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Measuring the Behavioral Component of Financial Fluctuations: An Analysis Based on the S&P 500*

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Abstract

To assess the evolution of the behavioral component of the financial market, this study estimates a Bayesian mixture model in which two types of investors coexist: one risk-averse, with standard subjective expected utility theory preferences, and one behavioral, with an S-shaped utility function. The analysis uses monthly data about the constituents of the S&P 500 index from January 1962 to April 2012. With the assumption that agents make investment decisions by ranking alternative assets according to their performance measures, a tuning parameter that blends the risk-averse and the behavioral rankings can be estimated using a criterion function. We detect a significant behavioral component that reaches peaks during recession periods. Moreover, our endogenously estimated behavioral component is highly correlated with the S&P 500 return index as well as with measures of (implied) financial volatility, market sentiments, and financial stress.

JEL-Classification: G01, G02, G11, G17, C58.

Keywords: behavioral finance, Bayesian mixture, endogenous market sentiment.

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1 Introduction

A primary assumption of the traditional approach to finance (LeRoy and Werner, 2000) is that, in making their investment decisions, agents maximize a well-conformed utility function that satisfies the requirements of the Subjective Expected Utility Theory (SEUT). Yet, the validity of this hypothesis has been questioned for its inability to account for systematic empirical puzzles, such as the persistent mispricing of assets and the presence of arbitrage opportunities in financial markets (Hirshleifer, 2001; Barberis and Thaler, 2003; Lamont and Thaler, 2003).[1] Moreover, substantial experimental evidence documents systematic violations of SEUT assumptions in risky decisions (for an extensive and comprehensive survey, Starmer, 2000). Therefore, scholars have begun introducing novel behavioral assumptions about individual preferences in their models. An intriguing research question that remains unanswered thus far is how to isolate and measure empirically the impact of behavioral views on the financial market movements. The present paper aims to tackle this research question. By using monthly data about the 500 components of the S&P 500 index from January 1962 to April 2012, we propose a Bayesian mixture approach and estimate the relative impact of the behavioral component on movements in the financial market. As in standard heterogeneous agent settings (Grossman and Stiglitz, 1980; De Long et al., 1990; Zeeman, 2007), the underlying model assumes that, in every period of time, the evolution of the asset prices reflects the interplay between the investment choices of two types of non-strategic financial agents: one risk-averse, endowed with a standard risk-averse utility function that satisfies the SEUT requirements, and one characterized by behavioral preferences. Of all the new (non-expected) utility theories proposed as alternatives to the SEUT, prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) is the most successful and serves as a natural benchmark for our methodology. According to the original formulation, agents' attitude toward risk changes over monetary outcomes, such that agents exhibit risk-averse preferences in the gain domain and risk-seeking preferences in the loss domain. Given the specification of the two categories of agents, the mixture depends on a weighting factor that expresses the relative weight of the behavioral view over the risk-averse one, such that the higher the value of the weighting factor, the closer the asset evaluations of the financial market are to those of the behavioral agents.

Our methodology is a powerful empirical instrument for analyzing financial data, and has two relevant features. First, the relative importance of the behavioral component is estimated in every period, by using an optimizing methodology that is based on performance measures: the Generalized Sharpe Ratio (Zakamouline and Koekebakker, 2009a,b) for risk-averse agents and the Z-ratio (Zakamouline, 2014) for behavioral agents. Performance measures have several advantages, from an empirical standpoint: they summarize,

[1]The equity premium puzzle represents one of the most intriguing empirical inconsistencies studied by financial economists. Stocks on average exhibit attractive risk-return performances, but investors appear to demand a substantial risk premium to prefer this asset over other, riskless investment opportunities.

in a single parameter, the interplay between the risk and return of the corresponding asset. Moreover, performance measures can be ordered in such a manner that assets with higher measures perform better.

The second main feature of our methodology concerns its recursive nature. To build their rankings and make their investment decisions, financial agents use substantial information about the past returns of assets. Because of its recursive structure, our methodology can be used to analyze the evolution of the behavioral component's evolution over time and, thus, its relationship with the economic cycle. For example, the assumptions underlying the S-shaped value function imply that behavioral agents' attitude toward risk changes along with the economic cycle. Therefore, in periods of (financial and economic) recession, behavioral agents are risk-seeking and willing to invest in riskier assets that might compensate for past (observed) losses, while in periods of expansion, they are risk-averse and prefer safer assets in order to capitalize on past (observed) capital gains.

Moving to the results, we confirm the presence of a substantial behavioral component that changes over time, according to the fluctuations of the financial market. With the specification based on the S-shaped utility functions, the weighting factor is significantly greater than zero and reaches its highest values when nearing periods marked by financial and economic crises. Consequently, the weighting factor might stem from alternative financial explanations, associated with market sentiment or market stress. To validate this interpretation, we study the relationship between the weighting factor and alternative measures of financial market stress, market sentiment , as well as a number of other financial and macro-related controls, measures of market volatility and market liquidity. Our behavioral indicator is significantly associated with both financial market stress and sentiment measures. In addition, when introduced as an additional independent covariate in a multifactor model to explain the evolution of market returns, our behavioral indicator also accounts for a substantial portion of the dependent variable's unexplained time variability. These findings are consistent, across several alternative designs for the weighting factor estimation.

Our methodology imposes no particular restriction on preferences of the behavioral agent, so to check for robustness - and in line with recent empirical findings (Tibiletti and Farinelli, 2003; Malmendier and Nagel, 2011; Guiso et al., 2013; Cohn et al., 2015) - we also replicate our analysis by considering a reverse-S-shaped value function that is concave in the loss domain and convex in the gain domain. Compared with the S-shaped specification, the correlation between the S&P 500 return index and the estimated weighting factor series under this alternative specification fades substantially, in support of the presence of pro-cyclical risk aversion in the financial market.

2 The two-agent framework

We propose a framework in which two types of agents coexist in the market and combine the two agents' choices to form what we refer to as the combined or blended view. We do not associate the combined view to the market as our approach is purely empirical and not based on a theoretical model of market equilibrium. The two agents are characterized by differing utility functions, but both seek to maximize their future utility, possibly by taking into account a naive asset allocation rule, then selecting the best-performing assets according to performance measures. The combination of the agents' views takes place within a Bayesian framework, where the SEUT utility function represents the prior view, which we associate it with the risk-averse agents. Rational agents make their investment decisions (prescriptive theory) by maximizing the SEUT, while we associate the S-shaped utility function, representing the conditional belief and describing how agents actually behave (descriptive theory), with behavioral investors. Within this Bayesian perspective, we seek to infer the posterior, our combined/blended view. Such a construction allows us to recover novel information about the optimal combination of risk-averse and behavioral views, which we then can use to measure, according to a properly defined criterion function, the relative importance of behavioral evaluations over risk-averse ones.

2.1 The risk-averse agent

The SEUT, risk-averse utility function (Morgenstern and Von Neumann, 1953; Markowitz, 1952) represents the prior in our Bayesian framework. In this regard, we consider CARA specification:

$$U(W) = -e^{-\lambda W}, \tag{1}$$

where λ is the coefficient of risk aversion, and W is the investor's wealth. According to the maximum principle, the performance measure relates to the level of maximum expected utility provided by a given asset. Following Hodges (1998) and Zakamouline and Koekebakker (2009b), we rely on the Generalized Sharpe Ratio (GSR) which is sensitive to higher-order moments and can be evaluated with a parametric or non-parametric methodology. In fact, the classical Sharpe ratio is a biased measure when departing from the normal distribution assumption (for the risky asset returns). The GSR, which is obtained by numerical optimization of the expected utility, is defined as:

$$GSR = \sqrt{-2\log(-E[U(\tilde{W})]}, \tag{2}$$

where the argument of the log is the expected wealth, $\tilde{W}$, which depends on the future returns of the risky asset.

By virtue of the GSR, all moments of the risky asset returns exert an impact on the performance measure, so we impose no constraints on the mean and variance of the distribution.

In addition, the GSR approaches the standard SR when the underlying distribution of the risky asset returns is close to Gaussian. Because of the deviation of asset returns from Gaussianity, we consider GSR to be the performance measure that the risk-averse investor adopts in making decisions about capital allocations and myopic asset allocations. In particular, the risk-averse investor prefers investment opportunities associated with a higher GSR.

2.2 The "behavioral" agent

Moving to the conditional belief of our Bayesian framework, we assume that the behavioral agent is characterized by a utility function that satisfies two conditions: (i) it contains a kink at the level of financial wealth that the investor uses as a reference to discriminate between gains and losses; and (ii) the concavity of the utility function (and, therefore, the investor's attitude toward risk) changes when moving from the loss to the gain domain.
Zakamouline (2014) proposed a generalized behavioral utility function that is characterized by a piecewise linear plus power utility function:

$$U(W) = \begin{cases} 1_{+}(W - W_0) \times (W - W_0) - (\gamma_{+}/\alpha)(W - W_0)^{\alpha}, & \text{if } W \geq W_0, \\ -\lambda(1_{-}(W_0 - W) \times (W - W_0) + (\gamma_{-}/\beta)(W_0 - W)^{\beta}), & \text{if } W < W_0, \end{cases} \tag{3}$$

where W_0 is the reference level of wealth; $1_{+}(\cdot)$ and $1_{-}(\cdot)$ are the indicator functions in $\{0, 1\}$ that define the linear part of the utility and assume unit values for positive or negative arguments, respectively, and 0 otherwise; γ_{+} and γ_{-} are real numbers that affect the shape of the utility; and the parameters $\lambda > 0$, $\alpha > 0$, and $\beta > 0$ are real numbers. The utility function in (3) is continuous and increasing in wealth; it admits first and second derivatives with respect to W. In this case, the expected generalized behavioral utility function can be approximated by a function of the mean and partial moments of the distribution. By applying the maximum principle, Zakamouline (2014) showed that the optimal allocation of a behavioral agent is obtained by maximizing the following Z-ratio:

$$Z_{\gamma_{-},\gamma_{+},\lambda,\beta} = \frac{E[x] - r_f - (1_{-}(W - W_0)\lambda - 1)LPM_1(x, r_f)}{\sqrt[\beta]{\gamma_{+}UPM_{\beta}(x, r_f) + \lambda\gamma_{-}LPM_{\beta}(x, r_f)}},$$

where x is the return of the risky asset, and LPM and UPM are the lower and upper partial moments, respectively, as defined by Fishburn (1977):

$$LPM_n(x, r) = \int_{-\infty}^{r} (r - x)^n dF_x(x) and$$
$$UPM_n(x, r) = \int_{r}^{\infty} (x - r)^n dF_x(x),$$

where n is the order of the partial moment of x at a threshold level r, usually set at the risk-free return, and $F_x(\cdot)$ is the cumulative distribution function of x. Similar to the GSR, higher values of the Z-ratio are preferred to lower values. In line with Kahneman and Tversky (1979), our formulation implies that the utility function is concave in the gain domain and convex in the loss domain and is steeper in the domain of losses, such that losses loom larger than corresponding gains.

2.3 The Bayesian mixture

Similar to Black and Litterman (1992), our methodology builds a mixture ranking by conditioning, in a Bayesian setting, the prior ordering of the risk-averse agent on the ranking of the behavioral category. In this perspective, we assume that the GSR of the risk-averse agent is the prior belief about how investors should make decisions, while the Z-ratio of the behavioral agent, represents the additional information to be used along the prior.

The Bayesian mixture between the GSR and the Z-ratio produces an aggregate measure that blends the prior and the conditional:

$$E\left[U^*\left(\tilde{W}(x)\right)\right]_p = \left[(\tau\sigma^2)^{-1} + \omega^{-2}\right]^{-1}\left[(\tau\sigma^2)^{-1}GSR + \omega^{-2}\mathbb{Z}_{\gamma_-\gamma_+,\lambda,\beta}\right] \tag{4}$$

where σ^2 and ω^2 are the variances for the GSR and $\mathbb{Z}_{\gamma_-\gamma_+,\lambda,\beta}$ performance measures, respectively. $\tau \in [0, \infty)$ is an uncertainty scaling parameter which acts as a weighting factor: the higher its value, the higher the level of uncertainty on the prior ordering and, therefore, the higher the relevance of the behavioral view. He and Litterman (1999), working in an asset-allocation framework, associated the prior with the equilibrium returns from the CAPM model, while the investors' view represents the conditional information. In our model, with its focus on a naive allocation, with agents interested in ranking assets to identify the best performers, the prior refers to the Sharpe Ratio, which is strictly related with the CAPM. The introduction of the behavioral perspective and the functional transformation of the corresponding returns for each agent represent novel features of our approach. We do not express the view or preference of agents in term of returns, as in Black and Litterman (1992), which might lead to question about the possible impact of the measure's scale in the mixture reported in Equation (4). We address this concern though by including a scale adjustment in the blending, where both the risk-averse and behavioral measures are divided by the respective variances. Finally, in our implementation, both the prior and the views are univariate, unlike in the Black and Litterman framework.

2.4 Setting up the empirical methodology

The purpose of our model is to determine the relationships among the evolution of the two representative agents' choices, of their blended view, and the related uncertainty factor

τ over time. Consider a market composed of K assets. We assume that the risk-averse (behavioral) investor allocates her wealth across the $M << K$ assets that have the highest GSR (Z-ratio). Note that the agents first define ranks on the basis of their reference performance measure, and then allocate on the M best performing assets. Here, agents invest in more than one asset, thus similarly to a portfolio decision or asset allocation framework. On the other side, we assume that agents are myopic as they disregard the effect of correlation across assets and do not optimize their portfolio weights.

Given the rankings, agents identify the best-performing assets (according to their maximized expected utility) to include in their portfolios. In particular, we assume that agents allocate their wealth using equal weights across a (relatively) small number of assets. Two main considerations motivated our choice of using an equally weighted allocation scheme. First, this limits the impact of portfolio weights estimation errors on the dynamic of τ. Second, it prevents from the occurrence of corner solution that alter the linkage between preferences and rankings. Moreover, DeMiguel et al. (2009) show that an equally weighted scheme is at least statistically equivalent to the Markowitz optimized portfolio, without leading to a higher Sharpe ratio. This characteristic is particularly suitable for our case.

The allocations can be carried out in terms of past performance, where the impact of the behavioral rankings is determined by an optimized criterion as a function of the uncertainty factor τ. That is, the optimal τ returns the level of uncertainty on the prior/risk-averse component (more uncertainty means that the conditioning component becomes more relevant) that provides the best past performance, according to the specified criterion.

To avoid a selection bias, we use a criterion function that does not impose (implicitly) risk-averse or risk-seeking preferences on the utility functions that are associated with the performance measures (as might happen if we consider the Sharpe ratio). Therefore, the chosen criterion is the one that evaluates past performances in terms of the cumulative returns (assuming risk neutrality) of an equally weighted portfolio in a given time window. Therefore, we set

$$r_p = \frac{1}{m} \sum_{l=t-m+1}^{t} r_{p,l}, \tag{5}$$

where $r_{p,l}$ is the time l return of the equally weighted portfolio, and m represents the time range for the portfolio evaluation (from time $t-m+1$ to time t). The portfolio is composed of the best-performing equities, according to Equation (4).

Let $\mathcal{A}_t(\tau)$ be the set that contains the M best assets selected across the K assets included in the market (with $M << K$) at time t. This set depends on the parameter τ, because a change in τ modifies the rankings produced by the agents. The set is also a function of time, because the impact of behavioral choices might change over time. Therefore, portfolio returns are represented as

$$r_{p,l} = \frac{1}{M} \sum_{j \in \mathcal{A}_t(\tau)} r_{j,l}, \tag{6}$$

where $r_{j,l}$ is the return of asset j at time l; we emphasize that the index j varies from 1 to K, although only M values are included in the set $\mathcal{A}_t(\tau)$. Because τ depends on the best-performing asset set, the portfolio cumulative return in Equation (5) is also a function of τ. The optimal choice of τ is determined by maximizing the portfolio returns, that is,

$$\begin{aligned} \max_{\tau} f(\tau) &= \frac{1}{m} \sum_{l=t-m+1}^{t} r_{p,l} \\ s.t. \quad r_{p,l} &= \frac{1}{M} \sum_{j \in \mathcal{A}_t(\tau)} r_{j,l}. \end{aligned} \tag{7}$$

The criterion function (7) is thus risk neutral, grounded on risky asset ranking based on a blend of risk-averse and behavioral preferences. Agents do not immediately react on news, but move their choices smoothly and, potentially, with some delay, as their reaction is associated with changes in asset ranks which, in turn, comes from changes on the asset performance measures. Given such a behavior, agents resemble momentum traders, as the criterion function might suggest (being an average over m points). However, the momentum effect which impact on agents choices is not standard as it refers to performance measures rather than to returns averages, and thus accounts for both "return" momentum and "risk" momentum. The optimal value τ^* provides the maximum cumulative return obtained by investing in a subset of risky assets traded in the market, then making decisions by blending the risk-averse and behavioral rankings. The estimated τ^* therefore represents the relevance of the behavioral view or, conversely, the reliability of the risk-averse ranking.[2] A high value of τ^* implies that, to obtain the optimal return, a risk-averse investor should have corrected her investment evaluations in a behavioral direction. A low value of τ^* instead implies that the investor should have continued making investment choices in accordance with her prior risk-averse ranking. The criterion function enables us to weight the components, risk-averse versus behavioral, on the basis of τ^*. Moreover, by solving Equation (7) period by period, we obtain a sequence of τ_t^* that gives further insight into the fluctuation and evolution of this factor. We regard the choice of this criterion function as quite natural, in that it focuses only on the expected return of the given portfolio, that is, a risk-neutral evaluation. Like most of the financial stress indices (Kliesen et al., 2012), the value of τ_t^* at a given time has no particular economic meaning. These indices usually capture market momentum, where it is possible to identify well-defined behaviors relative to a particular event. Our interest is, instead, on the evolution of τ_t^* over time as it describes, period by period, how closer the observed asset ranking gets to the risk-averse/behavioral ranking. Since the change in the evaluation of the two utility functions happens in the domain of losses (the behavioral agent becomes risk-seeking), we expect to capture some differences between the risk-averse and behavioral agents during turbulent periods in the market.

[2] The methodology for evaluating optimal choices when a subset of risky assets is selected from an investment universe is similar to the one adopted by Billio et al. (2015).

3 Empirical analysis

3.1 The S&P 500 in 1962–2012

As Siegel (1991) argued, the evolution of the stock market is one of the most sensitive indicators of the business cycle. Moreover, by using a bivariate model with two regimes, Hamilton and Lin (1998) found that economic recessions are the main determinant of the volatility of stock returns. Therefore, a focus on equities might help to reveal evidence about the relationship between economic and financial cycles and their association with agents' behavior.

Our reference market is composed of the equities that were in the S&P 500 index from January 1962 to April 2012. Consequently, we focus the analysis on the components of the S&P 500 market index across time. We downloaded the series of interest, the prices of the equities included in the index, from CRSP/COMPUSTAT at a monthly frequency. We recovered the US 3-Month Treasury Bill rate as a proxy for the risk–free rate.

Figure (1) illustrates the log level of the S&P 500 for the period under consideration, and the bands in the plot represent the financial crises, according to Kindleberger and Aliber (2011). Figure (2) reports the bands of economic recessions according to the National Bureau of Economic Research (NBER). Tables (1) and (2) report the timing of financial and economic crises, respectively. A match between the local minima in the log index and the bands for the financial crises is evident from the plot, as is correspondence with the economic recessions. For example, during the 1969–70 recession (the post-Vietnam era), a lower peak is clearly observable in Figure (2), which supports the notion that the financial market as a reliable indicator of the state of the economy.[3]

Table (3) presents some descriptive statistics grouped by decades. The average returns reveal that the period 1991–2000 was one of great expansion, while the period from 2000 to 2012 was one of considerable contraction in terms of average returns. The risk level of the last decade is comparable to that observed in the period 1971–1990, when oil market shocks and Black Monday occurred.

3.2 Model specification and empirical results

We apply the model introduced in Sections 2 and 3 on rolling windows of sixty monthly returns in order to take into account the time-varying structure of the returns series. Other periods can be used, but shorter periods increase the variability of performance measures and increase the rankings' uncertainty. In addition, the use of sixty months is consistent with the sample periods used to extract, for example, market factors, such as those based on long-term reversal (see Fama and French, 1996). In determining agent choices we assume they have the same wealth, set as $W = 1$, and assume that the wealth is constant over

[3] Our study does not focus on the real-time detection of changes in economic and financial cycles but on the association between them and the impact of behavioral decisions in the financial market.

each rolling window.
To implement our model and estimate the optimal value τ_t^*, we select only those assets with at least sixty observations from the 500 stocks included in the index. Thus, we exclude those with a limited history, where the evaluation of the risk-averse and behavioral performance measures, GSR and Z-ratio, might be characterized by excessive uncertainty. We obtain the variances of the performance measures using a block bootstrap procedure, setting the block size to a dimension of four in order to preserve any temporal dependence across the returns.[4] We repeat the procedure for each point (month) in time, excluding the first five years, 1962-1966, which initialize the computation. In the end, we obtain a time series of optimal values τ_t^*. Given the mixture specification, we recover a unique sequence τ_t^* which is filter by using a local-level model in a state space representation. This enables us to extract the level of the signal component, while preserving its time variation.[5] The filtering model is given as:

$$\begin{cases} \tau_t^* = \mu_t + \varepsilon_t, & \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \\ \mu_{t+1} = \mu_t + \xi_t, & \xi_t \sim N(0, \sigma_\xi^2), \end{cases} \tag{8}$$

where μ_t is the unobserved level, ε_t is the observation disturbance, and $\xi_{i,t}$ is the level disturbance at time t. We assume that both disturbances are identically and independently distributed according to a Gaussian density function. The estimated hyper-parameters of the model, using the filtered τ_t^* from the S-shaped utility function, are $\hat{\varepsilon}_{1,t} \sim N(0, 0.4547)$ and $\hat{\xi}_{1,t} \sim N(0, 0.0017)$. Figure (3) illustrates μ_t (henceforth, the filtered τ_t^*), which includes the economic recession bands according to NBER.

The first check we consider for the filtered τ_t^* refers to evaluating the significance of that quantity. For this purpose, we perform a TOBIT regression on the filtered τ_t^* by specifying the censored dependent variable in the model. Therefore, we set the lower bound equal to zero, as τ_t^* cannot be negative and will be zero when there is no uncertainty in the risk-averse component. Accordingly, we test whether the constant is significantly different from zero in the model

$$\mu_t = c + \epsilon. \tag{9}$$

Table (4) reports the results for the regressions in terms of decades and for the full sample. The filtered τ_t^* is statistically different from zero in all sub-samples and in the full sample. Other descriptive statistics included in the table show that the filtered τ_t^* series is concentrated around the mean, generally with positive asymmetry and a larger range during the 1970s and 1980s.

Examining the dynamic of the filtered τ_t^* in Figures (3) and (4) shows three local

[4] The bootstrap procedure has been applied to the returns. The measures have been computed in each iteration and the variances obtained on the cross-section of simulated measures.

[5] Thus, we filter out the noise and focus on the signal. See Durbin and Koopman (2012) for additional details on the local-level model.

maxima that coincide with the three longest economic recessions. The first is the oil crisis, 1973–1975, which corresponds to the highest value of the filtered τ_t^*. The second is the energy crisis, 1980-1982, which began during the Iranian revolution but one of the main reasons for which, according to Labonte and Makinen (2002), was the FED's monetary policy for inflation control. This energy crisis is often considered a "double-dip" recession (January 1980-July 1980) for that reason. An inflection point that is associated with this crisis in the series occurs at July 1980 and another one occurs during the crisis from December 1969 to November 1970. The last two recessions are similar to each other, as both occurred at the beginning of a decade (early 1980s and 1990s, respectively), and both were comparatively short, lasting for only eight months. In these cases, our estimated behavioral factor provides no particular pattern. The third-largest recession in the period under study is the sub-prime crisis (2007–2009) during which the level of the filtered τ_t^* after the recession begins to decay slowly, after which it remains substantially high at the beginning of the European sovereign debt crisis. We associate this finding with the increased impact of the behavioral rankings on market fluctuations during turmoil. As expected, we find that the local minima correspond with boom periods in the equity market index. For example, the first minimum is located in 1978, just before crisis in the early 1980s, and the other is located at the beginning of 2007, just before the sub-prime crisis. In the 1991–2000 the economy experienced a period of solid economic growth, where we found a relatively low dynamic in the filtered τ_t^*. In accordance with Kindleberger and Aliber (2011), Figure (4) depicts the estimated factor that includes the bands for the financial crisis. Naturally, financial and economic crises are highly interrelated and interdependent; except for the 1987 stock market crash, they follow each other in most cases. There is a local minimum in the estimated factor before the beginning of a crisis and then a local maxima during the crisis. As reported in Table (4), the periods 1971–1980 and 1981–1990 contain the highest average value and the highest average standard deviation for the filtered τ_t^*, probably because that there were two recessions in each of these decades.

Next, we analyze the relationship between the filtered τ_t^* and the systematic component of the financial market, as proxied by the equity index. Each optimal value of τ_t^* is associated with the equities included in the portfolio returns in (6) evaluated at the optimal value τ_t^*. If the mixed selection and the extrapolation of τ_t^* come from two types of investors, it should reflect the real fluctuations in the financial market and provide evidence in favor of the presence of the two categories of agents in the market. Consequently, the market returns can be explained by the portfolio returns generated by selecting the best-performing assets used to estimate τ_t^*.

In order to verify the previous argument, we estimate the following model:

$$r_{m,t} = c + \beta r_{\tau,t} + e, \tag{10}$$

where r_m is the S&P 500's return and r_τ is the return of the aggregated selection according to the optimal τ_t^*. Unlike the CAPM model, in this model the market return represents the dependent variable. Hence, according to our assumption, the model should return a high value for β and a constant that is close to zero. In the estimation, we use the equally weighted returns for the S&P 500 (the dependent variable) since the returns from the selection are defined according to an equally weighted allocation method. Table (5) reports the estimated coefficients. The constant captures the risk premium, which is slightly positive but close to zero, and the positive sign of the constant term is consistent with the hypothesis of efficiency of the market portfolio (see Sharpe, 1966; Fama, 1998). β, which is significant at the 1% confidence level, has a value close to 0.90.

We replicate the previous analysis using the S&P 100, which consists of the 100 most highly capitalized companies in the US market. In this case, we use the value-weighted return series for the S&P 100 because of the short length of the equally weighted series. We downloaded the series for the index, which is available from January 1973, from Datastream and report the results in Table (5). β is still significant at the 1% confidence interval, but it has a lower value of 0.78. The constant is not statistically significant. A lower beta in this case is reasonable because of the different underlying market focus; in fact, it is plausible that some of the selected assets are included in the S&P 500 but not in the S&P 100. However, the risk premium is not statistically different from zero, and β captures a high level of systematic risk.

As a double-check, we also conducted the analysis by considering the selection of the risk-averse agent, as implied by the GSR rankings. If we expect a that the two agents co-exist in the market, the GSR-based rankings should capture a lower systematic component of the market, that is, a lower β in the estimated model (10). Table (5) reports the results of the regression with the S&P 500 equally weighted returns and the S&P 100 value-weighted returns; the β coefficients for the returns are 0.83 and 0.64, respectively. These results confirm that the rankings provided by the aggregated measure reflect a higher systematic part of the market movements than the rankings resulting from the risk-averse utility function. Given these results, it reasonable to assume that the two types of agents co-exist in the market.

4 A Financial Interpretation of the behavioral component

That the sequence of filtered τ_t^* might reach its peaks in times of financial turbolences is in line with the approach followed to derive the indicator, as the rankings of the two agent categories are more likely to differ during economic crises and periods of finacial stress. We could also link these higher values of τ_t^* to a larger impact of the noise on agents' expectations. Since it is much more difficult to separate the true "signal" from the market, it is more likely that agents make choices based on a behavioral view. Therefore, the τ_t^* could be interpreted as a quantity associated with an agent's overall behavior in periods of market stress. To support this claim, we can relate the evolution of the τ_t^* to other indicators that monitoring the level of financial stress. As reported in Hakkio and Keeton (2009), financial stress can be viewed as an irregular functioning of financial markets. A financial stress index (FSI) captures the key features of this type of stress (i.e., increased uncertainty about fundamental value of assets, increased uncertainty about the behavior of other investors, increased information asymmetry, the flight-to-quality effect and the flight-to-liquidity effect).[6]

One popular FSI is that proposed by the Federal Reserve Bank of St. Louis (STLFSI). The STLFSI is derived from a collection of eighteen weekly data series: seven interest rate series, six yield spreads, and five financial series (such as bond indices, market volatility indices, financial ETFs and 10-year Treasury yields minus 10-year Treasury inflation-protected security yields. The STLFSI is interpreted as a measure of market uncertainty or of negative expectations of future market movements. We regress the filtered sequence τ_t^* on the STLFSI; the regression considers the changes in the two variables that are due to mild evidence of integration, which choice avoids the risk of spurious regression; the results are reported in Table (7).[7] The coefficient is statistically significant and positive, as expected. Both variables increase during turbulence. We obtain the same results by considering the Kansas City FSI (KCFSI) provided by the Federal Reserve Bank of Kansas City (Hakkio and Keeton, 2009). The main difference between the FSIs is the use of monthly data in the KCFSI. Table (7) reports the associated estimates. A potentially disappointing outcome is associated with the R-squared, which is low for both FSIs, but this result could be motivated by the fact that the assets behind the FSIs and τ_t^* differ. In fact, the former depend on mostly on bonds, while the latter derives only from equity data.

The outcome of this first regression suggests a relationship between the filtered τ_t^* and market stress. In case what the τ_t^* is capture is nothing more than market volatility or the market expectation about volatility levels, we regress our endogenously determined index on the VIX index. Table (7) includes these regression results, which show that the filtered τ_t^* captures a component that is unrelated to market volatility. In fact, the regression coefficient, despite being positive (in line with expectations), is only marginally statistically significant, and the regression provides a very low R-squared. This result supports our approach and shows that τ_t^* is not associated with the dispersion of market returns.

Despite these first intriguing results, the outcome remains unsatisfactory, particularly

[6] An FSI is generally obtained through Principal Component Analysis (PCA) on a set of indicators associated with financial stress. We do not discuss the derivation of FSI in detail but refer the reader to the cited papers for such a discussion.

[7] As a consequence of the shorter time series than those of the filtered τ_t^*, available for the STLFSI, the sample size for the regressions reported in Table (7) is shorter than the sample size of the filtered τ_t^*. Therefore, we adopted the STLFSI sample size in all regressions so results could be compared. Regressions for all the available data, with sample sizes differing across regressors, are reported as Additional Material in the Web Appendix.

with respect to the FSIs, as they are not purely equity-driven. (There is no equity-related FSI). Nevertheless, as the filtered τ_t^* captures the agent's behavior, it can be linked to market sentiment. In this case, we refer to the indices provided by Baker and Wurgler (2007), who defined investor sentiment as a belief about future asset cash flows and investment risks that is not justified in the current period. As Shleifer and Vishny (1997) indicated, betting against this sentiment is expensive and risky. Shleifer and Vishny's (1997) sentiment index combines proxies like investor mood, retail investor trades, mutual fund flows, trading volume, dividend premium, closed-end fund discount, option implied volatility, IPO first-day return, IPO volume, equity issues over total new issues, and insider trading. For the purpose of comparison, we consider the two versions of the index that Baker and Wurgler (2007) proposed: the main version (equation 3 in Baker and Wurgler, 2007, denoted hereafter as $BW^{\perp}$), which eliminates variation in the business cycle (the INDPRO, growth in consumer durable and non-durable goods, services, and a dummy variable for recessions according to NBER) from each variable of the index, and the raw version (equation 2 in BW).[8]

Table (7) shows the results for the linear regressions between our index and Baker and Wurgler's (2007) sentiment indices. Notably, the regression coefficients are not statistically significant (on both sentiment indices), and suggesting that the Baker and Wurgler (2007) indices capture different views on the market than those from the τ_t^*. An element that supports this interpretation is the approach adopted for the construction of the two indices. While Baker and Wurgler (2007) combined indicators that monitor the evolution of the market, our approach determines the τ_t^* in an endogenous manner. Therefore, it is reasonable that the views are extracted from the market data.

As further analysis of the behavior of the filtered τ_t^*, we evaluate its association with three other variables: the INDPRO, the liquidity from Pastor and Stambaugh (2001),[9] and the dummy for NBER recessions. The results are reported in Table (7), which shows the significance of the three variables, whose coefficients are in line with expectations: negative for liquidity and industrial production, as a decrease in those variables leads to an increase in the uncertainty (which we might associate with the filtered τ_t^*), and positive on the NBER recession dummy, as uncertainty is expected to be higher during recessions. Thus, we provide further evidence of the relation of the τ_t^* with both market uncertainty and stress, as monitored by the FSI, as well as with macroeconomic (or business-cycle-related) variables that can affect the evolution of the equity market. These analyses also show that our index, the filtered τ_t^*, differs from previous FSI and market sentiment indices. Finally, as a last check, we regress the filtered τ_t^* on the entire set of indicators and obtain a high

[8] Since we are considering changes in variables, the changes in sentiment measures are based on first principal components of the changes in the underlying series.

[9] This liquidity measure is obtained as an average of stock-level measures estimated with daily data. The principle behind the measure is that order flow causes larger return reversals when liquidity is lower in the market.

level of significance for the KSFSI, liquidity, industrial production, and NBER recessions. The overall R-square is close to 28% (Table (7)).
Given the findings, we believe that the filtered τ_t^* captures an endogenous market sentiment that differs from those proposed by Baker and Wurgler (2007) and from the FSI.
As a final check for this claim, we mimic the approach of Baker and Wurgler (2007), which corresponds to a regression of market returns on the sequence of filtered τ_t^*. However, to verify the relevance of our index and to ensure the robustness of the analyses' outcome — and given the fact that filtered τ_t^* provides additional information over that provided by the sentiment indices, the FSI, the VIX, and other macro-related quantities — we include all the quantities into the regressions. Selected results are reported in Table (8). Regressions are always run considering the first differences of all variables. We observe that the filtered τ_t^* is statistically significant and has a negative impact, which is expected, as the increase in the filtered τ_t^* leads to a decrease in market returns. More to the point, this result is confirmed in all regressions reported, which consider several combinations of FSI, sentiment indices, and other variables. We interpret this further evidence as a confirmation of the endogenous market sentiment interpretation of τ_t^*.

5 Robustness Checks

We perform two main checks to ensure the stability of our empirical analysis.[10] The results discussed here are shown in the associated tables included in the supplementary material. First, a change the number of assets included in the subset of the top performer, increasing K from 100 to 200[11], confirms our previous findings on the relationships among our index, the FSIs, market sentiment indices, and selected macroeconomic-related variables. Some slight differences emerge when a general regression is specified with all possible explanatory variables, but the main message is unchanged, as the filtered τ_t^* provides sentiment or uncertainty elements that are not included in other proxies for market sentiment or financial stress.

There is a vivid empirical literature that studies how investors' risk attitude is mediated by behavioral artifacts and changes over time along with the economic cycle. Guiso et al. (2013) elicited risk preferences using hypothetical lotteries in a repeated survey of Italian banks' clients and found that risk aversion increased substantially after the 2008 financial crises. Similarly, in a controlled experiment involving professionals, Cohn et al. (2015) found that, compared to expansion phases, financial crises trigger negative emotions and diminish risk-taking choices in incentivized lotteries. Together, these findings are difficult

[10]In addition to the elements described here, we also test the consistency of the assets ranking with the S-shaped utility function by varying the magnitude of the parameters as $\gamma_+ = 0.1$, $\gamma_- = -0.1$, $\lambda = 1.5$, and $\beta = \alpha = 2$. The order of ranks are invariant. Results are available upon request.

[11]We also test for $k = 50$, but given the higher turnover in the selected assets, we obtain a noise signal that is uninformative when we apply the local level model.

to reconcile with the predictions provided by the Prospect Theory, as they suggest that risk aversion is countercyclical.

As a second robustness check, we follow this literature and replicate our analysis by modifying the specification of the behavioral utility function. In particular, we assume that the preferences of the behavioral agent are now described by an inverse-S-shaped utility function with no loss aversion and that this utility function is concave in the loss domain and convex in the gain domain. The performance measures implied by the new behavioral utility function are based on the ratio proposed by Tibiletti and Farinelli (2003). The model uses the utility function proposed by Zakamouline and Koekebakker (2009b).[12] The estimations for the local level model in equation (8) for the filtered τ_t^* are $\hat{\epsilon}_{2,t} \sim NID(0, 0.1080)$ and $\hat{\xi}_{2,t} \sim NID(0, 0.0445)$.

We replicate the analyses over decades and for the entire sample, as we did in Section 4. Even in this case, the filtered τ_t^* for this utility function is statistically different from zero in all sub-samples and in the entire sample. Thereafter, we repeat the analysis for this alternative specification in terms of its association with market stress and sentiment indices and macro-finance-related variables. The results show evidence of a limited relationship between the alternative filtered τ_t^* and market stress and sentiment indices and between the alternative filtered τ_t^* and economic recession. These results corroborate our findings and the choice of the behavioral utility function made in Section 4. Finally, we consider the regressions between the market index and the alternative filtered τ_t^*, that is, those associated with 200 assets and with the inverse-S-shaped utility. The results are coherent with those from previous one, with limited relevance for the inverse-S-shaped utility filtered τ_t^*. For sake of brevity, we report the results in the Web Appendix.

6 Conclusion

By using monthly observations on the 500 components of the S&P 500 index from January 1962 to April 2012, we document a significant and time-varying behavioral component that reaches its peaks during economic and financial crises, such as the oil crisis in the 1970s and the 2009 financial burst.

Given its strong association with both financial market stress and sentiment measures, the behavioral component can be interpreted as an endogenous sentiment measure that differs from existing indices (Baker and Wurgler, 2007) in that it can be directly extrapolated from real (rather than experimental and survey) financial data. We also show that our estimated behavioral component accounts for a substantial portion of the unexplained variability of the market returns, even after controlling for a large number of standard financial and economic controls.

[12]To obtain this utility function, the parameters are $\gamma_+ = -\alpha, \gamma_- = \beta, 1_+ = 0, 1_- = 0, \lambda = 1.5, \alpha = 1.5$ and $\beta = 2$.

The flexibility of our methodology allows us to assess how results change when the underlying behavioral utility function is replaced with a different specification. Estimates from the S-shaped utility function with procyclical risk aversion account better for the evolution of the S&P 500 than do estimates from a reverse S-shaped specification with countercyclical risk aversion.

We believe that our results are also informative for researchers interested in corporate disclosure which involves the flow of information from firms to stakeholders (Healy and Palepu, 2001). Even if our measure behaves as a classical financial stress index (an increase of our behavioral component is associated with a market stress), it is intimately related to sentiment indicators. As much as investor sentiment captures the beliefs about future asset cash flows (Baker and Wurgler, 2007), τ_t^* reflects the extent to which fluctuations in the financial market can be exploited by investment decisions of behavioral agents. The existing relationship between corporate finance and sentiment indicators has been deeply investigated in the literature. For example, Bergman and Roychowdhury (2008) show that there is a strategic adjustment in the corporate disclosure policy as a response to the sentiment in the market. Brown et al. (2012) find that the propensity to disclose an adjusted earnings metric is related to the level of sentiment: the higher the level of the sentiment index, the more managers tend to over-report adjusted earnings (above what prescribed by the Generally Accepted Accounting Principles - GAAP). Moreover, sentiment indicators affect the degree of mispricing in different market contexts and influence analysts' forecasts in both the short and the long term (**??**).

Our findings are in line with this price effect as we document that an increase of the behavioral component is associated with a decrease in market returns. τ_t^* represents a factor that can influence corporate disclosure providing insight about the lead lag effect between the investor sentiment and the information disclosed by companies. Further analysis on the measure should provide evidence about the role of the behavioral component in corporate disclosure in the above mentioned stream of literature (i.e., opportunistic behavior).

References

Baker, M. and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2):129–151.

Barberis, N. and Thaler, R. (2003). *Handbook of the Economics of Finance*, volume 1, chapter A survey of behavioral finance, pages 1053–1128. Elsevier.

Bergman, N. K. and Roychowdhury, S. (2008). Investor sentiment and corporate disclosure. *Journal of Accounting Research*, 46(5):1057–1083.

Billio, M., Caporin, M., and Costola, M. (2015). Backward/forward optimal combination of performance measures for equity screening. *The North American Journal of Economics and Finance*, 34:63–83.

Black, F. and Litterman, R. (1992). Global portfolio optimization. *Financial Analysts Journal*, 48(5):28–43.

Brown, N. C., Christensen, T. E., Elliott, W. B., and Mergenthaler, R. D. (2012). Investor sentiment and pro forma earnings disclosures. *Journal of Accounting Research*, 50(1):1–40.

Cohn, A., Engelmann, J., Fehr, E., and Maréchal, M. A. (2015). Evidence for countercyclical risk aversion: an experiment with financial professionals. *The American Economic Review*, 105(2):860–885.

De Long, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, 98(4):703–738.

DeMiguel, V., Garlappi, L., and Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/n portfolio strategy? *Review of Financial Studies*, 22(5):1915–1953.

Durbin, J. and Koopman, S. J. (2012). *Time series analysis by state space methods*. Oxford: University Press.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, 49(3):283–306.

Fama, E. F. and French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance*, 51(1):55–84.

Fishburn, P. C. (1977). Mean-risk analysis with risk associated with below-target returns. *American Economic Review*, 67(2):116–126.

Grossman, S. J. and Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *American Economic Review*, 70(3):393–408.

Guiso, L., Sapienza, P., and Zingales, L. (2013). Time varying risk aversion. Technical report, National Bureau of Economic Research.

Hakkio, C. S. and Keeton, W. R. (2009). Financial stress: What is it, how can it be measured, and why does it matter? *Economic Review*, 94(2):5–50.

Hamilton, J. D. and Lin, G. (1998). Stock market volatility and the business cycle. *Journal of Applied Econometrics*, 11(5):573–593.

He, G. and Litterman, R. (1999). The intuition behind black-litterman model portfolios. *Goldman Sachs Investment Management Series*.

Healy, P. M. and Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, 31(1):405–440.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *The Journal of Finance*, 56(4):1533–1597.

Hodges, S. (1998). A generalization of the sharpe ratio and its applications to valuation bounds and risk measures. Technical report.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–292.

Kindleberger, C. P. and Aliber, R. Z. (2011). *Manias, panics and crashes: a history of financial crises*. Palgrave Macmillan.

Kliesen, K. L., Owyang, M. T., and Vermann, E. K. (2012). Disentangling diverse measures: A survey of financial stress indexes. *Federal Reserve Bank of St. Louis Review*, 94(5):369–398.

Labonte, M. and Makinen, G. (2002). The current economic recession: How long, how deep, and how different from the past? Technical report, Congressional Research Service.

Lamont, O. A. and Thaler, R. H. (2003). Anomalies: The law of one price in financial markets. *Journal of Economic Perspectives*, 17(4):191–202.

LeRoy, S. F. and Werner, J. (2000). *Principles of Financial Economics*. Cambridge: Cambridge University Press.

Malmendier, U. and Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics*, 126(1):373–416.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, 7(1):77–91.

Morgenstern, O. and Von Neumann, J. (1953). *Theory of games and economic behavior*. Princeton NJ: Princeton University Press.

Pastor, L. and Stambaugh, R. F. (2001). Liquidity risk and expected stock returns. Technical report, National Bureau of Economic Research.

Sharpe, W. F. (1966). Mutual fund performance. *Journal of Business*, 39(1):119–138.

Shleifer, A. and Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance*, 52(1):35–55.

Siegel, J. J. (1991). Does it pay stock investors to forecast the business cycle? *Journal of Portfolio Management*, 18(1):27–34.

Starmer, C. (2000). Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *Journal of Economic Literature*, 38(2):332–382.

Tibiletti, L. and Farinelli, S. (2003). Upside and downside risk with a benchmark. *Atlantic Economic Journal*, 31(4):387–387.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4):297–323.

Zakamouline, V. (2014). Portfolio performance evaluation with loss aversion. *Quantitative Finance*, 14(4):699–710.

Zakamouline, V. and Koekebakker, S. (2009a). A generalisation of the mean-variance analysis. *European Financial Management*, 15(5):934–970.

Zakamouline, V. and Koekebakker, S. (2009b). Portfolio performance evaluation with generalized sharpe ratios: Beyond the mean and variance. *Journal of Banking & Finance*, 33(7):1242–1254.

Zeeman, E. C. (2007). On the unstable behaviour of stock exchanges. *Journal of Mathematical Economics*, 1(1):39–49.

Tables

Crisis	Start date	End Date
1973 Oil Crisis	29-Oct-73	03-Oct-74
1987 Stock Market Crash	19-Oct-87	30-Dec-88
2000 Dotcom Bubble Burst	10-Mar-00	16-Apr-01
2001-9-11 Terrorist Attack	11-Sep-01	09-Oct-02
Subprime Crisis	03-Dec-07	09-Mar-09

Table 1: Financial crises in the U.S. (Kindleberger and Aliber, 2011).

Dates (Quarters)		*DURATION IN MONTHS*
December 1969(IV)	November 1970 (IV)	11
November 1973(IV)	March 1975 (I)	16
January 1980(I)	July 1980 (III)	6
July 1981(III)	November 1982 (IV)	16
July 1990(III)	March 1991(I)	8
March 2001(I)	November 2001 (IV)	8
December 2007 (IV)	June 2009 (II)	18

Table 2: Economic recessions in the U.S. (NBER, available at http://www.nber.org/cycles.html).

Period	*1962-1970*	*1971-1980*	*1981-1990*	*1991-2000*	*2001-2012*	*All-Sample*
Mean	0.0035	0.0043	0.0086	0.0124	0.0015	0.0060
Std	0.0384	0.0457	0.0474	0.0385	0.0466	0.0437
Skewness	-0.2874	0.1588	-0.6839	-0.5130	-0.5711	-0.4108
Kurtosis	2.9520	4.2453	6.5393	4.4303	3.7890	4.7155
Min	-0.0905	-0.1193	-0.2176	-0.1458	-0.1694	-0.2176
Max	0.1016	0.1630	0.1318	0.1116	0.1077	0.1630

Table 3: Descriptive statistics on the S&P 500 index between Jan 1962 and Apr 2012.

Year	*1962-1970*	*1971-1980*	*1981-1990*	*1991-2000*	*2001-2012*	*All-Sample*
c	1.0038	1.3851	1.1955	1.0109	1.0388	1.1408
$s.e$	0.0665	0.1543	0.1236	0.0266	0.0762	0.0303
pValue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Skewness	-0.0696	0.0503	0.5803	0.0002	0.0308	1.0816
Kurtosis	2.1024	1.8382	1.7605	1.9997	1.8031	3.2658
Min	0.8869	1.1180	1.0632	0.9636	0.9127	0.8869
Max	1.1178	1.6505	1.4258	1.0632	1.1619	1.6505

Table 4: Descriptive statistics on the filtered τ_t^* when the behavioural agent is endowed with an S-shaped utility function and $k = 100$. The table also reports (TOBIT) estimates (with robust standard errors) from regressing the behavioural component on the constant.

Dependent	S&P500	
Intercept	0.0037***	0.0025***
	(0.0009)	(0.0007)
$r_{\tau^*,t}$	0.9049***	
	(0.0175)	
r_{GSR}		0.883***
		(0.0121)
Adjusted-R-squared	0.8322	0.8976

Table 5: The first column reports results from regressing the S&P 500 index (equally weighted) on the returns of the $k = 100$ assets associated with τ_t^*. The second column reports results from regressing the S&P 500 index (equally weighted) on the highest returns of the assets selected according to the GSR. Robust standard errors are reported in the table. Significance levels are denoted as follows: $^* : p < 0.1$; $^{**} : p < 0.05$; $^{***} : p < 0.01$.

Parameter	Value	S.E	t-stat
(constant)	1.1839***	0.0106	111.9840
nEs_t	0.0020***	0.0005	4.2610
$aggEsAR(1)_{t,+}$	-0.1316***	0.0306	-4.3029
$aggEsAR(1)_{t,-}$	-0.0899***	0.0257	-3.4935
Adj-R^2	0.0737	obs	495

Table 6: Results from regressing the filtered τ_t^* on the number of earnings announcements in a given month (nEs_t) and both the positive and the negative indicators for the earnings announcements surprise in quarter t, $aggEsAR(1)_{t,+}$ and $aggEsAR(1)_{t,-}$. Robust standard errors are reported in the table.

	$\Delta\tau_t^*$									
(Intercept)	0.0006*	0.0006*	0.0006*	0.0006*	0.0010***	0 .0000	-0.0002	0.0006*	-0.0014	0.0001**
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0007)	(0.0004)
$\Delta BW^{\perp}$	-0.0004									
	(0.0003)									
ΔBW		0.0000								
		(0.0003)								
ΔSTLFSI			0.0040***							
			(0.0013)							
ΔKCFSI				0.0037***						0.0033***
				(0.0013)						(0.0009)
INDPRO					-0.0027***					-0.0013**
					(0.0006)					(0.0006)
LIQ						-0.0191***				-0.0090**
						(0.0060)				(0.0044)
NBER							0.0064***			0.0047***
							(0.0016)			(0.0011)
ΔVIX								0.0141*		
								(0.0121)		
$\Delta MDLI$									0.0927***	
									(0.0369)	
R^2	0.0088	0.0001	0.0702	0.0668	0.1161	0.0821	0.1774	0.0150	0.0480	0.2842
Adj-R^2	0.0039	0.0001	0.0656	0.0622	0.1117	0.0776	0.1733	0.0101	0.0432	0.2698
AIC	-1566.0575	-1564.284	-1579.039	-1578.3084	-1589.3132	-1581.6601	-1603.8963	-1567.3307	-1574.2433	-1626.1488
BIC	-1559.4311	-1557.6576	-1572.4126	-1571.6819	-1582.6868	-1575.0337	-1597.2699	-1560.7043	-1567.6169	-1609.5828
Sample	199402	199402	199402	199402	199402	199402	199402	199402	199402	199402
	201012	201012	201012	201012	201012	201012	201012	201012	201012	201012

Table 7: Results from regressing $\Delta\tau_t^*$ (with $k = 100$) on different economic, financial, and sentiment indicators between Feb 1994 and Dec 2010 (203 observations). Robust standard errors are reported in the table. Significance levels are denoted as follows: $^*: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$.

	r_{mkt}		
(Intercept)	0.0060*	0.0110***	0.0059***
	(0.0031)	(0.0024)	(0.0022)
$\Delta\tau_t^*$	-1.9375***		-1.1889***
	(0.7658)		(0.5093)
$\Delta BW^{\perp}$			
ΔBW		0.0074***	0.0068***
		(0.0020)	(0.0027)
ΔSTLFSI			
ΔKCFSI			
INDPRO			
LIQ		0.0828***	
		(0.0287)	
NBER		-0.0250***	
		(0.0065)	
ΔVIX		-0.6928***	-0.6922***
		(0.0492)	(0.0612)
R-squared	0.0461	0.5694	0.5273
Adjusted-R-squared	0.0413	0.5607	0.5201
AIC	-680.536	-835.938	-819.0185
BIC	-673.909	-819.371	-805.7657

Table 8: Results from regressing the S&P 500 market returns (r_{mkt}) on $\Delta\tau_t^*$ (with $k = 100$) and other economic, financial, and sentiment indicators between Feb 1994 and Dec 2010 (203 observations). Robust standard errors are reported in the table. Significance levels are denoted as follows: $^*: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$.

Figures

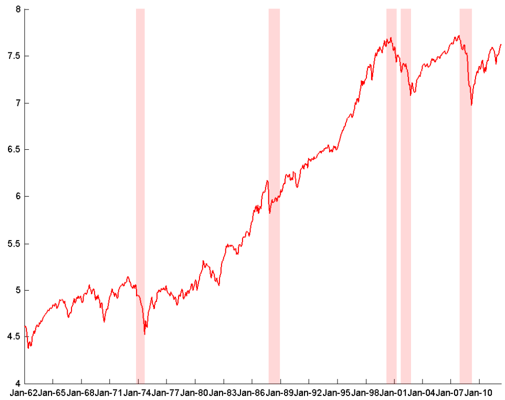

Figure 1: Log levels of the S&P 500 index between Jan 1962 and Apr 2012. Bands denote financial crises (Kindleberger and Aliber, 2011).

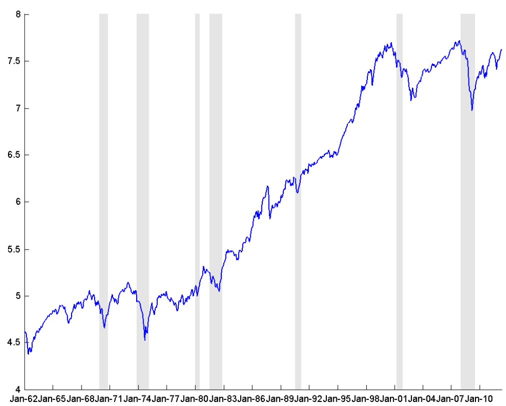

Figure 2: Log levels of the S&P 500 index between Jan 1962 and Apr 2012. Bands denote economic recessions (NBER).

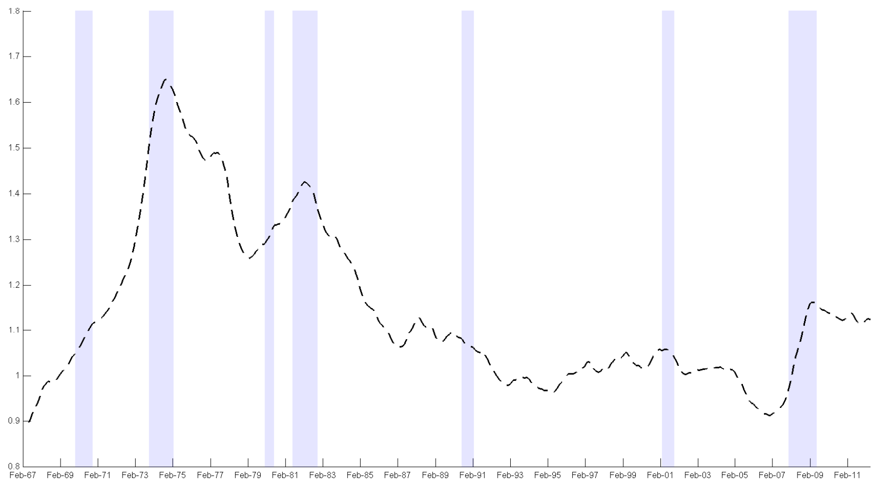

Figure 3: Filtered τ_t^*. Bands denote economic recessions in the U.S. (NBER).

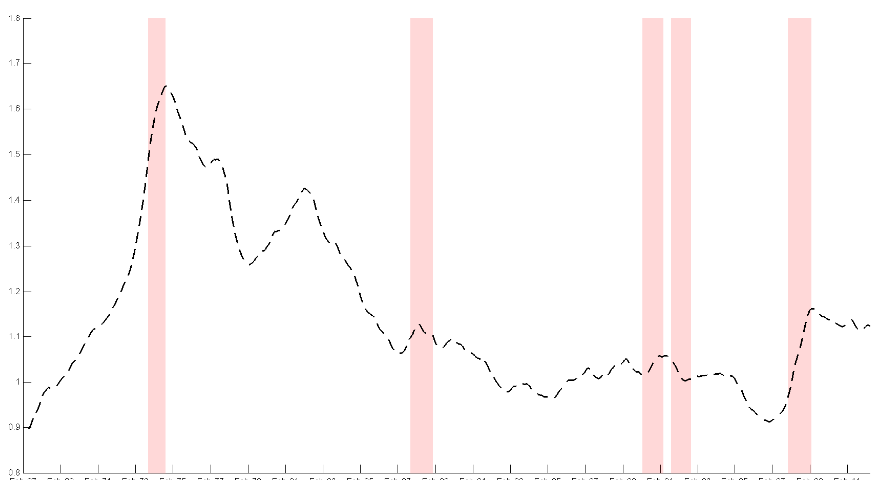

Figure 4: Filtered τ_t^*. Bands denote financial crises in the U.S. (Kindleberger and Aliber, 2011).