, the largest search engine in the world.[4]

Google makes public the Search Volume Index (SVI) of search terms via its product Google Trends (http://www.google.com/trends). 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.[5] 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

[4] 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.

[5] 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.

and panic, heightening the risk sensitivities of managers and investors across all markets and style categories." 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. A Principal Component Analysis (PCA) suggests that the first six factors that capture almost all the variation in the FEARS index are related to "Bankruptcy", "Depression", "Unemployment", "Debt", "Inflation", and "Job" accordingly, which echoes the perceived concerns of investors over the last 5 years.

The key to the construction of our FEARS index is the identification of relevant sentiment-revealing search terms. To identify search terms in a way that is as objective as possible, we proceed in the following steps. First, we follow the text analytics 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 (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.

We then examine daily realized volatilities across several asset classes. Since intraday transaction data is needed to calculate daily realized volatilities, we focus our attention on exchange-trade funds (ETFs). We examine four equity ETFs: the SPDR S&P500 (AMEX: SPY), the PowerShares QQQ Trust (NASDAQ: QQQQ), the iShares Russell 1000 Index (NYSE: IWB), and the iShares Russell 2000 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. Finally, we examine a commodity ETF: SPDR Gold Shares (NYSE: GLD). All six 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 six ETFs allow us to measure their realized volatility accurately using intraday transaction data from TAQ. Since volatility is well-known to be 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, $ARFIMA(p, d, q)$, which allows us to extract innovations in volatility.

When we examine the average predictive power of our FEARS index on future volatility innovations, we find it to be positive and significant across all six ETFs. An increase in the FEARS index today predicts a positive realized volatility innovation tomorrow, even after controlling for other existing predictors of future volatility such as current return and turnover. This positive predictive power of the FEARS index survives a horserace against equilibrium outcome measures like the VIX and an alternative sentiment measure constructed based on the fraction of negative words in the news. Moreover, the positive predictive power is not driven by a few large shocks during the recent financial crisis in 2008. Finally, a reverse causality test finds weak evidence that lagged volatility innovations predict our FEARS index, which suggests that the causal relation is likely to go from the FEARS index to volatility, rather than the other way around.

Several interesting patterns emerge when we examine the relative predictive power of the FEARS index across different search terms. For example, inflation-related search terms such as "inflation" and "cost of living" are very important predictors of future volatilities across asset classes. The SVI of "cost of living" is significant for all ETFs except the Gold ETF (GLD) and shows up among the top two predictors for four of them (SPY, QQQQ, TLT and IWM). The SVI on "inflation" is significant for all ETFs except the Russell 2000 ETF (IWM). In particular, it is the only significant search term for the Gold ETF, consistent with the notation that gold is the best hedge for inflation risk. In addition, depression related search terms ("depression", "great depression", "the great depression", and "recession") are also important predictors. Interestingly, "great depression" is always more powerful than simply "depression" in predicting future volatility and shows up among the top three predictors for four ETFs (SPY, QQQQ, TLT, and IWB). Another important set of search terms is related to bankruptcy ("bankruptcy", "chapter 7", and "chapter 13").

As a more direct test of the "noise trading" hypothesis, we also examine daily mutual fund flows. Since individual investors hold about 90% of total mutual fund assets, and they are more likely to be the "noise" traders, daily flows to mutual fund groups likely aggregate "noise" trading at the

asset class level.[6] We examine three groups of mutual funds that specialize in equity, intermediate Treasury bonds, and precious metals, which most closely resemble the ETFs we have examined. We document strong persistence in the 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. Specifically, an increase in the FEARS index predicts outflows from equity mutual funds, but inflows to mutual funds specializing in treasury bonds and precious metals (like gold). These results are strongly consistent with the well-documented flight-to-quality phenomenon and an increasing desire to hedge for inflation risk during crisis periods. We argue that these sentiment-driven flows lead to excessive volatility as predicted by standard noise trading models. As an aside, our FEARS index produces more intuitive predictive results than alternative sentiment measures. For example, an increase in VIX actually predicts *outflows* from mutual funds specializing in precious metals. The news-based sentiment measure predicts flows to equity and treasury mutual flows with the wrong sign and does not predict flows to mutual funds specializing in precious metal at all.

The rest of the paper is organized as follows. Section 2 describes data sources and how we construct our FEARS index. Section 3 discusses the estimation of realized volatility and its innovation. Section 4 documents a strong positive relation between the current FEARS index and future asset volatility, consistent with the prediction of a noise trading model. Section 4 provides additional support for the noise trading hypothesis by examining the daily mutual fund flows. Section 5 concludes.

## 2 Data and FEARS Index Construction

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

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

results in 40 unique words.[7]

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.[8] 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.[9]

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 the following three categories: Financial Distress, Job Loss and Business Conditions. Table 1 lists these 27 search terms.

The SVIs on these 27 terms cover the sampling period from 2004/01 - 2008/12. Google Insights

[7] The list is: 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.

[8] 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."

[9] The list is: 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.

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 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 FEARS index on search term $j$ as:

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

Components of the FEARS index may behave differently over time. To see which search terms are most important in driving the variation in the FEARS index, we conduct a Principal Component Analysis (PCA) to the Panel of FEARS index across all 27 search terms. 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 85% of the total variation in FEARS index across 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. We rotate these factors using a VARIMAX method so 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 the factor rotation, the total variance explained is different from those reported in Figure 3.

The first factor, which explains more than 46% of the total variance, loads significantly on many search terms, but most heavily on "Bankruptcy", "Bankruptcy Court" and "Job Bank." It

can thus be loosely labeled as a "Bankruptcy" factor. The second factor, which explains almost 26% of the total variance, loads primarily on "The Depression", "The Great Depression" and "Great Depression" and almost none on other search terms. Therefore, it is clearly a "Depression" factor. In a similar fashion, we can label the third factor, which accounts for 15% of the total variance, the "Unemployment" factor. Finally, the fourth, fifth and sixth factors are likely capturing "Debt", "Inflation" and "Job" accordingly. The search terms associated with the first six factors echo the perceived concerns of the general public during the last 5 years. These intuitive results again confirm that our FEARS index captures investors sentiment well.

For completeness, we also collect SVIs for a list of positive search terms. We construct the positive word list in the exact way we constructed the negative word list. We first identify 29 "primitive" words which are classified as both positive and economic words in the Harvard IV dictionary.[10] Next, we search each primitive word in Google Insights and recover the top ten related search terms, filtering out any non-economic search terms or search terms with not enough search volume. Our final list consists of 22 search terms.[11] Finally, SVIs on these 22 positive terms during the sampling period from 2004/01 - 2008/12 are collected. As in the case of the FEARS index, we define daily change in SVIs on the positive word $j$ as:

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

where $\Delta PSVI$ can be viewed as a measure of aggregate positive market sentiment.

Our daily news data which end in 2007 come from the Dow Jones Archive as in Tetlock (2009). The Chicago Board Options Exchange (CBOE) daily VIX index is obtained from CBOE. Other variables are constructed from standard data sources. The price and volume related variables are obtained from CRSP. The transaction-level data on the six ETFs are obtained from the New York Stock Exchange Trades and Quotes (TAQ) database. Except for the Gold ETF (GLD) which is only available from November 18, 2004, the data cover our five year sampling period from 2004/01 -2008/12.

[10] They are: associate, backer, benefit, bonus, buy, charity, compensate, contribute, cooperative, equity, gain, gold, guide, luxury, partner, partnership, patron, patronage, precious, productive, productivity, profit, profitable, reward, rich, security, treasure, valuable and worth.

[11] They are: employee benefits, benefits, buy house, buy dvd, buy car, buy online, charities, charity events, home equity private equity, capital gain, luxury hotels, luxury homes, luxury car, luxury resorts, business partner, business partnership, productivity, profit, profit margin, get rich, and net worth.

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 collect daily flow information on 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 daily flows to three groups of mutual fund. The first group (Equity) specializes in equity. The second group (MTB) specializes in "Intermediate Treasury Bond", which best resembles our Treasury-bond ETF (TLT). The third group (Metal) specializes in "precious metals", the best match for our Gold ETF (GLD). For each group, we compute the daily flow as the ratio between dollar flow (inflow minus outflow) and fund Total Net Asset (TNA).

## 3 Realized Volatility Innovations

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, Bollersleve, Diebold, and Ebens (2001), we implement the realized volatility estimation procedure. Similar to Antweiler and Frank (2004), we choose 15-minute periods when we sample the intraday returns $r^2_{i,t,d}$ 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

$$\upsilon_{i,t} = 250 \sum_{d=1}^{N} r^2_{i,t,d}.$$

The time series $\upsilon_{i,t}$ 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 $\widehat{\ln(\upsilon_{i,t})} = \ln(\upsilon_{i,t}) - \overline{\ln(\upsilon_{i,t})}$ 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, $ARFIMA(p, d, q)$:

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

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 estimate a simple $ARFIMA(0, d, 1)$ model.

The statistical estimates of ARFIMA models are presented in Table 3. 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 FEARS index. When we repeat our entire analysis using daily changes in log realized volatilities which do not use future information, we find even stronger predictive power for our FEARS index.

## 4 Predicting Future Realized 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

[12] We 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.

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 change will lead to more noise trading, greater mispricing and predict excessive future volatility. Intuitively, such predictive power can only be observed at higher frequencies as arbitrage activities tend to eliminate mispricing over time. Using Yahoo message board activities as a proxy for noise trading, Antweiler and Frank (2004) and Koski, Rice, and Tarhouni (2008) confirm the positive relation between noise trading and future volatility at the daily frequency for a small set of individual stocks.

After extracting 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 FEARS index on future volatility using the following regressions:

$$\epsilon_{i,t} = \beta_{0,i} + \beta_{1,i}\Delta FEARS_{t-1} + \beta'_{2,i}X_{i,t-1} + u_{i,t}, \tag{1}$$

where $\Delta FEARS_{t-1}$ is the lagged daily change (log difference) in the FEARS index; $X_{i,t-1}$ is a vector of control variables. It includes existing ETF-specific predictive variables. 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] 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 stock price declines while informed trades reduce volatility following stock price increases. In addition, it is well known that trading volume helps to predict volatility (see Jones, Kaul, and Lipson (1994)). For these reasons, we first include lagged daily return ($r_{i,t-1}$) and the lagged change in daily turnover ($\Delta turn_{i,t-1}$) in $X_{i,t-1}$. To the extent that return and trading volume may also proxy for investor sentiment, by including them as control variables, $\beta_1$ captures the incremental predictive power of the FEARS index that is not attributable to its correlation with existing sentiment proxies.

An alternative way of capturing negative sentiment, as discussed in Tetlock (2007), is to ex-

[13] See Black (1976), Christie (1982), French, Schwert, and Stambaugh (1987), and Glosten, Jagannathan, and Runkle (1993) among others.

amine negative words in news articles. Following Tetlock et al. (2008), for each article in the Dow Jones archive 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. This gives us a broad, daily sentiment measure based on the linguistic content of media articles across all stocks. We include the lagged change of the fraction of negative words ($\Delta Neg_Frac_{t-1}$) in $X_{i,t-1}$. To identify the negative words, Tetlock et al. (2008) uses the Harvard IV-4 psychosocial dictionary. Loughran and McDonald (2009) argue that some negative words in the Harvard dictionary do not have a truly negative meaning in 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. However, we obtain qualitatively similar results when using the Harvard IV-4 word list and the word list of Loughran and McDonald (2009).

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 lagged change in the log VIX index ($\Delta VIX_{t-1}$) in $X_{i,t-1}$.

In an alternative regression specification, we use the level instead of the change in the right-hand-side of regression (1) but find qualitative similar results. Specifically, we replace $\Delta FEARS_{t-1}$ with $FEARS_{t-1}$, $\Delta turn_{t-1}$ with $turn_{t-1}$ $\Delta Neg_Frac_{t-1}$ with $Neg_Frac_{t-1}$, and $\Delta VIX_{t-1}$ with $VIX_{t-1}$. This specification is closer to that in Antweiler and Frank (2004). We only report the results using regression (1) since using changes has the additional advantage of removing the time trend in the time-series.

### 4.1 Average predictive power

First, we are interested in estimating the average predictive power of SVIs across all 27 search terms. To achieve this objective, we run a panel regression for each ETF. Specifically, for each ETF, we estimate regression (1) across all 27 search terms. We include both time and search term fixed effects in the Panel regression. We begin by only including lagged daily return ($r_{i,t-1}$) and

lagged change in daily turnover ($\Delta turn_{i,t-1}$) in $X_{i,t-1}$, which allows us to estimate the regression using the full sampling period from 2004 to 2008. The results are presented in the left half of Table 4.

The first thing we notice is that changes in the FEARS index have strong incremental predictive power on next-day realized volatility innovations across all ETFs. An increase in the FEARS index today strongly predicts a higher realized volatility tomorrow. This predictive relation is stronger in equity asset classes, especially among larger stocks. A 1% increase in the FEARS index will lead to a 0.159% (t-value = 9.84) increase in the realized volatility for the S&P 500 ETF (SPY) and a 0.142% (t-value = 6.92) increase for the Russell 1000 ETF (IWB). The predictive power becomes slightly weaker when we move to smaller stocks. A 1% increase in the FEARS index will lead to a 0.127% (t-value = 7.98) increase in the realized volatility for the NASDAQ stock ETF (QQQQ) and a 0.078% (t-value = 5.08) increase for the Russell 2000 ETF. Interestingly, we find equally strong predictive power for the Treasury ETF. A 1% increase in the FEARS index will lead to a 0.134% (t-value = 6.43) increase in the realized volatility for the ETF– TLT. For the treasury ETF, the predictive power is likely coming from the discount rate channel given the fact that there is almost no uncertainty associated with the nominal cashflow. An increase in the FEARS reflects negative investor sentiment which either leads to a "flight-to-quality" or uncertainty in expected future interest rates, both of which can increase the volatility on treasury securities. Finally, we document a small yet marginally significant prediction for the Gold ETF. A 1% increase in the FEARS index will lead to 0.044% (t-value = 1.84) increase in the realized volatility. Overall, across different asset classes, the FEARS index provides significant incremental predictive power for future realized volatility.

We also confirm the strong asymmetric volatility effect well-known in the literature. The return today is strongly and negatively correlated with the realized volatility tomorrow. The only exception is the treasury ETF where the correlation is actually positive and significant. The turnover variable, on the other hand, has mixed predictive power across asset classes. While increased turnover today leads to higher volatility tomorrow for the treasury and gold ETFs (TLT and GLD), consistent with what is documented in the literature, it actually leads to lower volatility for the large stocks as represented by the S&P500 index and Russell 1000 index ETF (SPY, IWB). Such negative predictive relation is likely a joint result of strong contemporaneous correlation between volatility

and turnover and the mean-reversion in volatility. Finally, turnover does not seem to have a significant role for the Russell 2000 index and NASDAQ stock ETF (IWM and QQQQ). Overall, unlike our FEARS index, past return and turnover do not seem to have a consistent prediction for future volatility across different asset classes.

Finally, we include two alternative market aggregate measures of sentiment: change of the implied-volatility-based measure ($\Delta VIX_{t-1}$) and the news-based measure ($\Delta Neg_Frac_{t-1}$) and we rerun the regression (1). The regression stops at the end of 2007 due to the availability of the news-based sentiment measure. As a result, the regression also serves as a robustness check whether our previous results are driven by the financial crisis during 2008. The results are presented in the right half of Table 4. We find $\Delta VIX_{t-1}$ to have a significant positive regression coefficient, possibly capturing the strong persistence in volatility that is not fully accounted for using the ARFIMA model. We find that $\Delta Neg_Frac_{t-1}$ actually has a counter-intuitive significant negative relation with future volatility innovation: a higher fraction of negative words today strongly predicts a lower volatility tomorrow. This negative relation likely reflects the fact that news captures the sentiment with a delay which becomes an important drawback when predicting volatility at the daily frequency. For instance, when a negative shock hits the economy, price declines while volatility surges in response. However, it may taka a day or two for the negative shock to be reflected in the news. At that time, volatility starts to mean-revert and as a result, the fraction of negative words may be negatively correlated with future volatility. Most importantly, our FEARS index continues to be significantly positively correlated with future volatility after controlling for the alternative sentiment measures during this pre-crisis sampling period. The result suggests that (1) our FEARS index is likely to capture sentiment on a real-time basis and has additional predictive power about future volatility; (2) such predictive power is not driven by a few large shocks during the 2008 financial crisis.

Similar to a Granger-Causality test, we also examine the reverse predictive relation between the FEARS index and volatility innovations. Specifically, for each ETF, we regress daily changes in the FEARS index on lagged volatility innovations, lagged return and lagged changes in turnover across all 27 search terms. Again, we include both time and search term fixed effects in the Panel regression. The results are reported in Table 5. In contrast to the strong and positive predictive power of the FEARS index on future volatility, the predictive power of lagged volatility on the

current FEARS index is, at best, mixed. It is positive and significant only for the treasury ETF (TLT) but becomes negative and significant for Russell 1000 index ETF (IWB) and the NASDAQ stock ETF (QQQQ). It does not predict the FEARS index for the other three ETFs. Overall, these results suggest that the causal relation is likely to go from the FEARS index to the volatility, rather than the other way around. This is not entirely surprising given that the FEARS index is a broad-based measure of investor sentiment towards the overall economy while the realized volatilities are specific to particular asset classes.

### 4.2 Predictive power of different search terms

It is possible that the SVI on a particular search term might be more relevant for one asset class than the others. For instance, the SVI on "inflation" might be more directly linked to the Treasury ETF since expected inflation is an important component of long-term interest rate. To the extent that gold is one the best hedges for inflation, the SVI on "inflation" might be also related to the future volatility on the Gold ETF. On the other hand, the SVI on "recession" or "great depression" may reflect investors' concerns about the macroeconomy and the stock market and thus affect the future volatility of the equity-based ETFs.

To examine the relative predictive power of SVIs across different search terms, we run regression (1) for each search term separately. Specifically, for each ETF and each of the 27 search terms used to construct the FEARS index, we regress daily ARFIMA(0,d,1) realized volatility innovations on lagged changes in SVI in that search term, lagged returns and lagged changes in turnover. The t-value associated with the regression coefficient on the lagged changes in SVI measures the statistical predictive power of that particular search term. Table 6 reports, for each ETF, the search terms with $t$-values greater than 2. The search terms are reported in the order of the magnitudes of their $t$-values (reported next to the search term). The sampling period is 2004-2008 with the exception of GLD which only started in November of 2004.

Several interesting patterns emerge from the results reported in Table 6. First, inflation-related search terms such as "inflation" and "cost of living" are important predictors of future volatilities across asset classes. SVI on "cost of living" is significant for all ETFs except the Gold ETF (GLD) and shows up among the top two predictors for four of them (SPY, QQQQ, TLT and IWM). SVI on "inflation" is significant for all ETFs except the Russell 2000 ETF (IWM). In particular, it is

the only significant search term for the Gold ETF, consistent with the notation of gold being the best hedge for the inflation risk. As investors start to be concerned with inflation risk, they are more likely to trade GLD and their trades increase the volatility. Second, depression related search terms ("depression", "great depression", "the great depression", and "recession") are also important predictors. Interestingly, "great depression" is always more powerful than simply "depression" or "recession" in predicting future volatility and shows up among the top three predictors for the four ETFs (SPY, QQQQ, TLT, and IWB). Third, another important set of search terms is related to bankruptcy ("bankruptcy", "chapter 7", and "chapter 13"). Fourth, while job related search terms ("job search", "job opening", and "new job") are important for equity ETFs, they are less useful for the treasury ETF. Instead, search term "national debt" is very important for the treasury ETF (t-value = 3.49) but is much less so for equity ETFs. Finally, more search terms are useful for the larger stock index such as SPY and QQQQ than for the smaller stock index such as IWB and IWM. For example, 17 out of the 27 search terms are significant for SPY and 15 out of the 27 search terms are significant for QQQQ, which is consistent with the average predictive power of the FEARS index reported in Table 4.

### 4.3 Positive Search Terms

So far, we have documented that an increase in negative market sentiment as measured by our FEARS index strongly predicts greater asset volatility on the next day. We interpret this result in the context of the literature on "noise trading" starting from Black (1986). For example, in De Long et. al. (1990), 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 change will lead to more noise trading, greater mispricing and predict excessive future volatility.

However, sentiment can be both bearish and bullish so that large swings in positive sentiment will have similar effects in noise trading models as large swings in negative sentiment. For this reason we examine the search volume index (SVI) on positive search terms ($PSVI$). Empirically, although Tetlock (2007) and Tetlock et al. (2008) point out that negative words better capture sentiment, we would still expect the increase in $PSVI$ to be followed by an increase in asset

volatility under the "noise trading" explanation.

To construct a list of positive search terms, we perform the identical procedure discussed in section II. We settle on a list of 22 search terms like "get rich" and "luxury hotels." We examine the average predictive power of SVIs across all 22 positive search terms, and we run the same panel regression for each ETF. Specifically, for each ETF, we estimate regression (1) across all 22 positive search terms after replacing $\Delta FEARS_{t-1}$ with $\Delta PSVI_{t-1}$. We include both time and search term fixed effects in the panel regressions. We begin by only including lagged daily return ($r_{i,t-1}$) and lagged change in daily turnover ($\Delta turn_{i,t-1}$) in $X_{i,t-1}$, which allows us to estimate the regression using the full sampling period from 2004 to 2008. The results are presented in the left half of Table 7.

The first thing we notice is that for equity and treasury ETFs, an increase in $PSVI$ today strongly predict a higher realized volatility tomorrow, even after controlling for lagged return and turnover. This pattern is clearly consistent with a "noise trading" explanation. Although, the regression coefficients on $\Delta PSVI$ are significant for equity and treasury ETFs. The $t$-values are much smaller than those of $\Delta FEARS_{t-1}$ reported in Table 4, consistent with the findings of Tetlock (2007) and Tetlock et al. (2008) that negative words better capture sentiment. $\Delta PSVI$ does not predict the future volatility of the Gold ETF (GLD) which should not surprise us. Table 6 suggests that only the search term "Inflation" is related to the volatility on Gold and none of the positive search terms is related to "Inflation."

Table 7 also shows that the predictive power $\Delta PSVI$ becomes much weaker when we include two alternative aggregate-level measures of sentiment: implied-volatility-based measure ($\Delta VIX_{t-1}$) and the news-based measure ($\Delta Neg_Frac_{t-1}$). Now, $\Delta PSVI$ has significant incremental predictive power only for the large stock ETFs (SPY and IWB). However, the regression coefficients on $\Delta PSVI$ are still positive (except for GLD).

## 5 FEARS Index and Fund Flows

Sentiment or noise traders affect asset prices and volatilities via trading. To more directly examine trading triggered by noise traders, we also look at daily mutual fund flows. Since individual investors hold about 90% of total mutual fund assets, and they are more likely to be the "noise" traders,

daily flows to mutual fund groups likely aggregate "noise" trading at the asset class level, The daily mutual fund flow data is obtained from TrimTabs on three groups of mutual funds that specialize in equity (Equity), intermediate treasury bond (MTB), and precious metals (Metal) accordingly.

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 the fractionally integrated processes. Similar to observations made on the volume of individual stocks, we also find very strong persistence and long-memory components in these 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 $ARFMA(1, d, 1)$ model fits the underlying daily fund flows series 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. The 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. This issue has been documented and analyzed in detail by Edelen and Warner (2001) and Greene and Hodges (2002). 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, similar to the treatment in Yuan (2009), we lag our predictive variables by one day. In another words, we run the following regression:

$$flow_inno_{i,t+2} = \beta_{0,i} + \beta_{1,i}\Delta FEARS_t + \beta'_{2,i}X_{i,t} + u_{i,t+2}. \tag{2}$$

The one-day lag ensures that the LHS flow innovation does not contain time-$t$ information. At the same time, we underestimate the true predictive of our FEARS index since not all funds are reporting NTA with a delay. The vector $X$ again contains two alternative aggregate-level measures of sentiment: implied-volatility-based measure ($\Delta VIX$) and the news-based measure ($\Delta Neg_Frac$). The regression involving $\Delta Neg_Frac$ stops at the end of 2007 due to the availability of the news-based sentiment measure. The results of these predictive regressions are reported in Table 8.

We find that our FEARS index has significant incremental predictive power on future daily fund flow innovations. In the full sample from 2004 to 2008, the regression coefficient on $\Delta FEARS$ is negative and significant for Equity (t-value = 2.68) and is positive and significant for MTB and Metal (t-values are 4.40 and 2.21, respectively). Similar results are obtained after we exclude 2008 and include $\Delta Neg_Frac$ as an additional control, indicating that the incremental predictive power on FEARS index is not entirely driven by the recent financial crisis. Overall, these results suggest that an increase in the FEARS index predicts outflows from equity mutual funds but inflows to mutual funds specializing in treasury bonds and precious metals. These flow patterns are strongly consistent with the well-documented flight-to-quality phenomenon and increasing desire to hedge for inflation risk during crisis periods. Interestingly, our FEARS index produces more intuitive predictive results than alternative sentiment measures. For example, an increase in the CBOE market volatility index (VIX) actually predicts outflow from mutual funds specializing in precious metal, which is counter-intuitive. The news-based sentiment measure predicts flows to equity and treasury mutual flows with the wrong sign and does not predict flows to mutual funds specializing in precious metal at all.

Overall, given that daily mutual fund flows are likely capturing aggregate "noise" trading within these asset classes, we view the predictive power of our FEAR sindex on fund flows as strong and direct supporting evidence for the "noise trading" hypothesis of De Long et. al. (1990).

## 6 Discussion of Alternative Interpretations

So far we have found strong evidence that the attitudes of households as revealed by their search behavior have predictability for short-term market volatility as well as aggregate mutual fund flows. 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 use the model of De Long, Shleifer, Summers and Waldmann (1990) to interpret our results.

### 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. On the contrary, we should expect investor sentiment to be endogenous to macroeconomic events. As Qui and Welch (2006) put it: "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."

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 index as describing the subset of news events that drive investor sentiment.

### 6.2 Search as a Measure of Time-Varying Risk-Aversion or Uncertainty

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

While this is a possible interpretation of our evidence, there are two important caveats. First, we also find evidence that search volume for positive economic terms is positively related to future volatility. While it may be sensible to believe that negative search terms such as "recession" and "great depression" proxy for risk aversion, it seems unlikely that positive economic search terms such as "get rich" and "charities" also proxy for risk aversion. Second, there is little evidence that risk-aversion changes rapidly (see Brunnermer and Nagel (2008)) so that it seems unlikely 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 FEARS index remains a strong predictor of future asset volatility even after controlling for VIX.

# 7 Conclusion

Good forecasts of high-frequency volatility are critical to finance applications such as option pricing, portfolio allocation, and risk management. Despite advances in statistical modelling of volatility, there has been relatively little progress in uncovering and testing *economic* models of volatility (Engle, Ghysels and Sohn (2008)). Forecasting daily volatility is almost done entirely by looking at lagged volatility itself.

In this paper, we have shown that the economic attitudes of households as revealed by their search behavior has strong predictive power for daily volatility. By aggregating queries like "recession", "bankruptcy" and "credit card debt" we construct a Financial and Economic Attitudes Revealed by Search (FEARS) index. 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, trading volume, the CBOE market volatility index (VIX) and a news-based sentiment index. This evidence is consistent with the "noise trading" hypothesis of De Long et. al. (1990). Using daily aggregate mutual fund flows, we provide direct evidence for "noise" trading. For example, our FEARS index predicts daily mutual fund flows to various asset classes, consistent with the notion of a "flight-to-quality" in bad times.

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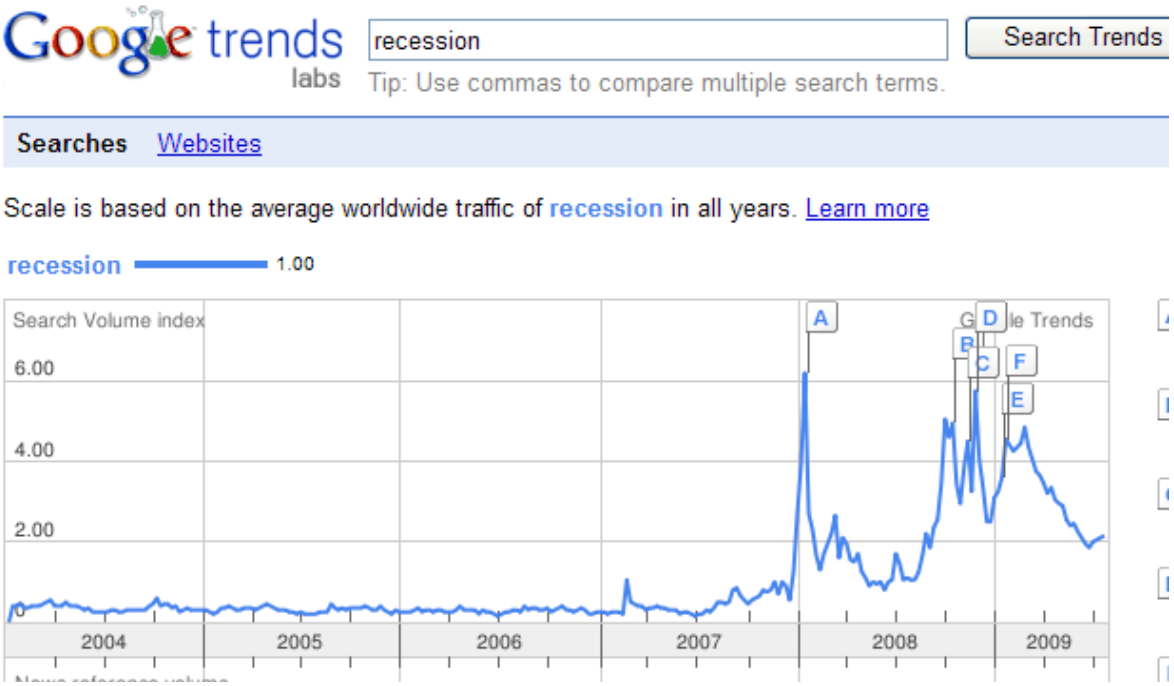
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**Figure 1: Illustrations of Google Trends Search**

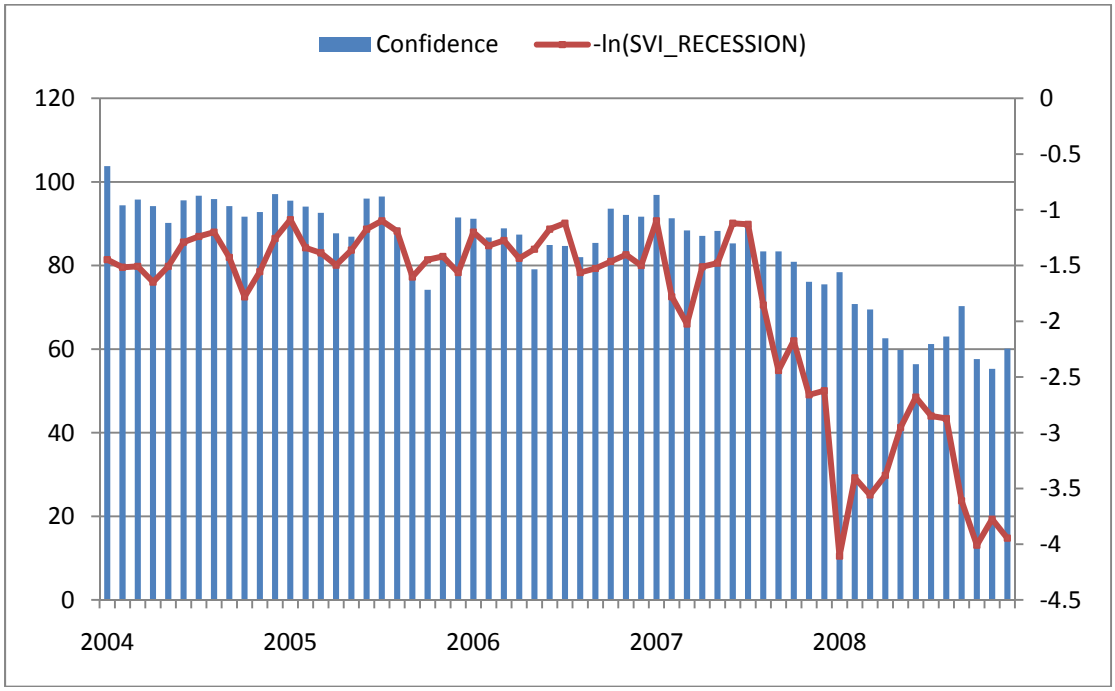
The figures represent the graphical outputs for Google Trends' search terms. The top panel plots weekly aggregate search frequency (SVI) for "credit card debt." SVI for "credit card debt" is the weekly search volume for "credit card debt" scaled by the average search volume of "credit card debt. Bottom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



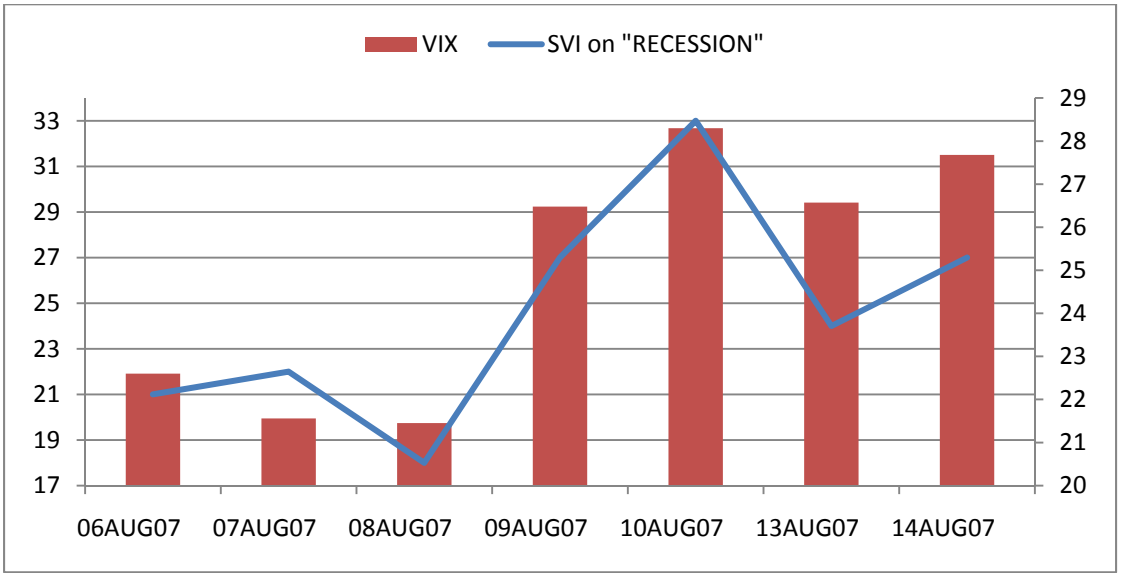



**Figure 3: Percentage of Variance Explained by Each Factor**

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.

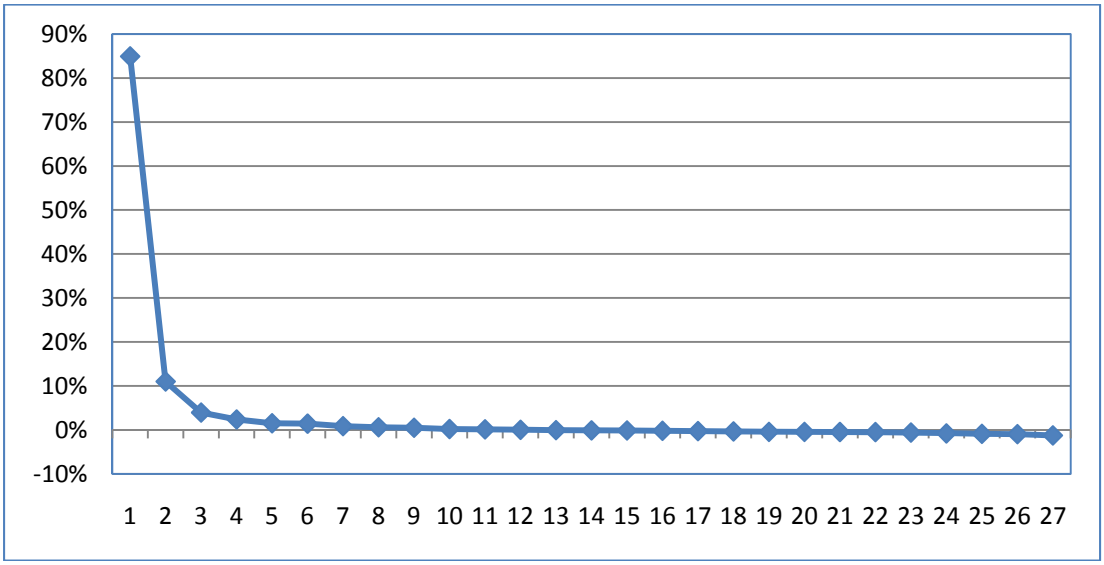


**Figure 4: Normalized Daily Log Realized Volatilities across ETFs**

This figure plots the daily normalized log realized volatilities. The six ETFs are: (1) SPDR S&P500 (AMEX: SPY), (2) PowerShares QQQ Trust (NASDAQ: QQQQ), (3) iShare Russell 1000 Index (NYSE: IWB), (4) iShare Russell 2000 Index (NYSE: IWM), (5) iShares Barclays 20+ Year Treasury Bond (NYSE: TLT and (6) SPDR Gold Shares (NYSE: GLD).

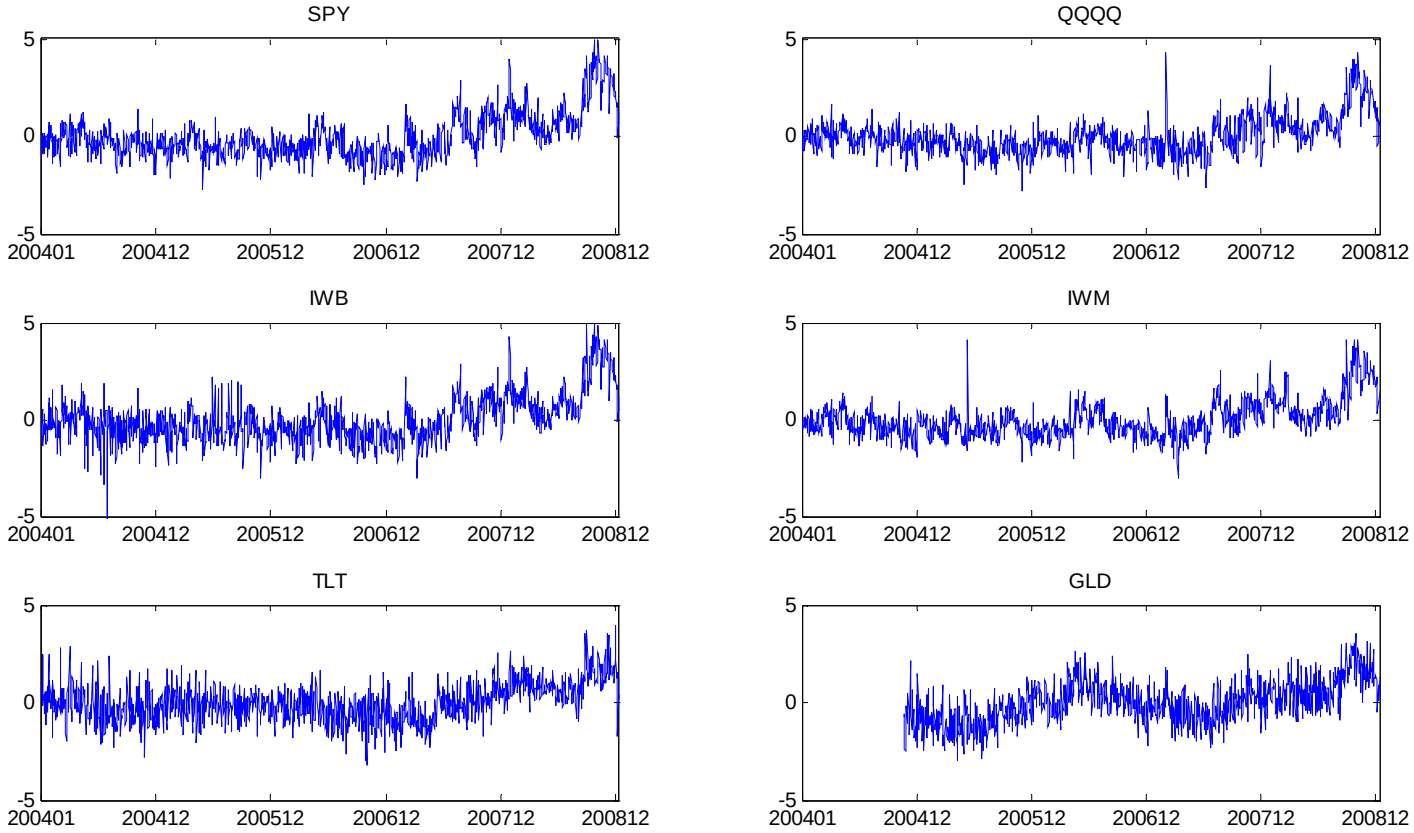
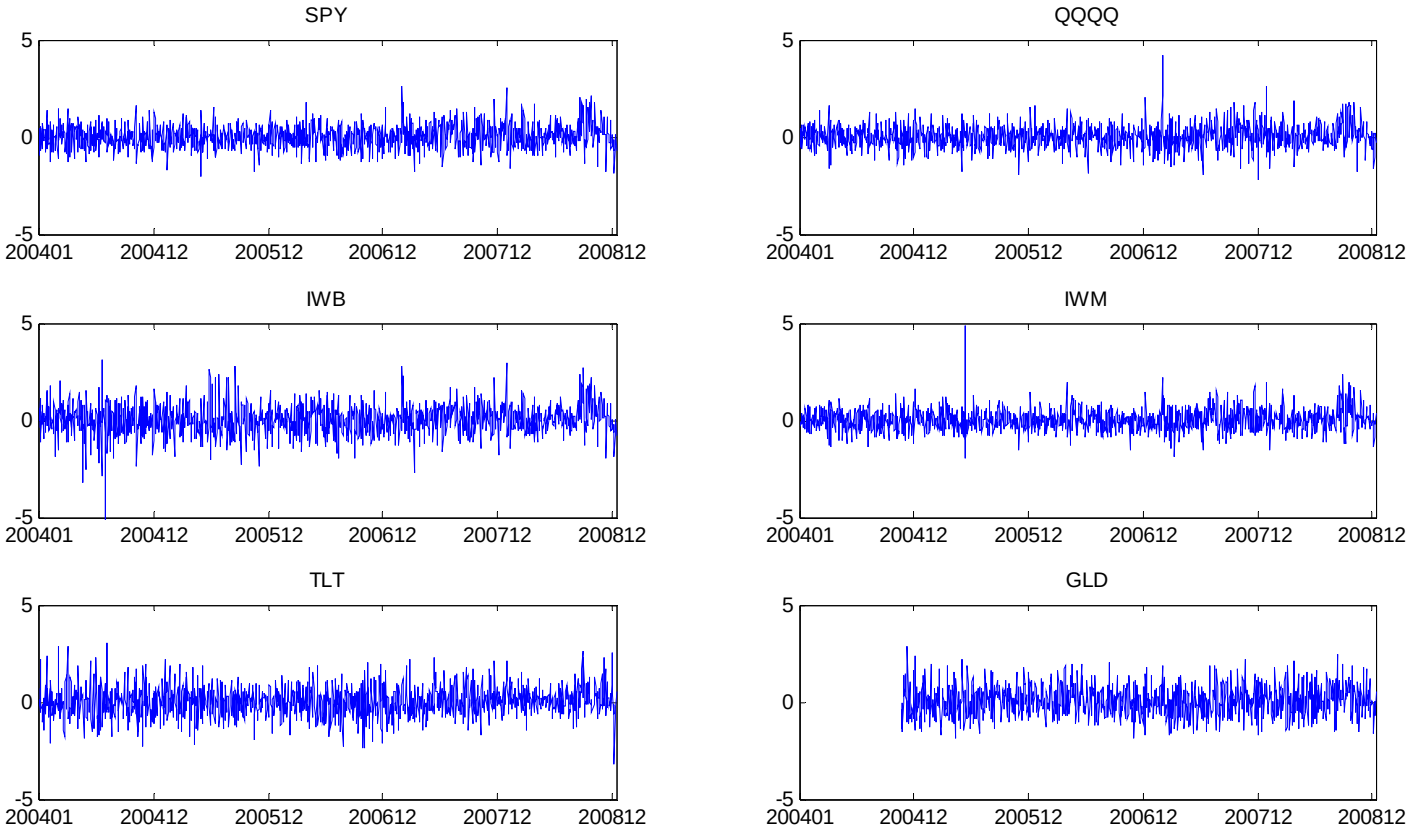


**Figure 5: ARFIMA(0,d,1) Daily Realized Volatilities Innovations across ETFs**

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 six ETFs are: (1) SPDR S&P500 (AMEX: SPY), (2) PowerShares QQQ Trust (NASDAQ: QQQQ), (3) iShare Russell 1000 Index (NYSE: IWB), (4) iShare Russell 2000 Index (NYSE: IWM), (5) iShares Barclays 20+ Year Treasury Bond (NYSE: TLT and (6) SPDR Gold Shares (NYSE: GLD).



## 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 three groups.

| FINANCIAL DISTRESS | JOB LOSS | BUSINESS CONDITIONS |
|---|---|---|
| bankruptcy | job search | national debt |
| bankruptcy court | job openings | the depression |
| chapter 7 | new job | great depression |
| filing bankruptcy | job opportunities | the great depression |
| chapter 13 | job application | inflation |
| cost of living | job bank | inflation rate |
| credit debt | unemployment benefits | recession |
| debt consolidation | unemployment rate | |
| credit card debt | unemployment office | |
| | unemployment insurance | |
| | debt collection | |

## 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 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 | Bankruptcy | The Depression | Unemployment Benefits |
| Search Term 2 | Bankruptcy Court | The Great Depression | Unemployment Insurance |
| Search Term 3 | Job Bank | Great Depression | Unemployment Office |
| % of variance explained | 46.3% | 25.9% | 15.0% |

| | Factor 4 | Factor 5 | Factor 6 |
|---|---|---|---|
| Search Term 1 | Credit Card Debt | Inflation | Job Opportunity |
| Search Term 2 | Credit Debt | Inflation Rate | Job Search |
| Search Term 3 | Debt Consolidation | Recession | Job Openings |
| % of variance explained | 8.2% | 8.1% | 1.8% |

## Table 3: 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 1000 Index (NYSE: IWB), (4) iShare Russell 2000 Index (NYSE: IWM), (5) iShares Barclays 20+ Year Treasury Bond (NYSE: TLT and (6) SPDR Gold Shares (NYSE: GLD).

| | QQQQ | SPY | IWB | IWM | TLT | GLD |
|---|---|---|---|---|---|---|
| d | 0.476 | 0.494 | 0.488 | 0.492 | 0.454 | 0.482 |
| Std.Error | *0.03* | *0.01* | *0.02* | *0.01* | *0.04* | *0.02* |
| MA(1) | -0.179 | -0.150 | -0.248 | -0.167 | -0.386 | -0.390 |
| Std.Error | *0.04* | *0.03* | *0.03* | *0.03* | *0.06* | *0.04* |

## Table 4: Predicting Realized Volatilities using FEARS Index: Across ETFs

This table reports the results of predictive regressions. For each ETF, we regress daily ARFIMA(0,d,1) realized volatility innovations on lagged changes in FEARS index and other lagged control variables across all 27 search terms. We include both time and search term fixed effects in the Panel regression. The lagged control variables include lagged return (ret), lagged changes in turnover (Δturn), lagged changes in the (log) VIX index (ΔVIX) and lagged changes in the faction of negative words (ΔNeg_Frac). The regression involving ΔNeg_Frac ends in 2007 due to the availability of news data required to construct the ΔNeg_Frac variable. The six ETFs are: (1) SPDR S&P500 (AMEX: SPY), (2) PowerShares QQQ Trust (NASDAQ: QQQQ), (3) iShare Russell 1000 Index (NYSE: IWB), (4) iShare Russell 2000 Index (NYSE: IWM), (5) iShares Barclays 20+ Year Treasury Bond (NYSE: TLT and (6) SPDR Gold Shares (NYSE: GLD).

| | Sample period: 2004 - 2008 | | | | | Sample period: 2004 - 2007 | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ETF | Intercept | ΔFEARS | ret | Δturn | $R^2$ | Intercept | ΔFEARS | ret | Δturn | ΔVIX | ΔNeg_Frac | $R^2$ |
| SPY | 0.008 | 0.159 | -10.749 | -0.068 | 5.2% | -0.014 | 0.104 | -22.265 | -0.129 | 0.208 | -48.773 | 9.2% |
| | *0.47* | *9.84* | *-40.68* | *-6.69* | | *-0.78* | *6.15* | *-25.06* | *-11.72* | *1.93* | *-14.88* | |
| IWB | 0.030 | 0.142 | -11.909 | -0.027 | 3.9% | 0.007 | 0.085 | -24.568 | -0.043 | 0.037 | -38.355 | 5.9% |
| | *1.33* | *6.92* | *-35.03* | *-5.37* | | *0.27* | *3.7* | *-21.63* | *-7.81* | *0.27* | *-8.78* | |
| IWM | 0.008 | 0.078 | -1.635 | 0.008 | 0.6% | -0.016 | 0.014 | 1.377 | -0.055 | 2.319 | -25.488 | 6.1% |
| | *0.47* | *5.08* | *-12.86* | *0.84* | | *-0.94* | *1.88* | *9.49* | *-5.61* | *39.93* | *-8.39* | |
| QQQQ | 0.002 | 0.127 | -10.544 | -0.001 | 6.0% | -0.021 | 0.082 | -12.871 | 0.029 | 0.871 | -29.122 | 8.5% |
| | *0.13* | *7.89* | *-43.44* | *-0.21* | | *-1.12* | *4.73* | *-24.14* | *3.61* | *10.03* | *-8.75* | |
| TLT | -0.006 | 0.134 | 1.787 | 0.059 | 0.4% | -0.045 | 0.084 | -2.762 | 0.076 | 0.670 | -64.888 | 1.5% |
| | *-0.27* | *6.43* | *2.82* | *8.9* | | *-1.76* | *3.58* | *-3.19* | *10.32* | *8.37* | *-14.34* | |
| GLD | 0.038 | 0.044 | -3.812 | 0.066 | 0.7% | 0.009 | 0.073 | -5.749 | 0.035 | 0.706 | 29.119 | 1.6% |
| | *1.52* | *1.84* | *-11.12* | *7.4* | | *0.33* | *2.73* | *-12.06* | *3.68* | *8.3* | *5.8* | |

*Time series of GLD starts in November 18, 2004.

## Table 5: Predicting the FEARS Index: Across ETFs

This table reports the results of predictive regressions. For each ETF, we regress daily changes in FEARS index on lagged ARFIMA(0,d,1) realized volatility innovations (v_inno) and other lagged control variables across all 27 search terms. We include both time and search term fixed effects in the Panel regression. The lagged control variables include lagged return (ret), lagged changes in turnover (Δturn) and lagged changes in the faction of negative words (ΔNeg_Frac). The regression involving ΔNeg_Frac ends in 2007 due to the availability of news data required to construct the ΔNeg_Frac variable. The six ETFs are: (1) SPDR S&P500 (AMEX: SPY), (2) PowerShares QQQ Trust (NASDAQ: QQQQ), (3) iShare Russell 1000 Index (NYSE: IWB), (4) iShare Russell 2000 Index (NYSE: IWM), (5) iShares Barclays 20+ Year Treasury Bond (NYSE: TLT and (6) SPDR Gold Shares (NYSE: GLD).

| | Sample period: 2004 - 2008 | | | | |
|---|---|---|---|---|---|
| ETF | Intercept | v_inno | ret | Δturn | $R^2$ |
| SPY | -0.003 | 0.003 | -0.523 | -0.060 | 0.8% |
| | *-0.47* | *1.27* | *-5.77* | *-13.73* | |
| IWB | -0.002 | -0.012 | -0.369 | -0.012 | 0.5% |
| | *-0.37* | *-7.8* | *-4* | *-9.13* | |
| IWM | -0.003 | -0.003 | -0.002 | -0.035 | 0.4% |
| | *-0.43* | *-1.23* | *-0.04* | *-9.22* | |
| QQQQ | -0.003 | -0.018 | -0.634 | -0.005 | 0.5% |
| | *-0.44* | *-9.71* | *-7.61* | *-2.46* | |
| TLT | -0.003 | 0.009 | 0.314 | -0.018 | 0.3% |
| | *-0.44* | *5.89* | *1.87* | *-9.56* | |
| GLD* | -0.003 | 0.000 | 0.425 | -0.017 | 0.3% |
| | *-0.45* | *-0.13* | *4.84* | *-7.09* | |

*Time series of GLD starts in November 18, 2004.

## Table 6: Search Terms with Significant Predictive Power

For each ETF and each of the 27 search terms used to construct the FEARS index, we regress daily ARFIMA(0,d,1) realized volatility innovations on lagged changes in SVI in that search term, lagged returns and lagged changes in turnover. The t-value associated with the regression coefficient on the lagged changes in SVI measures the statistical predictive power of that particular search term. This table reports, for each ETF, the search terms with t-values greater than 2. The search terms are reported in the order of their t-values (reported next to the search term). The sampling period is 2004-2008 (with the exception of GLD).

| SPY | | QQQQ | | TLT | |
|---|---|---|---|---|---|
| COST OF LIVING | 3.66 | GREAT DEPRESSION | 3.50 | GREAT DEPRESSION | 4.02 |
| BANKRUPTCY | 3.65 | COST OF LIVING | 3.27 | THE GREAT DEPRESSION | 3.91 |
| GREAT DEPRESSION | 3.63 | CHAPTER 13 | 3.12 | COST OF LIVING | 3.69 |
| JOB SEARCH | 3.62 | RECESSION | 2.65 | THE DEPRESSION | 3.54 |
| DEBT CONSOLIDATION | 2.95 | BANKRUPTCY | 2.63 | NATIONAL DEBT | 3.49 |
| CREDIT CARD DEBT | 2.92 | INFLATION | 2.56 | RECESSION | 3.27 |
| INFLATION | 2.83 | THE DEPRESSION | 2.54 | INFLATION | 2.80 |
| JOB OPENINGS | 2.75 | INFLATION RATE | 2.42 | DEBT CONSOLIDATION | 2.79 |
| THE GREAT DEPRESSION | 2.75 | DEBT CONSOLIDATION | 2.36 | BANKRUPTCY | 2.23 |
| THE DEPRESSION | 2.71 | JOB SEARCH | 2.35 | INFLATION RATE | 2.10 |
| RECESSION | 2.69 | THE GREAT DEPRESSION | 2.34 | | |
| NEW JOB | 2.53 | CREDIT CARD DEBT | 2.26 | | |
| CHAPTER 7 | 2.53 | CREDIT DEBT | 2.23 | | |
| NATIONAL DEBT | 2.48 | NATIONAL DEBT | 2.19 | | |
| CHAPTER 13 | 2.45 | CHAPTER 7 | 2.14 | | |
| INFLATION RATE | 2.08 | | | | |
| JOB APPLICATION | 2.01 | | | | |

| IWB | | IWM | | GLD* | |
|---|---|---|---|---|---|
| BANKRUPTCY | 3.01 | RECESSION | 2.65 | INFLATION | 2.62 |
| NEW JOB | 2.88 | COST OF LIVING | 2.52 | | |
| GREAT DEPRESSION | 2.58 | NEW JOB | 2.34 | | |
| INFLATION | 2.58 | BANKRUPTCY | 2.25 | | |
| CHAPTER 7 | 2.46 | GREAT DEPRESSION | 2.21 | | |
| JOB OPENINGS | 2.41 | | | | |
| COST OF LIVING | 2.37 | | | | |
| THE GREAT DEPRESSION | 2.35 | | | | |

*Time series of GLD starts in November 18, 2004.

## Table 7: Predicting Realized Volatilities using Positive-Words-SVIs (PSVI): Across ETFs

This table reports the results of predictive regressions. For each ETF, we regress daily ARFIMA(0,d,1) realized volatility innovations on lagged changes in SVIs on Positive-words-SVIs (ΔPSVI) and other lagged control variables across all 27 search terms. We include both time and search term fixed effects in the Panel regression. The lagged control variables include lagged return (ret), lagged changes in turnover (Δturn), lagged changes in the (log) VIX index (ΔVIX) and lagged changes in the faction of negative words (ΔNeg_Frac). The regression involving ΔNeg_Frac ends in 2007 due to the availability of news data required to construct the ΔNeg_Frac variable. The six ETFs are: (1) SPDR S&P500 (AMEX: SPY), (2) PowerShares QQQ Trust (NASDAQ: QQQQ), (3) iShare Russell 1000 Index (NYSE: IWB), (4) iShare Russell 2000 Index (NYSE: IWM), (5) iShares Barclays 20+ Year Treasury Bond (NYSE: TLT and (6) SPDR Gold Shares (NYSE: GLD).

| | Sample period: 2004 - 2008 | | | | | Sample period: 2004 - 2007 | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ETF | Intercept | ΔPSVI | ret | Δturn | $R^2$ | Intercept | ΔPSVI | ret | Δturn | ΔVIX | ΔNeg_Frac | $R^2$ |
| SPY | 0.017 | 0.070 | -10.751 | -0.056 | 5.0% | -0.005 | 0.040 | -22.254 | -0.116 | 0.201 | -54.132 | 5.0% |
| | *0.93* | *3.69* | *-36.02* | *-4.85* | | *-0.24* | *2.07* | *-21.98* | *-9.33* | *1.64* | *-14.74* | |
| IWB | 0.035 | 0.073 | -11.929 | -0.022 | 3.8% | 0.014 | 0.051 | -24.903 | -0.039 | -0.005 | -42.953 | 3.8% |
| | *1.58* | *3.08* | *-31.34* | *-3.95* | | *0.53* | *1.96* | *-19.37* | *-6.2* | *-0.03* | *-8.83* | |
| IWM | 0.013 | 0.036 | -1.931 | 0.016 | 0.8% | -0.009 | 0.010 | 1.285 | -0.048 | 2.288 | -26.573 | 0.8% |
| | *0.8* | *2.03* | *-13.08* | *1.55* | | *-0.53* | *0.52* | *7.48* | *-4.32* | *34.84* | *-7.85* | |
| QQQQ | 0.007 | 0.044 | -10.565 | 0.004 | 5.9% | -0.015 | 0.023 | -12.808 | 0.036 | 0.916 | -33.404 | 5.9% |
| | *0.42* | *2.35* | *-38.61* | *0.6* | | *-0.79* | *1.16* | *-21.1* | *4.12* | *9.34* | *-8.98* | |
| TLT | 0.001 | 0.048 | 2.150 | 0.058 | 0.3% | -0.037 | 0.030 | -2.320 | 0.077 | 0.680 | -70.152 | 0.3% |
| | *0.06* | *1.98* | *3.01* | *7.73* | | *-1.41* | *1.11* | *-2.35* | *9.16* | *7.55* | *-13.87* | |
| GLD | 0.040 | -0.037 | -3.849 | 0.065 | 0.7% | 0.011 | -0.011 | -5.756 | 0.033 | 0.742 | 26.077 | 0.7% |
| | *1.59* | *-1.33* | *-10.06* | *6.51* | | *0.4* | *-0.35* | *-10.79* | *3.07* | *7.84* | *4.73* | |

*Time series of GLD starts in November 18, 2004.

## Table 8: Predicting Daily Mutual Fund Flows using FEARS Index: Across Asset Classes

This table reports the results of predictive regressions. We consider three mutual fund groups specializing in medium-term Treasury bond (MTB), equity (Equity) and precious metal (Metal) accordingly. 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 the fund flow, we use ARFIMA(1,d,1) model to extract daily flow innovations. For each fund group, we regress its flow innovations on lagged changes in FEARS index and other lagged control variables *two* days ago, across all 27 search terms. We include both time and search term fixed effects in the Panel regression. The lagged control variables include lagged changes in the (log) VIX index (ΔVIX) and lagged changes in the faction of negative words (ΔNeg_Frac). The regression involving ΔNeg_Frac ends in 2007 due to the availability of news data required to construct the ΔNeg_Frac variable.

| | Sample period: 2004 - 2008 | | | | Sample period: 2004 - 2007 | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Fund | Intercept | ΔFEARS | ΔVIX | $R^2$ | Intercept | ΔFEARS | ΔVIX | ΔNeg_Frac | $R^2$ |
| MTB | 0.023 | 0.911 | 3.339 | 0.15% | -0.121 | 0.913 | 0.947 | -358.001 | 0.43% |
| | *0.1* | *4.4* | *4.99* | | *-0.49* | *4.05* | *1.24* | *-8.47* | |
| Equity | -0.428 | -0.326 | -9.310 | 1.81% | -0.221 | -0.323 | -8.323 | 128.896 | 1.88% |
| | *-3.27* | *-2.68* | *-23.75* | | *-1.71* | *-2.74* | *-20.78* | *5.84* | |
| Metal | -0.388 | 1.248 | -3.767 | 0.03% | 0.079 | 1.278 | -7.957 | -121.104 | 0.07% |
| | *-0.64* | *2.21* | *-2.07* | | *0.11* | *1.99* | *-3.65* | *-1.01* | |