# Investors’ Uncertainty and Stock Market Risk

(*Journal of Behavioral Finance*, Forthcoming)

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May 2018

**Abstract**

We propose a novel approach to model investors' uncertainty using the conditional volatility of investors' sentiment. Working with weekly data on investor sentiment, six major U.S. stock indices, and alternative measures of uncertainty, we run various tests to validate our proposed measure. The estimates show that investors' uncertainty is greater during economic downturns, and it is linked with lower investors' sentiment. In addition, the results support the existence of a positive conditional correlation between sentiment and returns. This positive spillover between sentiment and returns is interpreted as a positive link between investors' uncertainty and market risk. We also find that investors’ uncertainty and market risk are strongly driven by their lagged values. Our measure consistently captures periods of high uncertainty as shown by a positive and highly statistically significant correlation with other existing measures of uncertainty.

*JEL Classification:* G20, G21, G23
*Keywords:* Conditional Volatility; Dynamic Correlation; DCC-GARCH; Investors’ Uncertainty; Sentiment; Stock Market Risk

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## 1. Introduction

The economics of uncertainty is of great importance in finance for both researchers and practitioners as it has helped us to understand how investors make decision in the presence of uncertainty. Following Knight (1921) that distinguished the notion of uncertainty from risk, a strand of literature emerged to conceptualize uncertainty and its impact on asset prices.[1] In the wake of the recent financial crisis, understanding investors' uncertainty and its possible link to stock market and the broader economy has gained even more attention. Ozuguz (2009) studies investors' uncertainty and stock returns by empirically examining the dynamics of investors' beliefs about the state of the economy. Anderson, Ghysels and Juergens (2009) examine the impact of risk and uncertainty on stock returns, while Pastor and Veronesi (2012 and 2013), and Kang and Ratti (2013) investigate the role of policy uncertainty in explaining the variability of stock returns. Moreover, Bali, Brown and Tang (2014) introduce an index of macroeconomic uncertainty and examine its impact on stock returns, and Andrei and Hasler (2015) theoretically and empirically find that investors' attention and uncertainty are key determinants of asset prices.

Despite the growing evidence on the importance of uncertainty, the inherent difficulty in measuring uncertainty remains a challenge for those studying this concept. Considering that uncertainty is an intrinsically unobservable concept, prior studies have used different methods such as implied volatility of stock returns (Leahy and Whited, 1996; Bloom et al., 2007), volatility shocks of stock returns (Bloom, 2009), conditional volatility of Bayesian filter of macro-fundamentals (Ozugus, 2009), conditional volatility of macro-variables using both macro

[1] See, for example, Trojani and Vanini, (2004), Bloom, Bond and Van Reenen (2007), Brock, Durlauf and West (2007), Epstein and Schneider (2007), Epstein and Schneider (2008), Bloom (2009), Pástor and Veronesi (2012, 2013), Bloom (2014), Kast, Lapied and Roubaud (2014), Mele and Sangiorgi (2015), Jurado, Ludvigson and Ng (2015), and Baker, Bloom and Davis (2016).

and firm-level datasets (Jurado et al., 2015), and newspaper coverage frequency of certain keywords (Baker et al., 2016) to measure uncertainty.

Our novel approach involves capturing investors' uncertainty by estimating the conditional volatility of a widely used measure of sentiment, the bull-bear spread in Investors Intelligence survey (II Sentiment). Our measure captures the dispersion in expectations of market participants, which we interpret as investors' uncertainty about the future. With this new measure, we set to study the link between investors' uncertainty and stock market risk. We measure stock market risk as the conditional volatility of major stock market indices (Center for Research in Security Prices, CRSP; New York Stock Exchange, NYSE; American Stock Exchange, AMEX; National Association of Securities Dealers Automated Quotations, NASDAQ; Dow Jones Industrial Average, DJIA; and the S&P500).

Conditional volatilities of both stock returns and sentiment are initially estimated using the popular Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and GARCH-in-mean models (Engle, 1982; Bollerslev, 1986 and 1987; Engle et al., 1987). Lee, Jiang and Indro (2002) also use II sentiment in a GARCH framework to show the impact of sentiment on the conditional volatility of stock returns.[2] To study the time varying correlation between investors' uncertainty and stock market risk, we employ the Dynamic Conditional Correlation GARCH (DCC-GARCH) method (Engle, 2002). Our data on sentiment and stock market indices goes from July 1987 through December 2012. According to National Bureau of Economic Research (NBER), there are three recession periods in our sample. Therefore, this sample period allows us to observe the dynamics of investors' uncertainty and risk during recession and non-recession periods.

[2] There is a growing literature that

The contribution of this paper is important as we capture the dynamics between investor's uncertainty and stock market risk. Although the conventional view in finance ignores the possible role of investors' uncertainty in an efficient market (Friedman, 1953; Fama, 1965) or capital asset pricing models assume that all investors have homogenous expectations about expected returns (Sharpe, 1964; Lintner, 1965), the behavioral view shows that investors' uncertainty (i.e., changes in the dispersion of sentiment) or increased investors' heterogeneity can induce systematic risk (Lee, Shleifer and Thaler, 1991) and move asset prices not only in short-run but also in the long-run (Shleifer and Summers, 1990). Our modeling approach is consistent with Black (1986), who points out that uncertainty about the future makes financial markets imperfect and somewhat inefficient. We expect investors' uncertainty to be linked to stock market risk: uncertainty creates "noise", which stimulates investors' physiological biases (Daniel, Hirshleifer and Subrahmanyam, 1998), making investors more prone to irrationally trade on "noise" versus information. In the presence of noise trading, prices drift further from the fundamentals (Zhang, 2006), which results in higher liquidity in terms of trading volume (Greene and Smart, 1999) and consequently higher risk.[3]

We find statistically significant conditional volatility in investors' sentiment. To the best of our knowledge we are the first to study and document the importance of this volatility. In addition, we find strong evidence that investors' uncertainty and risk have a significant positive time-varying conditional correlation across all indices. This indicates that investors' uncertainty transmits to stock market. In the presence of uncertainty, investors have higher psychological

[3] Using *The Wall Street Journal*'s "Investment Dartboard" column as a proxy for noise trading, Greene and Smart (1999) find a substantially higher trading volume for analyst recommended stocks in this column.

biases (Daniel et al., 1998), are more likely to trade irrationally, which push prices further away from fundamentals (Zhang, 2006) and consequently increase the volatility of stock market.

Our measure of investors' uncertainty is consistent with known alternative approaches to capture uncertainty. We observe a relatively high and statistically significant correlation (at the 1% level) between our measure of uncertainty and Jurado et al. (2015)'s Macro Uncertainty and Baker et al. (2016)'s Economic Policy Uncertainty. More importantly, all measures consistently capture periods of high uncertainty such as the Black Monday of 1987, the recession of the early 1990s, the terrorist attacks of September 11 of 2011 and the recession of the early 2000 and the recent financial crisis of 2007-2009.

Our results are consistent with the important strand of literature that examines the impact of investors' sentiment and uncertainty on stock market. Lee et al. (2002) suggest sentiment as a significant factor in explaining the conditional volatility of stock returns. Ozuguz (2009) shows a negative relationship between investors' uncertainty and asset values. Anderson, et al., (2009) empirically examine the impact of risk and uncertainty on stock returns. After finding evidence for uncertainty-return trade-off compared to the traditional risk-return trade-off, they test how uncertainty and risk are priced in the cross section of stock returns. Pástor and Veronesi (2013) develop a general equilibrium model to show that political uncertainty commands a risk premium with a larger magnitude during economic downturns. Bali et al. (2014) find evidence of a significant negative relation between investors' uncertainty and stock returns. In addition, they argue that investors' uncertainty and negative market volatility risk premium are not the same. Andrei and Hasler (2015) show investors' attention and uncertainty increase the volatility of stock return and risk premia. In addition, our results are consistent with previous work on how risk is strongly driven by lagged values. For our measure of investors' uncertainty, the highly statistically significance of the autoregressive terms provide strong evidence of momentum in investors' uncertainty.

The remainder of the paper proceeds as follows. Section 2 describes the data while Section 3 presents the model to characterize the dynamics of sentiment and investors' uncertainty. We also propose a joint estimation of returns, sentiment, market risk, and investors' sentiment. Section 4 presents and discusses the results. Section 5 concludes.

## 2. Data

The dataset we use in this paper is obtained in weekly intervals from July 1987 through December 2012 from Datastream. We use Investors Intelligence (II), which is a widely cited measure of sentiment that collects investors' opinion every week (See, e.g., Solt and Statman, 1988; Clarke and Statman, 1988; Lee, Jiang and Indro, 2002; Brown and Cliff, 2004; Verma and Soydemir, 2006; and Johnk and Soydemir, 2015). Every Wednesday, editors of Investors Intelligence report the percentage of bullish, bearish, or neutral investors, based on the previous Friday's newsletters' recommendations. We also obtain the returns of six major stock indices, namely, CRSP, NYSE, AMEX, NASDAQ, S&P500 and DJIA from Datastream as proxies for the overall performance of the stock market. Returns are calculated as 100 times the natural logarithm difference of indices.[4] CRSP returns are available on Professor Kenneth French's data library.[5] We use National Bureau of Economic Research (NBER) recession dummy variable obtained from the Federal Reserve Bank of St. Louis to distinguish between recession and non-recession periods.

[4] $R_t = (Log\ I_t - Log\ I_{t-1}) \cdot 100$, where $R_t$ is the return of during week $t$, $I_t$ is the index and $Log$ is the natural logarithm.
[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 1 reports the descriptive statistics for II sentiment and stock indices. As reported in Panel A, CRSP, which is the proxy for the whole stock market, has the highest (0.19) and NYSE has the lowest (0.11) average returns. In terms of standard deviation, NASDAQ is the most (3.19) and AMEX is the least (2.28) volatile index. All indices are negatively skewed; CRSP has the lowest (-0.68) and AMEX has the highest (-1.93) level of skewness. All indices also have a large positive kurtosis; CRSP has the lowest (8.95) and AMEX has the highest (27.32) level of kurtosis. Panels B and C suggest higher average returns and lower volatility for non-recession periods, consistent with GARCH-in-mean literature (see, e.g., Engel, Lilien, & Robins, 1987). Figure 1 presents the time series graph of investors' opinion (II sentiment). Consistent with Panels B and C, II sentiment index appears to have a lower mean and a higher volatility during recessions. This is in line with the notion that investors are more bearish during recession periods, and more important for the purpose of this paper, it shows some evidence that volatility in the sentiment can be linked to high uncertainty during these periods.

## 3. Modeling Investors' Uncertainty and Stock Market Risk

### *3.1. Sentiment Dynamics and Defining Investors' Uncertainty*

Miller (1977, p.1151) explains that in practice the concept of uncertainty implies that reasonable men may differ in their forecasts. This idea is consistent with the construction of the sentiment index as Brown and Cliff (2004, p. 2) explain that the sentiment represents the expectations of market participants relative to a norm or average market performance: a bullish (bearish) investor expects returns to be above (below) average. Ideally at each point in time, we would like to observe the divergence of opinion across investors and then obtain a measure of investors' uncertainty based on the dispersion of opinions. However, at each time we only have a single measure of the average sentiment.

To be able to capture a measure of investors' uncertainty consistent with Miller (1977) and Brown and Cliff (2004), we model the dynamics of the sentiment as well as its conditional volatility. The mean dynamics of the sentiment series captures the norm, or how average sentiment evolves over time, while the conditional volatility captures investors' uncertainty. Formally, let $S_t$ be investors' sentiment at time $t$ as obtained by the Investors Intelligence survey (sentiment index). Then we model the mean dynamics of this sentiment index as

$$S_t = \omega_0 + \sum_{i=1}^{p_1} \omega_{1,i} S_{t-i} + \sum_{i=1}^{p_2} \omega_{2,i} \varepsilon_{t-i} + \omega_4 U_t + \varepsilon_t \tag{1}$$

which is just a general form of an autoregressive moving average process of orders $p_1$ and $p_2$. The shocks $\varepsilon_t$ to investors' sentiment have mean zero and variance $\sigma_t^2$. Moreover, $U_t$ denotes the investors' (conditional) uncertainty and it is modeled as

$$U_t \equiv \sigma_t^2 = \sum_{i=1}^{p_3} \vartheta_{1,i}\, \varepsilon_{t-i}^2 + \sum_{i=1}^{p_4} \vartheta_{2,i} \sigma_{t-i}^2 + e^{(\vartheta_3 + \vartheta_4 I_{NBER})} \tag{2}$$

which is the conditional volatility of $\varepsilon_t$.

The system of equations (1) and (2) that model the joint dynamics of investors' sentiment $S_t$ and investors' uncertainty $U_t$ can be viewed as a GARCH-in-mean process augmented with $e^{(\vartheta_3 + \vartheta_4 I_{NBER})}$. $I_{NBER}$ is an indicator variable equal to one when the economy is in an NBER recession, zero otherwise. Hence $\vartheta_4$ is aimed to capture any potential effect of recession on investors' uncertainty. The vector of parameters $(\omega_0, \omega_1', \omega_2', \omega_4, \vartheta_0, \vartheta_1', \vartheta_2', \vartheta_3, \vartheta_4)$ on equations (1) and (2) with $\omega_j' = (\omega_{j,1}, \omega_{j,2}, \dots, \omega_{j,p_j})$ and $\vartheta_j' = (\vartheta_{j,1}, \vartheta_{j,2}, \dots, \vartheta_{j,p_j})$ for $j = 1,2$ will be estimated jointly via maximum likelihood. Investors' uncertainty $U_t$ is interpreted as the bull-bear spread of the sentiment $S_t$ and captures divergence of opinion among market participants, and hence, captures investors' uncertainty about the market.[6]

Figures 1 and 2 appear to suggest that both, investor sentiment and index returns, posit unusually large volatility in some periods. Hence estimation of the dynamics of the mean of any of these series is likely have heteroskedastic errors. Popular tools to model episodes of higher conditional volatility are the ARCH and GARCH models of Engle (1982) and Bollerslev (1987). In addition, DCC - GARCH method would be appropriate to study the link between both series in addition to modeling their volatilities.

*3.2. Joint Dynamics of Sentiment, Uncertainty, Returns, and Risk*

We now turn to explain how this modeling approach helps us identify the link between investors' uncertainty and stock market risk. The idea is that in addition to modeling the dynamics of sentiment $S_t$ and uncertainty $U_t$, we can augment the model with returns and risk. Consider the following system of two mean equations for stock return and investors' sentiment:

$$R_t = \gamma_{R,0} + \gamma_{R,1} R_{t-1} + \delta_{R,1} S_{t-1} + \varepsilon_{Rt} \quad (3)$$

$$S_t = \gamma_{S,0} + \gamma_{S,1} R_{t-1} + \delta_{S,1} S_{t-1} + \varepsilon_{St} \quad (4)$$

where $R_{it}$ is the return and as before $S_t$ is the sentiment. This simple vector autoregressive specification allows us to capture the joint mean dynamic of both series, while at the same time modeling heteroskedastic variances and a time dependent covariance between the error terms.

[6] Newsletters employed to construct the index are written by (current or retired) sophisticated investors and market experts, hence, II bull-bear spread can be considered as a proxy for institutional investors' sentiment (Brown and Cliff, 2004). On the other hand, newsletters recommendation are primarily targeting and influencing individual investors, hence, II bull-bear spread depicts the changing mood of individual investors (Lee, Jiang and Indro, 2002).

Let the vector of two error terms $\varepsilon_t = [\varepsilon_{Rt}, \varepsilon_{St}]'$ have a conditional time-variant variance-covariance matrix $H_t$ given by

$$H_t = \begin{bmatrix} E_{t-1}(\varepsilon_{Rt}^2) & E_{t-1}(\varepsilon_{Rt}\varepsilon_{St}) \\ E_{t-1}(\varepsilon_{St}\varepsilon_{Rt}) & E_{t-1}(\varepsilon_{Rt}^2) \end{bmatrix} \equiv \begin{bmatrix} K_t & E_{t-1}(\varepsilon_{Rt}\varepsilon_{St}) \\ E_{t-1}(\varepsilon_{St}\varepsilon_{Rt}) & U_t \end{bmatrix} \quad (5)$$

where we capture market risk as the conditional variance of market return, $K_t \equiv E_{t-1}(\varepsilon_{Rt}^2)$, and as before investors' uncertainty is captured by the conditional variance of sentiment, $U_t \equiv E_{t-1}(\varepsilon_{St}^2)$. We assume that the vector of error terms follow a multivariate normal distribution, $\varepsilon_t | \Omega_{t-1} \sim N(0, H_t)$, that we use to model the dynamics of the variance-covariance matrix $H_t$. For the estimation it helps to specify $H_t$ as

$$H_t = D_t P_t D_t \quad (6)$$

where $D_t$ is a $(2 \times 2)$ diagonal matrix that contains the time-varying standard deviations from univariate GARCH models with $\sqrt{h_{ii,t}}$ on the $i$th diagonal, for $i = 1,2$. The main elements of interest are the off-diagonal elements of the $(2 \times 2)$ time-varying $P_t$ correlation matrix. We follow Engle (2002) and use a two-step approach to estimate the elements of $H_t$. In the first step we use univariate GARCH models in each of the equations (3) and (4) to obtain the standard deviations in $D_t$. In the second step we adjust the first step residuals using $u_{it} = \varepsilon_{it}/\sqrt{h_{ii,t}}$, and then use these adjusted residuals to obtain the conditional correlation coefficients. The time-varying variance-covariance matrix of $u_{it}$ is given by

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \quad (7)$$

This is a $(2 \times 2)$ matrix with $\alpha$ and $\beta$ being non-negative scalars. We estimate equation (7) under the restriction that $\alpha + \beta < 1$. $\bar{Q}$ is the unconditional variance-covariance matrix of $u_t$ and we can simply write it as $\bar{Q} = E(u_t u'_t)$. This estimation does not restricts the main diagonal elements of $P_t$ to be equal to one. To make sure this is true, we need to rescale $P_t$ :

$$P_t = \text{diag}\left(\frac{1}{\sqrt{q_{11,t}}}, \frac{1}{\sqrt{q_{22,t}}}\right) Q_t \text{diag}\left(\frac{1}{\sqrt{q_{11,t}}}, \frac{1}{\sqrt{q_{22,t}}}\right) \tag{8}$$

where $q_{11,t}$ and $q_{22,t}$ are just the diagonal elements of $Q_t$. Then absolute value of the off-diagonal elements of $P_t$ will be less than one and the diagonal elements of $P_t$ will be equal to one as long as $Q_t$ is positive definite. Following equation (8), the time-varying correlation coefficients between sentiment $S_t$ and index returns $R_t$ will be the off-diagonal element of $P_t$ and will be given by $\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t} \times q_{jj,t}}$ for $i, j = 1,2$ when $i \neq j$.

The maximum likelihood is then given by:

$$\begin{aligned} l_t(\theta, \varphi) = -\sum_{t=1}^{T} (n \log(2\pi) + \log|D_t|^2 + \varepsilon'_t D_t^{-2} \varepsilon_t) \\ - \sum_{t=1}^{T} (\log|P_t| + u'_t R_t^{-1} u_t - u_t u'_t) \end{aligned} \tag{7}$$

where $\theta$ is the vector of coefficients to be estimated that belongs to the matrix $D_t$, and $\varphi$ is the vector of coefficient of interest that belongs to $P_t$. In Engle (2002)'s two-step approach the first component of the right-hand side serves to estimate $\theta$. Given the estimates of $\theta$ in the second step the estimation of $\varphi$ comes from the second component on the right-hand side.

## 4. Empirical Results

### *4.1. Sentiment and Uncertainty*

We start with the estimation of the dynamics of investors' sentiment in equation (1) without modeling uncertainty, i.e., $\varepsilon_t$ is assumed to be homoscedastic and $\omega_4$ is set to be equal to zero.[7] We use the Bayesian Information Criterion (BIC) to obtain the optimal orders $p_1$ and $p_2$ as reported in Table A.1 in the Appendix. The minimum BIC is obtained for the values of $p_1 = 2$ and $p_2 = 0$, and following Lo and Piger (2005) we will use those values for the rest of the paper.

Before turning to the joint estimation of equations (1) and (2) we need to test for the existence of ARCH errors in equation (1). Following the format of Breusch-Pagan test for heteroscedasticity in $\varepsilon_t$, Column 4 of Table 3 reports the Ljung-Box Q-statistics of the squared fitted error terms of equation (1). The relatively large Q-statistics at different displacements associated with small p-values show strong evidence to reject the null of homoscedastic errors. We interpret this result as strong empirical support for the importance of the dynamics of investors' uncertainty $U_t$.

The different columns of Table 4 report various specifications of the maximum likelihood joint estimation of equations (1) and (2). The first column shows our benchmark specification where we assume a GARCH(1,1) structure. The highly significant estimates of $\vartheta_{1,1}$ and $\vartheta_{2,1}$ in the variance equation provide additional support to importance of modeling investors' uncertainty. The positive estimates of $\vartheta_{1,1}$ and $\vartheta_{2,1}$ are consistent with the existence of a positive momentum in investors' uncertainty, meaning that greater (smaller) uncertainty in the previous period is followed by greater (smaller) uncertainty in the current period. This is also true for the sentiment equation where the sum of the autoregressive terms $\omega_{1,1}$ and $\omega_{1,2}$ is positive as well.

[7] Augmented Dickey Fuller and the Kwiatkowski–Phillips–Schmidt–Shin unit root tests confirmed the stationarity of the $S_t$ series.

The specification in column 2 aims at testing the role of investors' uncertainty on invertors' sentiment. The negative and statistically significant (at the 10% level) $\omega_4$ estimate shows that episodes in which there is higher uncertainty across investors are negatively related to investors' sentiment, making investors bearish. Column 3 tests the impact of economic cycles on uncertainty. The estimate of the coefficient on the NBER recession dummy ($\vartheta_4$) is positive and statistically significant at the 1% level, suggesting that investors' uncertainty is greater during the recession periods. As a robustness check the specification in column 4 includes both, the roles of uncertainty on sentiment, and of recessions on uncertainty. Consistent with previous results, economic downturns increase investors' uncertainty, and higher uncertainty is linked to bearish investors' sentiment.

*4.2. Sentiment, Uncertainty, Return and Risk*

Table 5 presents the estimates of the DCC - GARCH model in which we jointly estimate equations for sentiment $S_t$, uncertainty $U_t$, returns $R_t$, and risk $K_t$. In the mean equations, the autoregressive terms for the returns $\gamma_{R,1}$ are statistically significant and negative for all index returns, except for NASDAQ. A negative autoregressive term indicates the presence of momentum or positive feedback trading (Antoniou, Koutmos and Pericli, 2005), which creates herding mentality and causes investors to buy (sell) when market inclines (declines). Momentum causes the market to further incline in booms and further decline in busts. In contrast, the autoregressive terms are statistically significant and positive for sentiment estimates of $\gamma_{S,1}$ , suggesting that investors' opinion adjusts based on the market.

Consistent with the estimates of equations (1) and (2), the positive and highly significant estimates of $a$ and $b$ in the uncertainty equation across all specifications provide strong support in favor of the importance of uncertainty dynamics. The sum of the estimated coefficients of the multivariate DCC equations ($\alpha + \beta$) is close to 1 for all of the six specifications, suggesting that the joint volatility of returns (risk) and volatility of sentiment (uncertainty) is highly persistence.

A key result from the DCC - GARCH model of sentiment and return is the positive estimates of the conditional correlations between sentiment and return. They are all positive and statistically significant across all specifications in Table 5. This result provides strong support for the existence of volatility spillovers sentiment and return, which can be interpreted as a strong positive link between uncertainty and risk. Our findings are consistent with previous theoretical and empirical studies: investors' uncertainty creates "noise" and makes the market more liquid because some investors irrationally trade on noise as if it were information (Black, 1986). In the presence of uncertainty, investors' physiological biases increase (Daniel et al., 1998), pushing prices further away from fundamentals (Zhang, 2006). Uncertainty can induce systematic risk (Lee et al., 1991), increase the volatility of stock return (Andrei and Hasler, 2015) and command a risk premia. In their recent work, Pástor and Veronesi (2013) develop a general equilibrium model to show that political uncertainty commands a risk premium with a larger magnitude during economic downturns.

## 5. Alternative Measures of Uncertainty

As a way to provide additional validation to our measure of investors' uncertainty, we compare it against two recent and influential measures of uncertainty, namely the Macro Uncertainty measure by Jurado et al. (2015) and the Economic Policy Uncertainty by Baker et al. (2016). Figure 5 plots all three measures of uncertainty. We can observe that all measures of uncertainty are consistent at capturing periods of high uncertainty such as the Black Monday of 1987, the recession of the early 1990s, the terrorist attacks of September 11 of 2011 and the recession of the early 2000 and the recent financial crisis of 2007-2009.

In addition, we obtain the pair-wise correlation coefficients among all measures of uncertainty to further check how closely these measures are related. Table 6 presents the correlation matrix. Our measure of uncertainty has a significantly high correlation with Jurado et al. (2015)'s Macro Uncertainty and Baker et al. (2016)'s Economic Policy Uncertainty. For example, our Uncertainty (NYSE) has a correlation of 0.5128, 0.5058 and 0.4756 with Jurado et al. (2015)'s Macro Uncertainty and 0.4075 with Baker et al. (2016)'s Economic Policy Uncertainty all of which are statistically significant at the 1% level.

Note that our proposed measure of uncertainty can be useful to open new areas of research. For example, our measure of uncertainty can be employed in the study of the dynamics of alternative stock market sectors (e.g., financials, utilities, consumer discretionary), international stock indices and financial contagion (see, e.g., Chiang et al., 2007), or to further study asymmetric effects (see, e.g., Bauwens et al., 2006).

## 6. Conclusion

This paper sets to provide a novel approach to capture investors' uncertainty in markets. We use the (conditional) volatility in investors' sentiment to capture divergence in opinion and then estimate various volatility equations between return and sentiment using weekly data from 1987 through 2012. We employ dynamic conditional correlation analysis (DCC-GARCH) to identify a statistically significant positive correlation between investors' uncertainty and market risk.

After comparing our measure of uncertainty with Jurado et al. (2015)'s Macro Uncertainty and Baker et al. (2016)'s Economic Policy Uncertainty, we observe a relatively high and statistically significant correlation at the level of 1%. More importantly, all measures consistently capture periods of high uncertainty such as the Black Monday of 1987, the recession of the early

1990s, the terrorist attacks of September 11 and the recession of the early 2000 and the recent financial crisis of 2007-2009.

In the periods of uncertainty, as investors’ opinion diverges, bull-bear spread widens. Our findings support the hypothesis that divergence of opinion is linked with higher volatility in the market, which is viewed as greater stock market risk. We also find that there is a positive feedback between lagged uncertainty and today's uncertainty. Moreover, we find that greater investors' uncertainty makes investors more bearish, and that episodes of economic downturns are characterized by greater investors' uncertainty.

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**Table 1. Descriptive Statistics for Investors' Opinion (II) and Stock Indices**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| **Variables** | Obs | Mean | Std Dev | Min | Max | Skewness | Kurtosis |
| **Panel A: Full Sample** | | | | | | | |
| Investors' Opinion (II) | 1328 | 13.14 | 15.65 | -34.2 | 44.1 | -0.51 | 2.77 |
| CRSP Returns | 1328 | 0.19 | 2.41 | -17.98 | 12.62 | -0.68 | 8.95 |
| NYSE Returns | 1327 | 0.11 | 2.37 | -21.73 | 12.13 | -1.03 | 11.62 |
| AMEX Returns | 1327 | 0.13 | 2.28 | -29.96 | 11.43 | -1.93 | 27.32 |
| NASDAQ Returns | 1327 | 0.15 | 3.19 | -29.18 | 17.38 | -1.13 | 12.13 |
| SP500 Returns | 1327 | 0.12 | 2.46 | -28.37 | 12.37 | -1.60 | 19.15 |
| DJIA Returns | 1327 | 0.13 | 2.41 | -30.92 | 11.95 | -1.90 | 25.54 |
| **Panel B: Non-Recession** | | | | | | | |
| Investors' Opinion (II) | 1180 | 14.72 | 14.92 | -34.2 | 44.1 | -0.55 | 2.94 |
| CRSP Returns | 1180 | 0.23 | 2.14 | -13.71 | 9.33 | -0.63 | 7.11 |
| NYSE Returns | 1179 | 0.17 | 2.05 | -13.37 | 7.74 | -0.65 | 6.28 |
| AMEX Returns | 1179 | 0.18 | 2.2 | -29.96 | 11.43 | -2.17 | 33.71 |
| NASDAQ Returns | 1179 | 0.18 | 2.94 | -29.18 | 17.38 | -1.34 | 15.24 |
| SP500 Returns | 1179 | 0.17 | 2.29 | -28.37 | 12.37 | -1.77 | 24.87 |
| DJIA Returns | 1179 | 0.18 | 2.28 | -30.92 | 11.95 | -2.19 | 33.38 |
| **Panel C: Recession** | | | | | | | |
| Investors' Opinion (II) | 148 | 0.56 | 15.72 | -32.2 | 30.4 | -0.06 | 2.1 |
| CRSP Returns | 148 | -0.16 | 3.95 | -17.98 | 12.62 | -0.41 | 6.17 |
| NYSE Returns | 148 | -0.32 | 4.08 | -21.73 | 12.13 | -0.92 | 8.31 |
| AMEX Returns | 148 | -0.22 | 2.8 | -11.77 | 6.59 | -0.78 | 4.97 |
| NASDAQ Returns | 148 | -0.16 | 4.76 | -17.5 | 13.11 | -0.43 | 4.38 |
| SP500 Returns | 148 | -0.33 | 3.5 | -15.77 | 7.82 | -0.82 | 5.26 |
| DJIA Returns | 148 | -0.34 | 3.23 | -13.85 | 6.55 | -0.71 | 4.72 |

This table reports the descriptive statistics for investors' opinion and stock indices. Full sample is reported in Panel A, non-recession periods in Panel B and recession periods in Panel C. Investors' opinion is captured as Investors Intelligence (II) bull-bear spread. The six stock indices are CRSP (value-weighted returns from Center for Research in Security Prices), NYSE (New York Stock Exchange), AMEX (American Stock Exchange), NASDAQ (National Association of Securities Dealers Automated Quotations), S&P500 and DJIA (Dow Jones Industrial Average).

**Table 3. Ljung-Box Q-statistics Autocorrelations Test of II Sentiment**

| (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|
| Displacement | AC | PAC | Q-Stat | p-value |
| 1 | 0.1217 | 0.1217 | 19.702 | 0.0000 |
| 2 | 0.0158 | 0.0009 | 20.036 | 0.0000 |
| 3 | 0.0415 | 0.0408 | 22.332 | 0.0001 |
| 4 | 0.051 | 0.0416 | 25.795 | 0.0000 |
| 5 | 0.0017 | -0.0102 | 25.799 | 0.0001 |
| 6 | 0.0916 | 0.0927 | 37.006 | 0.0000 |
| 7 | 0.0524 | 0.028 | 40.679 | 0.0000 |
| 8 | 0.0257 | 0.0145 | 41.563 | 0.0000 |
| 9 | 0.0231 | 0.013 | 42.279 | 0.0000 |
| 10 | 0.0458 | 0.0319 | 45.085 | 0.0000 |
| 11 | 0.0739 | 0.0634 | 52.402 | 0.0000 |
| 12 | 0.0559 | 0.0311 | 56.594 | 0.0000 |

This table reports the Autocorrelations (AC) and Partial Autocorrelations (PAC) of the squared fitted error terms from the estimation of equation (1) along with the Ljung-Box Q-statistics.

**Table 4. Joint Estimation of Investors' Sentiment and Investors' Uncertainty**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Investors' Sentiment $S_t$ | | | | |
| $\omega_0$ | 15.135*** | 18.678*** | 15.053*** | 21.013*** |
| | (1.647) | (2.665) | (1.675) | (3.594) |
| $\omega_{1,1}$ | 1.170*** | 1.166*** | 1.171*** | 1.167*** |
| | (0.028) | (0.029) | (0.026) | (0.028) |
| $\omega_{1,2}$ | -0.225*** | -0.225*** | -0.226*** | -0.225*** |
| | (0.028) | (0.029) | (0.027) | (0.028) |
| $\omega_4$ | | -0.188* | | -0.312** |
| | | (0.103) | | (0.158) |
| Investors' Uncertainty $U_t$ | | | | |
| $\vartheta_{1,1}$ | 0.035*** | 0.035*** | 0.021*** | 0.021*** |
| | (0.008) | (0.008) | (0.006) | (0.006) |
| $\vartheta_{2,1}$ | 0.947*** | 0.945*** | 0.959*** | 0.958*** |
| | (0.014) | (0.014) | (0.010) | (0.010) |
| $\vartheta_3$ | | | -1.073*** | -1.016*** |
| | | | (0.376) | (0.359) |
| $\vartheta_4$ | | | 0.993*** | 1.003*** |
| | | | (0.270) | (0.257) |
| Observations | 1328 | 1328 | 1328 | 1328 |
| $\chi^2$ | 13628.57 | 12756.03 | 13853.17 | 12585.79 |
| p-value | 0.000 | 0.000 | 0.000 | 0.000 |

This table reports the maximum likelihood joint estimation of equations (1) and (2). Numbers in parentheses are standard errors. ***, ** and * denote significance level at 1%, 5%, and 10%, respectively.

**Table 5. DDC-GARCH Estimates: Joint Estimation of Returns, Sentiment, Risk, and Uncertainty**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $R_t$: | CRSP | | NYSE | | AMEX | | NASDAQ | | S&P500 | | DJIA | |
| Return $R_t$ and Sentiment $S_t$: | $R_t$ | $S_t$ | $R_t$ | $S_t$ | $R_t$ | $S_t$ | $R_t$ | $S_t$ | $R_t$ | $S_t$ | $R_t$ | $S_t$ |
| $\gamma_{R,0}$ , $\gamma_{S,0}$ | 0.343*** | 0.836*** | 0.384*** | 0.750*** | 0.253*** | 0.724*** | 0.432*** | 0.687*** | 0.282*** | 0.792*** | 0.254*** | 0.738*** |
| | (0.0659) | (0.185) | (0.0641) | (0.174) | (0.0753) | (0.184) | (0.0833) | (0.176) | (0.0698) | (0.186) | (0.0730) | (0.182) |
| $\gamma_{R,1}$ , $\gamma_{S,1}$ | -0.0974*** | 0.279*** | -0.130*** | 0.715*** | -0.100*** | 0.354*** | -0.00957 | 0.427*** | -0.143*** | 0.344*** | -0.0887*** | 0.358*** |
| | (0.0313) | (0.0626) | (0.0328) | (0.0738) | (0.0305) | (0.0659) | (0.0302) | (0.0524) | (0.0314) | (0.0616) | (0.0299) | (0.0635) |
| $\delta_{R,1}, \delta_{S,1}$ | 0.00131 | 0.944*** | -0.00684** | 0.947*** | -0.00117 | 0.947*** | -0.00903** | 0.951*** | -0.00191 | 0.946*** | -0.000759 | 0.947*** |
| | (0.00314) | (0.00854) | (0.00313) | (0.00774) | (0.00329) | (0.00830) | (0.00378) | (0.00799) | (0.00324) | (0.00852) | (0.00332) | (0.00831) |
| Risk $K_t$ and Uncertainty $U_t$: | $K_t$ | $U_t$ | $K_t$ | $U_t$ | $K_t$ | $U_t$ | $K_t$ | $U_t$ | $K_t$ | $U_t$ | $K_t$ | $U_t$ |
| $c$ | 0.220** | 0.381 | 0.339** | 0.968 | 0.119 | 0.319 | 0.307** | 0.509 | 0.0623 | 0.293 | 0.0869* | 0.310 |
| | (0.0970) | (0.269) | (0.140) | (0.746) | (0.0771) | (0.221) | (0.135) | (0.533) | (0.0428) | (0.183) | (0.0516) | (0.206) |
| $a$ | 0.204*** | 0.0335** | 0.228*** | 0.0689** | 0.0923*** | 0.0263** | 0.208*** | 0.0384 | 0.113*** | 0.0267*** | 0.0897*** | 0.0258** |
| | (0.0558) | (0.0146) | (0.0658) | (0.0339) | (0.0282) | (0.0113) | (0.0715) | (0.0246) | (0.0278) | (0.0102) | (0.0276) | (0.0107) |
| $b$ | 0.772*** | 0.949*** | 0.718*** | 0.882*** | 0.893*** | 0.959*** | 0.775*** | 0.936*** | 0.890*** | 0.960*** | 0.904*** | 0.960*** |
| | (0.0570) | (0.0241) | (0.0744) | (0.0672) | (0.0228) | (0.0190) | (0.0657) | (0.0489) | (0.0229) | (0.0160) | (0.0208) | (0.0178) |
| $a+b$ | 0.976*** | 0.9825*** | 0.946*** | 0.9509*** | 0.9853*** | 0.9853*** | 0.983*** | 0.9744*** | 1.003*** | 0.9867*** | 0.9937*** | 0.9858*** |
| Multivariate DCC Equations | | | | | | | | | | | | |
| $\alpha$ | 0.0192*** | | 0.00581 | | 0.0236*** | | 0.0416** | | 0.0156 | | 0.0389** | |
| | (0.00713) | | (0.00413) | | (0.00885) | | (0.0206) | | (0.0193) | | (0.0186) | |
| $\beta$ | 0.958*** | | 0.986*** | | 0.943*** | | 0.653*** | | 0.935*** | | 0.767*** | |
| | (0.00587) | | (0.00221) | | (0.0195) | | (0.0825) | | (0.203) | | (0.118) | |
| Correlations of Sentiment and Return | 0.405*** | | 0.360*** | | 0.409*** | | 0.334*** | | 0.444*** | | 0.421*** | |
| | (0.0461) | | (0.0567) | | (0.0462) | | (0.0296) | | (0.0356) | | (0.0337) | |
| Observations | 1327 | | 1326 | | 1326 | | 1326 | | 1326 | | 1326 | |
| $\chi^2$ | 15203 | | 18820 | | 15079 | | 16889 | | 15817 | | 15265 | |
| p-value | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | |

This table reports the estimation results from DCC-GARCH. II bull-bear spread is Investor's opinion as captured by Investors Intelligence. Six stock indices are CRSP (value-weighted returns from Center for Research in Security Prices), NYSE (New York Stock Exchange), AMEX (American Stock Exchange), NASDAQ (National Association of Securities Dealers Automated Quotations), S&P500 and DJIA (Dow Jones Industrial Average). Numbers in parentheses are standard errors. ***, ** and * denote significance level at 1%, 5%, and 10%, respectively. The mean equations that model return and sentiment are $R_t = \gamma_{R,0} + \gamma_{R,1} R_{t-1} + \delta_{R,1} S_{t-1} + \varepsilon_{Rt}$ and $S_t = \gamma_{S,0} + \gamma_{S,1} R_{t-1} + \delta_{S,1} S_{t-1} + \varepsilon_{St}$ where $\varepsilon_t = [\varepsilon_{Rt}, \varepsilon_{St}]'$ and $\varepsilon_t | \Omega_{t-1} \sim N(0, H_t)$. The variance equations that model risk and uncertainty are $K_t = c + a\varepsilon_{t-1}^2 + b_i K_{t-1}$ and $U_t = c + a\varepsilon_{t-1}^2 + b_i U_{t-1}$. The DCC equation $Q_t = (1-\alpha-\beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}$, and $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} \times q_{jj,t}}}$, where $i, j = 1, 2$ for $i \neq j$. The null for the $\chi^2$ test is $H_0\colon \alpha = \beta = 0$.

**Table 6. Correlation Analysis among Measures of Uncertainty**

| | Uncertainty (CRSP) | Uncertainty (S&P500) | Uncertainty (NYSE) | Uncertainty (NASDAQ) | Uncertainty (AMEX) | Uncertainty (DJIA) | Macro Uncertainty (h1) | Macro Uncertainty (h3) | Macro Uncertainty (h12) |
|---|---|---|---|---|---|---|---|---|---|
| Uncertainty (CRSP) | 1 | | | | | | | | |
| Uncertainty (S&P500) | 0.9804* | 1 | | | | | | | |
| Uncertainty (NYSE) | 0.8994* | 0.8674* | 1 | | | | | | |
| Uncertainty (NASDAQ) | 0.9596* | 0.9518* | 0.9454* | 1 | | | | | |
| Uncertainty (AMEX) | 0.9817* | 0.9992* | 0.8720* | 0.9546* | 1 | | | | |
| Uncertainty (DJIA) | 0.9794* | 0.9993* | 0.8678* | 0.9523* | 0.9996* | 1 | | | |
| Macro Uncertainty (h1) | 0.4977* | 0.4790* | 0.5128* | 0.5475* | 0.4831* | 0.4721* | 1 | | |
| Macro Uncertainty (h3) | 0.4918* | 0.4744* | 0.5058* | 0.5430* | 0.4782* | 0.4674* | 0.9993* | 1 | |
| Macro Uncertainty (h12) | 0.4629* | 0.4476* | 0.4756* | 0.5186* | 0.4506* | 0.4402* | 0.9902* | 0.9946* | 1 |
| EP Uncertainty | 0.4132* | 0.4055* | 0.4075* | 0.4371* | 0.4150* | 0.4093* | 0.4612* | 0.4550* | 0.4288* |

This table reports the correlation matrix between the uncertainty measure reported in this paper, Jurado et al. (2015) and Baker et al. (2016) using monthly data from 1987-2012. The first six uncertainty measures are estimated from DCC-GARCH using Investor's opinion as captured by Investors Intelligence and six major stock indices including CRSP (value-weighted returns from Center for Research in Security Prices), S&P500, NYSE (New York Stock Exchange), AMEX (American Stock Exchange), NASDAQ (National Association of Securities Dealers Automated Quotations) and DJIA (Dow Jones Industrial Average). Macro Uncertainty (h1, h3 and h12) are macro uncertainty measures for 1, 3 and 12 months as computed in Jurado et al. (2015). EP Uncertainty is the news-based economic policy uncertainty as measured in Baker et al. (2016). * denotes level of significance at 1%.

## Appendix

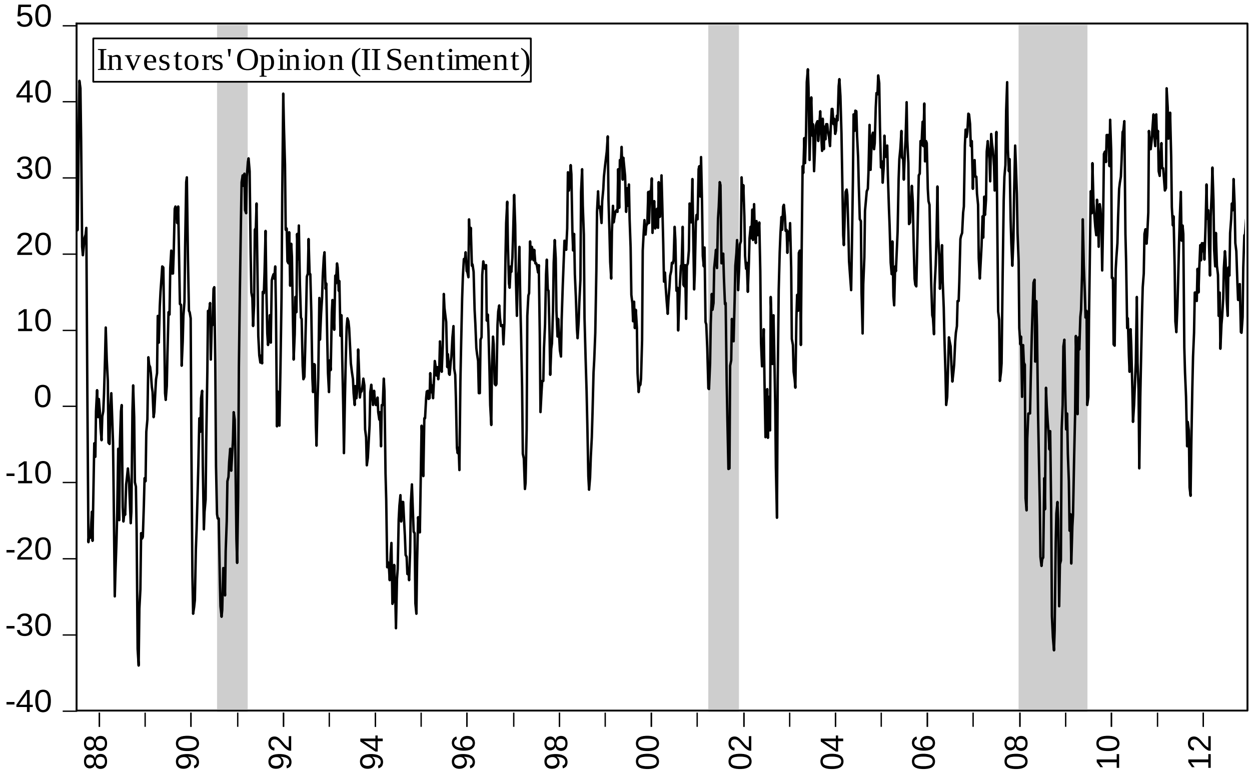
**Table A.1. BIC Order Selection for the Sentiment Equation**

| | $p_2 = 0$ | $p_2 = 1$ | $p_2 = 2$ | $p_2 = 3$ | $p_2 = 4$ |
|---|---|---|---|---|---|
| $p_1 = 0$ | 11088.0 | 9724.4 | 8979.1 | 8537.9 | 8314.8 |
| $p_1 = 1$ | 7947.9 | 7892.1 | 7888.2 | 7891.9 | 7898.2 |
| $p_1 = 2$ | 7882.9 | 7887.9 | 7893.7 | 7898.7 | 7891.7 |
| $p_1 = 3$ | 7887.3 | 7894.4 | 7898.9 | 7905.6 | 7897.2 |
| $p_1 = 4$ | 7894.1 | 7885.4 | 7905.4 | 7895.7 | 7904.4 |

Notes: This table reports the Bayesian Information Criterion (BIC) statistics to obtain the orders to $p_1$ and $p_2$ in equation (1). The minimum BIC is obtained when $p_1 = 2$ and $p_2 = 0$.

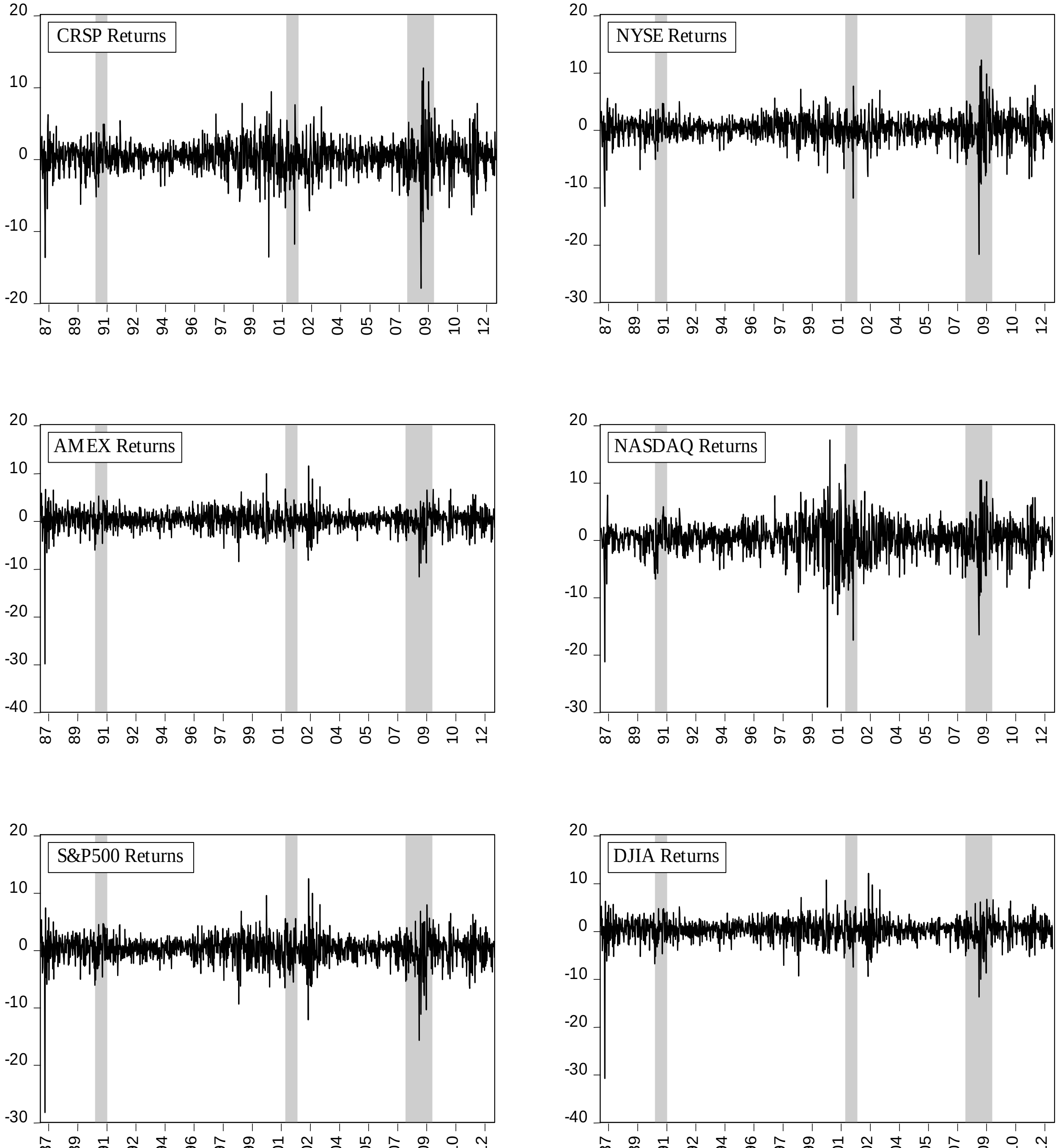
**Figure 1. Investors' Opinion (II sentiment)**

This figure investors' opinion (sentiment) measured by Investors Intelligence (II) bull-bear spread. Shaded areas denote U.S. recessions obtained from the National Bureau of Economic Research (NBER).



## Figure 2. Index Returns

This figure presents returns of the six stock indices: CRSP (value-weighted returns from Center for Research in Security Prices), NYSE (New York Stock Exchange), AMEX (American Stock Exchange), NASDAQ (National Association of Securities Dealers Automated Quotations), S&P500 and DJIA (Dow Jones Industrial Average). Shaded areas denote U.S. recessions obtained from the National Bureau of Economic Research (NBER).



## Figure 3. Dynamic Correlation between Investors' Uncertainty and Stock Market Risk

This figure presents dynamic correlations between investors' uncertainty and risk of six major stock indices captured by DCC – GARCH: CRSP (value-weighted returns from Center for Research in Security Prices), NYSE (New York Stock Exchange), AMEX (American Stock Exchange), NASDAQ (National Association of Securities Dealers Automated Quotations), S&P500 and DJIA (Dow Jones Industrial Average). Shaded areas denote U.S. recessions obtained from the National Bureau of Economic Research (NBER).