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Keywords: Economic uncertainty, Volatility forecasting, Realized volatility, Uncertainty measures
JEL: D80, E30, E44, G12, G17

The Effects of Economic Uncertainty on Financial Volatility: A Comprehensive Investigation

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Abstract

We investigate the effects of economic uncertainty on the return volatility of financial assets, including equities, bonds, foreign exchange and commodities. We use several popular measures of economic uncertainty, and find the uncertainty displays significant but heterogeneous effect on financial volatility. Economic uncertainty constructed in a data rich environment shows strong effects for most financial assets. In particular, the first principal component of the economic uncertainty measures provides a good balance of the effects. The effects of economic uncertainty on financial volatility appear to be closely related to the state of the economy and are more pronounced around recession periods. Furthermore, our out-of-sample analysis shows that investors can use economic uncertainty to predict financial volatility, from both the statistical and economic perspectives.

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1. Introduction

Since the seminal work of Bloom (2009), a growing body of literature has sought to measure economic uncertainty and analyze its effects on the aggregate economy and financial markets. Numerous theoretical and empirical studies have shown that economic uncertainty can have substantial effects on the business cycle, real production, corporate investment, financial crises, asset prices, and other

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factors (e.g., Bloom et al. (2018); Ordoñez (2013); Pastor and Veronesi (2012); Bali et al. (2014); Bali and Zhou (2016); Bali et al. (2017); Basu and Bundick (2017); Schaal (2017); Choi et al. (2018); Rossi et al. (2015); Anderson et al. (2009); Segal et al. (2015); Kim and Kung (2017); Drechsler (2013); Kelly et al. (2016); Baker et al. (2016); Carriero et al. (2017); Gulen and Ion (2015)).

In this paper, we comprehensively investigate the effects of economic uncertainty on financial volatility. Rather than focusing on a single measure of economic uncertainty and a specific financial asset, we use several popular measures of economic uncertainty and consider a wide range of asset classes including equities, bonds, foreign exchange and commodities. We have documented significant but heterogeneous effects of different economic measures on different assets and have also found the first principal component of these measures reaches a good balance of the impacts. Furthermore, we show that investors can use economic uncertainty to predict financial volatility in the out-of-sample analysis, from both statistical and economic perspectives.

Our paper contributes to three strands of literature. First, we enrich the literature on the effects of economic uncertainty on financial markets. Several channels were documented in literature through which the economic uncertainty could affect asset price and their fluctuations, such as interest rates/discount rates (e.g., Connolly et al. (2018); Phan et al. (2018); Kaminska and Roberts-Sklar (2018); Bekaert et al. (2018)), changes in the economic agents' decision making processes (e.g., Hansen and Sargent (2019); Chow et al. (2018); Gulen and Ion (2015); Valencia (2017); Kim and Kung (2017)), and sentiment related actions (e.g., Brunnermeier and Pedersen (2009)) The impact of uncertainty on bond returns (Buraschi et al. (2013), Bali et al. (2018)), stock returns (Anderson et al. (2009), Bali and Zhou (2016),Bali et al. (2017),Xyngis (2017)), hedge fund returns (Bali et al. (2014)), option prices/returns and trading activity (Aramonte (2014); Kelly et al. (2016); Beber and Brandt (2008)), currency trading returns (Berg and Mark (2018)), and house prices (Strobel et al. (2018)) were also empirically tested. Apart from returns, relatively few literature (starting from Schwert (1989)) has discussed the impact of economic uncertainty on volatility. Our empirical results provide extensive evidence showing that economic uncertainty affects financial volatility and that the effect is heterogeneous across different asset classes and market conditions. In particular, the impact is greater when the market is in recession.

Second, we contribute to the literature on measuring economic uncertainty using different methods and compare their information contents in terms of their effects on financial volatility. Research has shown that measurements such as the dispersion based (Bloom (2009); Bachmann et al. (2013); Rossi et al. (2015); Scotti (2016); Jo and Sekkel (2017); Sheen and Wang (2017); Jurado et al. (2015)), real economic variable volatility based (Bali et al. (2014)), option implied (Bloom (2009), Bali and Zhou (2016), Drechsler and Yaron (2010)), and textual analysis based economic policy uncertainty (EPU) measures (Baker et al. (2016)) are neither statistically nor conceptually identical (Kozeniauskas et al. (2018)). Our empirical results support this finding and suggest that the effects of the information content on financial volatility vary significantly. In addition, our results indicate that the big data based measure has the greatest impact followed by the survey based and small data based measures. The commonly used EPU and variance risk premium (VRP) measures have little impact on volatility for most asset classes. Combining the uncertainty measures using principal component analysis (PCA) provides a balanced uncertainty measure that has a considerable impact on financial volatility.

Third, our out-of-sample analysis contributes to the literature on using macroeconomic information to predict volatility. Studies such as Paye (2012), Christiansen et al. (2012), Engle et al. (2008), Engle et al. (2013), Conrad et al. (2014), Chiu et al. (2018), and Flannery and Protopapadakis (2002) have highlighted the importance of using macroeconomic variables and their announcement in the forecasting volatility components. However, compared with the macroeconomic variables, only a small body of studies have examined the role of uncertainty in volatility prediction (see Kaminska and Roberts-Sklar (2018), Christou et al. (2018), Watugala (2018), Bakas and Triantafyllou (2018)). Unlike these studies, which focus on a particular asset class or one uncertianty index, we conduct an extensive investigation of the predictive power of economic uncertainty using the major asset classes and multiple uncertainty measures. Our results suggest that the macroeconomic information based measurements have significant predictive power for most of the asset classes during recession periods while the EPU and VRP measures only work for a particular class. The principal components of all of the measures also provide favorable predictive power over the single uncertainty measures. The statistical significance is also confirmed by a utility-based evaluation.

The remainder of this paper is organized as follows. Section 2 presents a general discussion of the construction of economic uncertainty measures. Section 3 describes the data we use in the empirical investigation. Section 4 reports our empirical results from both in-sample and out-of-sample analyses. Section 6 concludes the paper and provides some thoughts about the directions for future research.

2. The Measures of Economic Uncertainty

Economic uncertainty can be measured using different data sources and methods. Because uncertainty is conceptually always linked to variation, some researchers use the volatility of either financial series, such as the VRP (Bali and Zhou (2016)), or macroeconomic variables (Bali et al. (2014)) to measure economic uncertainty. It can also be approached via the measurement of dispersions from the cross-sectional firm profits (Bloom (2009)) to the professional/public surveys (Sheen and Wang (2017)). Textual analysis can also be used to construct uncertainty measures such as the EPU (Baker et al. (2016). Other econometric techniques, such as (S)VAR (Carriero et al. (2017)) and a variety of decomposing methods can also be used to measure uncertainty (Sheppard (2018); Bekaert and Hoerova (2014)). As Kozeniauskas et al. (2018) point out, there is a wide range of tools for measuring uncertainty and the commonly used uncertainty measures are neither conceptually nor statistically identical. Therefore, we provide a brief summary of the commonly used measures in Table 1 with respect to their information sets, such as macroeconomic series, survey and professional forecast errors, news reports, and key financial variables.

[Insert Table 1 here]

The first set of measures is based on the information extracted from macroeconomic and financial series. Most of these measures view uncertainty as the volatility of model based prediction errors. Unlike the early studies, which were based on particular macroeconomic variables, the leading examples of these measures use large groups of series and dimension reduction techniques. For example, Jurado et al. (2015) construct an uncertainty measure based on 132 macroeconomic series using the average of the volatilities of the residuals from factor-augmented regressions. Carriero et al. (2017) construct an uncertainty measure which defined as the common factors that drive the movements of both conditional mean and volatility of macroeconomic variables. Henzel and Rengel (2017) measure the uncertainty as the factors that account for the common dynamics in the volatility of the model residuals. Similarly, Bali et al. (2014) use the principal component method to construct an uncertainty measure. These measures are widely used in the literature to document the effects of uncertainty on a variety of financial assets (e.g., Bali et al. (2017), Connolly et al. (2018), Strobel et al. (2018), Xyngis (2017), Bali et al. (2018), Bakas and Triantafyllou (2018)).

The second set of measures is based on the information extracted from surveys. Unlike the macroeconomic series based measures, the survey based measures form expectations not only based on the facts but also on the economic agents' beliefs. Accordingly, these measures reflect the dispersion of the views and disagreements across agents. For example, Sheen and Wang (2017) construct measures based the dispersions of forecasts of a wide range of 35 macroeconomic series from both household and professional surveys at various frequencies. Similar dispersion based measures are developed in Bachmann et al. (2013) and Bloom (2009). Measures based on the dispersion of professional forecasts can be found in Scotti (2016), Rossi et al. (2015), and Jo and Sekkel (2017). Survey based measures are used in literature such as Valencia (2017) etc.

The third set of measures is based on the textual analysis of news articles and reports. The logic behind these kinds of measures is that macroeconomic uncertainty triggers discussions in the media and generates professional reports that contain words such as "uncertainty." For example , Baker et al. (2016) use the frequency of articles in 10 leading U.S. newspapers that contain terms related to economic and policy uncertainty to form the EPU measure. Ahir et al. (2018) and Alexopoulos and Cohen (2015) construct similar measures using the quarterly Economist Intelligence Unit country reports and articles published in the New York Times. In addition to constructing direct measures, news articles are used to augment key financial measures such as VIX (Manela and Moreira (2016)). Text based measures are widely used in the literature (e.g., Gulen and Ion (2015), Christou et al. (2018), Strobel et al. (2018), Phan et al. (2018), and Berg and Mark (2018)). Although widely used as a measure of economic uncertainty, the text based measures also reflect the general political uncertainty, such as during an election cycle. Therefore, the measures may contain a substantial amount of noise when economic uncertainty is the primary concern.

The last set of measures is based on key financial variables. These measures are usually derived from the market prices of financial assets. The logic is that market price comprises the market participants' collective subjective evaluations of uncertainty. Examples of these measures include the VRP (Bali and Zhou (2016)), VIX (Bloom (2009)), corporate bond spread (Bachmann et al. (2013)), and dispersion of stock returns and profit growth (Bloom (2009)). Alessandri and Mumtaz (2018) mention that VIX is only a proxy that is at best weakly related to macroeconomic predictability. These kinds of measures are used in Byun (2016), Beber and Brandt (2008), and Kaminska and Roberts-Sklar (2018).

We use the following six uncertainty measures in our empirical analyses: the big data based macroeconomic uncertainty (MacUnc, Jurado et al. (2015)) measure and its small data based counterpart (SMU, Carriero et al. (2017)), the survey based uncertainty index (SUI, Sheen and Wang (2017)), the EPU Index (Baker et al. (2016)), and the VRP (Bali and Zhou (2016)). We also construct a measure that combines all of the above measures using PCA. We select at least one measure from each of the abovementioned sets of measures to provide good coverage of the different information sources. For the macroeconomic information based measures, we select one big data and one small data based measure to test whether the big data measures are empirically preferable. Because we are focusing on the impact on volatility, we do not select the measures that are constructed directly on asset volatility, which means we ignore measures such as VIX to avoid predicting volatility with previous volatility. The first principal components of all of the selected measures are then selected to extract the common component. As each component only reflects partial information on economic uncertainly, the principal components can collectively provide a more complete view of the uncertainty and reduce the noise of the individual measures.

3. Data and sample

The dataset used in this paper comprises a group of uncertainty measures and several volatility series regarding a range of financial assets. The data span over 25 years from January 1990 to July 2014 due to the data availability[1].

3.1. Uncertainty measures

We use six uncertainty measures, namely, the big data based MacUnc, the small data based SMU, the survey based SUI, the EPU, the VRP [2], and a measure that combines all of above using PCA.

The principal component is included to eliminate the idiosyncratic parts of each of the five individual measures. The first principal component covers 59% of the total variation in our dataset [3]:

$$PC = 0.519 \times \text{SUI} + 0.517 \times \text{SMU} + 0.515 \times \text{MacUnc} + 0.365 \times \text{EPU} + 0.254 \times \text{VRP}$$

All of the parameters in the principal component (PC) are positive, indicating that they are all positively correlated. Measured by the magnitude of the parameters[4], SUI, SMU, and MacUnc cover

[1] The uncertainty measure in Carriero et al. (2017) publicly available on ReStat website only extends to July 2014.

[2] MacUnc data are available on the website of authors of Jurado et al. (2015). The EPU data comes from the public website of Baker et al. (2016). The authors of Bali and Zhou (2016) provide the VRP data from January 1990 in their personal website. The SUI data is acquired from the author of Sheen and Wang (2017) by request.

[3] The second and third principal components account for 20% and 13% of the total variation, respectively. These values are significantly lower than the first.

[4] All of the measures are standardized to ensure the comparability of the parameters.

similar amounts of information followed by EPU, and the VRP covers the least amount of information on economic uncertainty. These findings are consistent with the concern that the EPU contains substantial noise when used to measure economic uncertainty and the risk aversion components embedded in the VRP are only loosely related to economic uncertainty (see the discussions in Ozturk and Sheng (2018) and Bekaert et al. (2013) respectively).

[Insert Figure 1 and Table 2]

Figure 1 shows the standardized individual uncertainty measures and the first principal component across time with the three NBER recession periods marked in gray. For the individual measures, the three notable peaks for MacUnc, SMU, and SUI are matched reasonably well by the NBER recessions, while the EPU exhibits many more notable local peaks during the non-recession periods when political events such as the U.S. presidential elections occur. The VRP is much volatile than the other measures and some of its peaks deviate from the economic recessions to financial crises, such the Asian financial crisis in 1998. Compared to the small data based SMU, the large data based MacUnc has lower local volatility, probably because MacUnc uses much more variables and the noise in the individual variables is more likely to be canceled out. The first principal components extract the common parts in these measures and all of the local peaks match the NBER recessions. The summary statistics of the uncertainty measures are provided in Table 2 and confirm the visual conclusions in Figure 1. The correlations between EPU/VRP and the other measures are significantly lower and the correlations between the two are also lower than the correlations between the other measures. This suggests that at least statistically, the uncertainties measured by the EPU, VRP, and the rest of the measures are significantly different.

3.2. Volatility of financial assets

To provide better coverage of the financial market, multiple asset classes are considered. For the equity market, we use the S&P500 to represent the large market cap and value stocks, and the NASDAQ 100 index for small market cap and growth stocks. For the fixed income and interest rate markets, we use the 10 year T-Note futures to represent the market mainly driven by interest rate changes and the high-yield bond index from the Federal Reserve Economic Data (FRED) to represent the market in which the credit risk is the major concern[5]. The currency market is represented by the

[5]The selected index is the ICE BofAML U.S. High Yield Master II Total Return Index Value from FRED, which tracks the performance of the U.S. dollar denominated below investment grade rated corporate debt publically issued in

trade weighted Doller Index from FRED[6]. The commodity market is represented by the S&P GSCI, which is a tradable index that is readily available to market participants on the Chicago Mercantile Exchange. The index currently comprises 24 commodities from all of the commodity sectors, namely, energy products, industrial metals, agricultural products, livestock products, and precious metals. The wide range of coverage provides a high level of diversification and makes the index a good overall measure of the commodity market.

The volatility is measured by the logarithm of the monthly realized variance:

$$\log RV_t = \log\left(\sum_{i=1}^{N_t} r_{i,t}^2\right)$$

where $r_{i,t}$ denotes the daily log-returns at the i-th day in month t and N_t is the number of trading days in month t. The log value is commonly used when examining volatility, especially when using linear regressions (Paye (2012)), and automatically ensures the positivity of volatility without additional constraints on the parameters.

[Insert Figure 2 and Table 3 here]

Figure 2 plots the log-variances of the different assets considered, with the shaded areas indicating the NBER-recession periods. All of the assets display high volatility during the recession periods, especially during the 2008 financial crisis. Yet, the different series also exhibit idiosyncratic dynamics. For example, the commodity index reacts strongly to the recession during the early 1990s, whereas the equity indices react more strongly in subsequent recessions. The change in the volatility of the credit market is also more violent than in the other markets. These differences reinforce our concern that economic uncertainty has heterogeneous effects on different markets. The summary statistics of the uncertainty measures are provided in Table 3 and confirm the visual conclusions in Figure 2. The correlations between the different series are generally low, indicating that the markets are substantially different from each other. Comparing the first and second columns, the correlations with the two markets representative of the equity markets also exhibit notable differences, which may imply that different forces are driving their volatility.

the U.S. domestic market.

[6]A weighted average of the foreign exchange value of the U.S. dollar against a subset of the broad index currencies that circulate widely outside the country of issue. The major currencies index includes the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden.

4. Empirical Results

4.1. The model

We use a simple regression setup to investigate the impact of economic uncertainty (U) on asset volatility ($\log RV$):

$$\log RV_t = \alpha + \beta \log RV_{t-1} + \phi U_{t-1} + \epsilon_t \tag{1}$$

The first order lag of log RV is included to control the autocorrelation of the variance process so that ϕ can measure the partial effects of economic uncertainty independent from the volatility clustering. As a result, the natural benchmark model is the AR(1) of $\log RV$. This setup is widely used in the literature (e.g., Schwert (1989) and Christiansen et al. (2012)) [7]. To make the parameters comparable across equations with different uncertainty measures, we standardize $\log RV$ and U so that $\alpha = 0$ and ϕ measures the increase in volatility as a result of a one standard deviation increase in the uncertainty measure.

4.2. The overall impact of uncertainty on volatility

Table 4 reports the overall impact of uncertainty on the volatility across the different asset classes. In most cases, the economic uncertainty significantly affects the asset volatility in the following month. The impact measured by the magnitude of ϕ varies across the different measures and different assets, thus indicating considerable heterogeneity.

[Insert Table 4 here]

For the macroeconomic information based measures (MacUnc and SMU), most of the assets respond significantly to the changes in the uncertainty measures, indicating that the uncertainty embedded in the macroeconomic fundamentals is an important driving force of the volatility of financial assets. For instance, a one standard deviation increase in MacUnc results in a 0.201 standard deviation increase in the subsequent $\log RV$ of the S&P 500 index. The only exception is the lack of an effect on the NASDAQ 100 index. A possible explanation for this is that the main component of this index is high-tech companies whose performance is mainly driven by research and technical breakthroughs. These forces are loosely related to the macroeconomic fundamentals. Across the different asset classes, as measured by the magnitude of ϕ, the fixed income markets represented by

[7] Although the AR(2) model has a relatively smaller BIC, we use the AR(1) model for simplicity and the main results do not change if we use AR(2) as our benchmark model.

the 10 year T-Note futures are more affected than the equity markets, especially SMU. Connolly et al. (2018) suggest that using the T-bonds to hedge uncertainty serves as a channel for linking macroeconomic uncertainty to the interest rate. Compared with the fixed income markets, the fluctuations in high yield bonds are mainly driven by macroeconomic uncertainty. This result confirms the finding in Alessandri and Mumtaz (2018) that the credit market helps to propagate economic uncertainty and emphasizes the strong comovement between uncertainty and the credit conditions. Bekaert and Hoerova (2016) also highlight the close relationship between the bond market and uncertainty. Because the forces driving the volatility of the exchange rate and the commodity markets are closely linked to the macroeconomic conditions, uncertainty has a greater impact on these markets than on the stock market. The empirical importance of the big data based measures is highlighted by the finding that the largest effects are mostly observed in the cases when uncertainty is measured by MacUnc.

These findings are confirmed by the survey based SUI measure. Although the magnitude of the effect observed using SUI is a littler smaller than that for the big data based MacUnc measure, the patterns are similar to those found in the previous analysis. Unlike the MacUnc and SMU measures, the information used in constructing the SUI is only drawn from personal surveys on macroeconomic variables. Thus, the similar results confirm our conjecture that even when measured using subjective data, the macroeconomic uncertainly is an essential driving force of financial volatility.

The news based EPU measure fails to affect the volatility of the financial markets. Even when it does have a significant impact, the magnitude is relatively smaller than that of the other uncertainty measures. This finding reinforces the concern in the literature (Ozturk and Sheng (2018)) that news-based uncertainty measures might put a high bar on some policy related events, which would not be directly related to the economic fundamentals or uncertainty. The only statistically significant impact at the 5% level is found in the currency market where policy/political uncertainty have a much greater impact than in the other markets.

Although the VRP has a significant effect on the volatility of different markets, the magnitude of the effect is much smaller than that observed for the macroeconomic information based measures. The only exception is the equity market, where the effects of the two types of measures are of a similar magnitude. This is consistent with Bekaert and Hoerova (2016), who highlight the relationship between the VRP and risk-aversion, and show that the latter is closely related to the equity markets (Bekaert and Hoerova (2014)).

The principal component has a significant effect on the volatility of all of the asset classes except for the NASDAQ 100. The magnitudes of the effects in some cases, such as the bond (both T-Note and high yield bonds) and currency markets, are higher than any of the individual measures. In other cases, the combined measure also provides a good balance between the different types of uncertainty captured by the individual measures.

4.3. Decomposition of the impact

To document the potential differences in the magnitudes of the effects, we also consider the following extended regression with a structural break setup:

$$\log RV_t = \alpha + \theta I_{t-1} + \beta \log RV_{t-1} + \gamma \log I_{t-1} RV_{t-1} + \phi U_{t-1} + \delta I_{t-1} U_{t-1} + \eta_t \tag{2}$$

where the indicator function I_t equals one in the NBER recessions. The parameter δ documents the difference in the magnitude of the impact of economic uncertainty on asset volatility in different market conditions. Because we use standardized the log volatility and economic uncertainty measures, δ measures the effects in terms of standard deviations. Because the principal components of the individual measures deliver a good balance of effects, we focus on the results where PC is used as the uncertainty measure.

[Insert Table 5 here]

First, we find a positive δ for all of the assets, thus indicating that uncertainty has a stronger effect on volatility during the recession periods. The magnitude of the effects during the recession periods (measured by $\delta + \phi$) is at least double that during the expansion periods (measured by ϕ).

Second, the magnitude and statistical significance of the effects for the different market conditions are heterogeneous across the different financial markets. Among the different markets, the commodity market has the largest asymmetric effects followed by the SP500 and bond markets. Although the coefficient δ for the currency market is not statistically significant, its magnitude still indicates economic importance. Again, as with the full sample results, the fact the NASDAQ 100 index has the smallest δ suggests that uncertainty does not significantly affect the volatility of the index even during a recession. Alfaro et al. (2018) provide a possible explanation, which they term the "finance uncertainty multiplier," for the asymmetric effects of uncertainty shocks during different periods. They point out that higher uncertainty is always accompanied by financial friction, and the interaction of these factors heightens the effect of uncertainty. In their paper, the addition of financial friction roughly doubles the impact of uncertainty shocks.

Third, different from δ, we find a negative γ for all of the assets, which means that the impact of lagged volatility for future volatility is decreasing and the lagged volatility become less informative. This is consistent with the fact volatility changes violently during recessions and the autocorrelation between volatility and its lags is weaker in recession than expansion periods.

4.4. The implications of uncertainty for volatility forecasts

The significant impact of economic uncertainty on the volatility of financial assets has straightforward implications concerning the uncertainty in volatility forecasts.

In equations 1, the parameters are estimated with the full sample, the results are not directly related to volatility forecasts. A more reasonable approach is to use the recursive estimation method:

$$\log RV_{t+1} = \alpha_t + \beta_t \log RV_t + \phi_t U_t + \nu_t \tag{3}$$

where parameters $(\alpha_t, \beta_t, \phi_t)$ are estimated using the whole information up to the month t[8].

The initial estimation period (pre-sample) is from 1990:01 to 1999:12 and the forecast evaluation period spans from 2000:01 to 2014:07. The pre-sample dataset contains enough estimations for the initial regression while still leaving the desired number of observations for the out-of-sample period used for the forecast evaluations[9]. We evaluate the out-of-sample forecasting performance based on the mean square forecast error:

$$\text{MSFE}(m) = \frac{1}{T-p} \sum_{t=p+1}^{T} (\widehat{\log RV_t^{(m)}} - \log RV_t)^2$$

where T is the length of the volatility series, p is the length of pre-sample period, m refers to the model used, and the hatted value is the model based forecast. The R^2_{OS} is then defined as the proportional reduction in the mean squared forecast error (MSFE) for the predictive regression forecast relative to

[8] An alternative setup is to estimate the parameters with a rolling window estimation where the sample size is fixed instead of expanding with t. We report the results for expanding method based on two considerations: 1) the number of observations in the monthly data is limited and we want to use as much data as possible; and 2) the results from the rolling window estimation are similar.

[9] The principal component in the out-of-sample investigation is also constructed based on recursive settings in which only historical data are used to estimate the covariance matrix.

the benchmark:

$$R^2_{OS} = \frac{\text{MSFE}(b) - \text{MSFE}(uc)}{\text{MSFE}(b)} \times 100\%$$

where b is the AR(1) benchmark model and uc is the uncertainty measure included equation 1. R^2_{OS} is widely used in the literature (e.g., Campbell and Thompson (2008)) and its statistical significance is established in Clark and West (2007). In particular, Clark and West (2007) test whether the proposed model under-performs the benchmark (i.e., $R^2_{OS} \leq 0$) against a one-sided alternative $R^2_{OS} > 0$. If the model fails to under-perform, a significant out-of-sample volatility predictability gain can be claimed due to the economic uncertainty.

[Insert Table 6 here]

Table 6 reports the R^2_{OS} for the full sample and the expansion ($R^2_{OS,exp}$) and recession ($R^2_{OS,rec}$) periods. For the full sample results, the CWstat from Clark and West (2007) is also used to evaluate the statistical significance. For each individual measure, the principal component and a "kitchen sink" (KS) setup that simultaneously includes all five individual measures are considered. The KS method is introduced as an alternative aggregation method to the principal component in terms of using multiple combined measures.

For the macroeconomic and survey information based measures, we find significantly positive R^2_{OS} for all of the assets except the NASDAQ 100, which suggests that the economic uncertainty significantly improves the predictability of financial volatility. The decomposed results confirm that the improvements mainly occur during NBER recessions. The higher R^2_{OS} for MacUnc than SMU highlights the importance of constructing uncertainty measures based on larger pools of variables. The EPU only helps to predict the volatility of the bond markets and the VRP only works for the SP500, bond markets, and currency market. Similar to the in-sample results, the principal component provides satisfactory results in boosting the R^2_{OS}. Unlike the principal component approach, the KS method does not always generate a positive R^2_{OS}.

4.5. Economic value of the uncertainty measures

In addition to the statistical measures in Table 6, we evaluate the economic value of the uncertainty measures using the utility-based framework presented in Bollerslev et al. (2018), where an investor with mean-variance preferences makes monthly allocations of wealth between risky and risk-free assets with a constant Sharpe ratio. In contrast to the approach of Fleming et al. (2001), which depends on forecasts for both returns and volatilities, this framework relies exclusively on the volatility forecasts. The expected utility[10] for investing in this portfolio at time t is (dropping in constant terms):

$$U(x_t) = E_t(x_t r^e_{t+1}) - \frac{\gamma}{2} Var_t(x_t r^e_{t+1}) = x_t E_t(r^e_{t+1}) - \frac{\gamma}{2} x_t^2 E_t(RV_{t+1}) \tag{4}$$

where x_t is the weight of the risky asset in this portfolio, r^e_{t+1} is the excess return, and γ denotes the degree of risk aversion of the investor's utility function. The Sharpe ratio, defined as $SR \equiv E_t(r^e_{t+1})/\sqrt{E_t(RV_{t+1})}$, is assumed to be a constant [11] so that the optimal weight x_t^* relies solely on the volatility forecast $E_t(RV_{t+1})$:

$$x_t^* = \frac{1}{\gamma} \frac{E_t(r^e_{t+1})}{E_t(RV_{t+1})} = \frac{SR/\gamma}{\sqrt{E_t(RV_{t+1})}}.$$

The corresponding expected utility then becomes:

$$U(x_t^*) \quad = \quad x_t^* SR \sqrt{E_t(RV_{t+1})} - \frac{\gamma}{2} x_t^{*2} E_t(RV_{t+1}) = \frac{SR^2}{2\gamma}.$$

By definition, the utility of a risk-free position is normalized to zero ($U(0) = 0$). Therefore, the investor would receive the same utility by either trading the risky asset optimally while paying a fee equal to $\frac{SR^2}{2\gamma}$ (in a utility sense) or investing all of his money in the risk-free asset.

The investor relies on the model to determine the expected conditional variance and then plugs it into the optimal weight. Thus, a model (denoted as θ) based position on the risky asset is $\frac{SR/\gamma}{\sqrt{E_t^\theta(RV_{t+1})}}$ and the corresponding expected utility can be expressed as:

$$U_t^\theta = \left(\frac{SR^2}{\gamma} \frac{\sqrt{E_t(RV_{t+1})}}{\sqrt{E_t^\theta(RV_{t+1})}} - \frac{SR^2}{2\gamma} \frac{E_t(RV_{t+1})}{E_t^\theta(RV_{t+1})} \right)$$

Bollerslev et al. (2018) suggest evaluating this expected utility empirically (and refer to it as the

[10]The utility is measured in the same unit of portfolio return which is equivalent to the $UoW(x)$ in Bollerslev et al. (2018).

[11]Bollerslev et al. (2018) provide a good discussion of this assumption.

"realized utility") by averaging the corresponding realized expressions over the out-of-sample period:

$$U_t^{\theta} = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{SR^2}{\gamma}\frac{\sqrt{RV_{t+1}}}{\sqrt{E_t^{\theta}(RV_{t+1})}} - \frac{SR^2}{2\gamma}\frac{RV_{t+1}}{E_t^{\theta}(RV_{t+1})}\right)$$

The realized utility measures the fee, on average, that investor would be willing to pay to trade the risky asset instead of the risk-free asset. We multiply this difference in the realized utility by 12 so that it can be interpreted as the annual portfolio management fee that an investor would be willing to pay to have access to the augmented model instead of the benchmark model. The statistical significance of this difference can be tested by the Diebold-Mariano (DM) test. In this paper, we take the corresponding monthly Sharpe ratio and the coefficient of risk aversion to be SR = 0.4 and γ =2, respectively.

Following the same procedure used for the out-of-sample volatility forecast in section 4.4, the data from 1990:01 to 1999:12 are used as the initial estimation period and the out-of-sample utility evaluation period spans from 2000:01 to 2014:07. To obtain the forecast of the realized volatility, we assume that the residuals of the regression models are normally distributed, and thus the forecast of the model for volatility can be expressed as

$$\widehat{RV_{t+1}} = \exp(\widehat{\alpha_t} + \widehat{\beta_t}\log RV_t + \widehat{\phi_t}U_t + \frac{\widehat{\sigma}^2}{2}).$$

Table 7 shows that the economic uncertainty generates large economic gains for the mean-variance investor, consistent with the large R_{OS}^2 statistics in Table 6. Except for the NASDAQ 100 index, the utility gains from MacUnc are consistently positive and economically large, ranging from 0.45% to 2.87%. Using the S&P 500 as an example, an investor would be willing to pay an annual portfolio management fee of up to 0.84% to have access to the model with economic uncertainty instead of the benchmark model. Notably, the economic uncertainty in the high yield bond market delivers the largest utility gain among all of the assets.

[Insert Table 7 here]

The utility gains for MacUnc are generally larger than the gains provided by SMU and SUI. The principal component approach works better than the KS method in most cases. EPU and VRP do not provide enough incentives for the investor to switch from the benchmark model. The decomposed results confirm that the improvements mainly occur during NBER recessions.

5. Conclusion

We investigate how economic uncertainty affects financial volatility by using a number of economic uncertainty measures, namely the large dataset based MacUnc (Jurado et al. (2015)), the small dataset based SMU (Carriero et al. (2017)), the VRP (Bali and Zhou (2016)), the EPU index (Baker et al. (2016)), the SUI (Sheen and Wang (2017)), and a measure combining the first principal components of the above five indices. We consider several financial assets, including equities, bonds, foreign exchange and commodities, and find that the different uncertainty measures have heterogeneous effects. Moreover, we highlight the superiority of the economic uncertainty indices constructed in data-rich environments and show that the first principal components of the uncertainty measures provide a balanced uncertainty measure that has a considerable impact on financial volatility. The out-of-sample forecasting power depends on the economic conditions and appears to be concentrated around recession periods. Our empirical results shed light on the link between macroeconomic information and financial volatility based on the economic uncertainty indices.

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Table 1: Literature Survey

Variable Name	Reference	Fre	Available Date	Information set	Description
Macroeconomic information based uncertainty measure					
Macroeconomic Uncertainty	Jurado et al. (2015)	M	1960:7-2018:6	132 macro and 147 financial variables.	An average of the volatilities of the residuals of macro-economic variables.
Macroeconomic Uncertainty	Carriero et al. (2017)	M	1960:9-2014:7	18 macro and 12 financial series.	The factor driving the dynamics in conditional mean and volatility of the macroeconomic variables.
Economic Uncertainty Index	Bali et al. (2014)	M	1994:1-2017:12	8 macroeconomic series.	The first principal component of conditional volatilities of 8 economic indicators.
Macroeconomic Uncertainty	Henzel and Rengel (2017)	M	-	164 macroeconomic series.	The factor driving the dynamics of volatilities of the residuals.
Survey and forecast based uncertainty measures					
Macroeconomic Uncertainty	Sheen and Wang (2017)	M	1961:1-2016:2	35 forecast series from surveys.	The factors driving the dynamics of the dispersions of various forecasts.
Uncertainty Index	Scotti (2016)	D	2003:5-2017:10	6 macroeconomic varble and forecast.	A weighted average of the square of expectation errors of the macroeconomic variable.
FDISP	Bachmann et al. (2013)	M	1968:5-2011:12	Business Outlook Survey	Defined as the disagreement in business expectations from the survey data.
Macroeconomic Uncertainty	Rossi et al. (2015)	Q	1968:3-2017:3	GDP forecasts from SPF	The difference between the GDP forecast error realization and its ex-ante probability.
GDP Forecasts Dispersion	Bloom (2009)	H	1962:2-1998:2	Livingstone profe-ssional forecasters	Standard deviation of the cross-sectional GDP forecasts.
Macroeconomic Uncertainty	Jo and Sekkel (2017)	Q	-	4 forecast series from SPF	The common factor in the forecast errors from the SPF forecasts for a few variables.
News based uncertainty measures					
EPU	Baker et al. (2016)	M	1985:1-2018:10	10 leading U.S. newspapers	Reflects the frequency of newspaper articles containing terms related to economic and policy uncertainty.
News Implied VIX	Manela and Moreira (2016)	M	1889:7-2016:3	All articles of the Wall Street Journa.	Derived from the co-movement between the coverage of the Wall Street Journal and VIX by machine learning.
World Uncertainty Index	Ahir et al. (2018)	Q	1996:1-2018:3	Economist Intelli-gence Unit reports.	Reflects the frequency of the word “uncertainty” in the Economist Intelligence Unit country reports.
GEU	Alexopoulos and Cohen (2015)	M	-	New York Times	Calculated based on a detailed textual analysis of articles published in The New York Times.
Financial variables based uncertainty measures					
VRP	Bali and Zhou (2016)	M	1990:1-2017:12	VIX and realized vo-latility of S&P 500	The difference in the expected variance between the risk-neutral and objective measures.
VXO (or VIX)	Bloom (2009)	D	1986:1-Present	S&P 500 options	Extracted from options, reflecting the investor’s expectation about the equity market volatility in the following month.
Corporate Bond Spread	Bachmann et al. (2013)	M	1968:5-2011:12	Corporate and trea-sury bond yield	The monthly spread of the 30-year Baa-rated corporate bond over the 30-year treasury bond yield.
Stock Returns Dispersion	Bloom (2009)	M	1962:7-2006:12	Firm level stock returns	Standard deviation of the cross-sectional firm stock returns.
Profit Growth Dispersion	Bloom (2009)	Q	1962:3-2005:1	Firm level profit growth	Standard deviation of the cross-sectional firm profit growth.

Table 2: Summary Statistics for the Uncertainty Measures

Variable	Mean	Std	Skew	Kurt	AR(1)	JB *p-val*	ADF *p-val*
			Panel A : Economic Uncertainty Indexes				
MacUnc	0.648	0.089	2.146	9.101	0.987	0.001	0.024
SMU	0.984	0.133	1.757	7.921	0.866	0.001	0.011
SUI	-0.541	0.551	2.553	12.48	0.937	0.001	0.001
EPU	109.9	41.83	1.307	4.882	0.715	0.001	0.001
VRP	17.35	21.32	3.566	26.44	0.260	0.001	0.001
PC	0.000	1.716	2.353	11.13	0.926	0.001	0.018
			Panel B : Correlations of Economic Uncertainty Indexes				
	MacUnc	SMU	VRP	EPU	SUI	PC	
MacUnc	1.000						
SMU	0.800	1.000					
SUI	0.779	0.744	1.000				
EPU	0.314	0.417	0.468	1.000			
VRP	0.275	0.213	0.212	0.359	1.000		
PC	0.884	0.887	0.891	0.627	0.435	1.000	

Note: This table shows the summary statistics of several economic uncertainty measures (Panel A) and the correlations between them. The reported statistics include the sample mean (Mean), standard deviation (Std), skewness (Skew), kurtosis (Kurt), first-order autocorrelation coefficients (AR(1)), the p-value from the Jarque-Bera test for normality (JB *p-val*), and the ADF test for stationary statistics (ADF *p-val*). The sample period is from 1990:01 to 2014:07.

Table 3: Summary Statistics for Financial Volatility

Variable	Mean	Std	Skew	Kurt	AR(1)	JB *p-val*	ADF *p-val*
S&P500	-6.439	0.941	0.649	3.613	0.739	0.001	0.001
NAS100	-5.550	0.969	0.574	2.958	0.771	0.004	0.021
T-Note	-8.271	0.669	0.109	3.032	0.589	0.500	0.001
HYB	-9.811	1.144	0.603	3.094	0.572	0.003	0.001
Dollar	-8.085	0.711	0.007	3.555	0.623	0.122	0.001
GSCI	-5.993	0.899	0.205	3.176	0.739	0.256	0.010

Panel B: Correlations of the Economic Uncertainty Indexes

	S&P500	NAS100	T-bond	HYB	Dollar	GSCI
S&P500	1.000					
NAS100	0.779	1.000				
T-bond	0.456	0.365	1.000			
HYB	0.627	0.393	0.548	1.000		
Dollar	0.386	0.213	0.397	0.400	1.000	
GSCI	0.571	0.393	0.337	0.483	0.392	1.000

Note: This table shows the summary statistics of log realized volatility for different financial assets. The realized volatility series are defined as the log of the realized variance. The reported statistics include the sample mean (Mean), standard deviation (Std), skewness (Skew), kurtosis (Kurt), first-order autocorrelation coefficients (AR(1)), the p-value from the Jarque-Bera test for normality (JB *p-val*), and ADF test for stationary statistics (ADF *p-val*). The sample period is from 1990:01 to 2014:07.

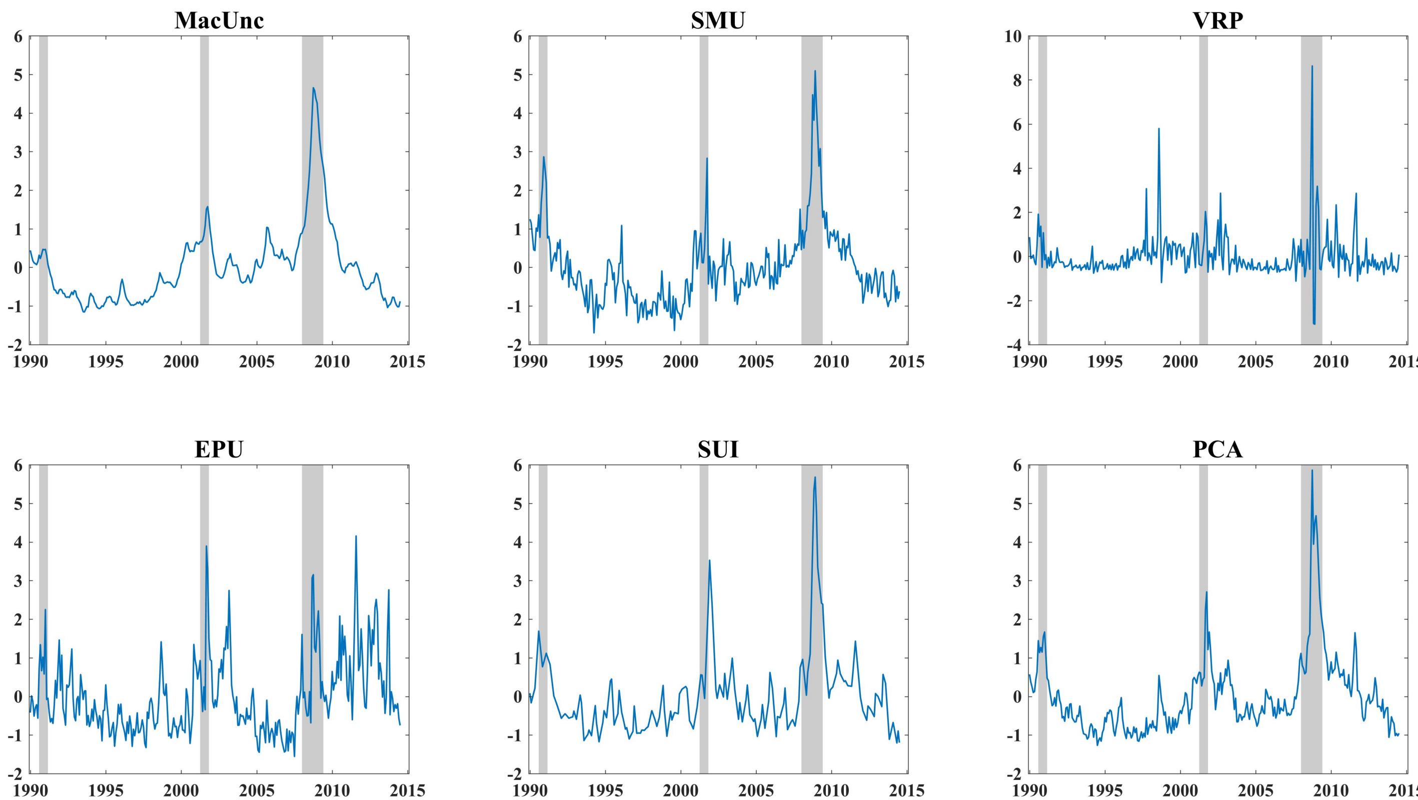

Figure 1: Time Series of the Uncertainty Measures

Note: Figure 1 shows the standardized economic uncertainty indexes over the full sample period from 1990:01 to 2014:07. The shadow regions indicate NBER-dated business-cycle recessions.

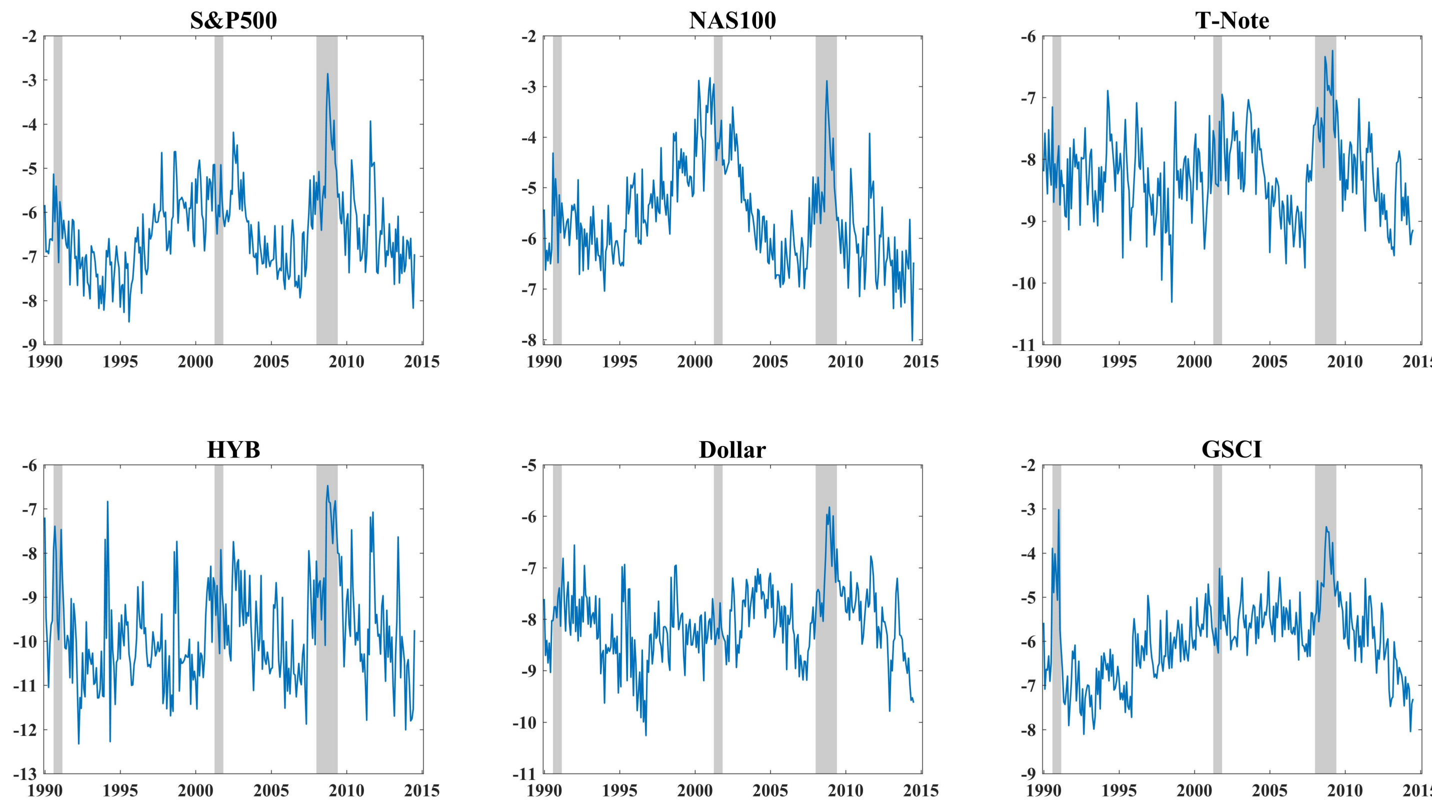

Figure 2: Time Series of Financial Volatility

Note: Figure 2 shows the log realized volatility of the financial assets over the full sample period from 1990:01 to 2014:07. The shadow regions indicate NBER-dated business-cycle recessions.

Table 4: The overall impact of uncertainty on volatility

	$\log RV_{t+1} = \alpha + \beta \log RV_t + \phi U_t + e_{t+1}$											
	MacUnc	SMU	VRP	EPU	SUI	PC	MacUnc	SMU	VRP	EPU	SUI	PC
	S&P 500						NAS100					
β	0.625***	0.703***	0.641***	0.741***	0.668***	0.621***	0.749***	0.772***	0.732***	0.786***	0.757***	0.758***
	(0.050)	(0.038)	(0.068)	(0.046)	(0.044)	(0.049)	(0.043)	(0.040)	(0.047)	(0.040)	(0.047)	(0.046)
ϕ	0.201***	0.085**	0.188***	-0.003	0.132***	0.186***	0.068*	0.001	0.097***	-0.049	0.045	0.038
	(0.055)	(0.042)	(0.064)	(0.042)	(0.039)	(0.051)	(0.039)	(0.035)	(0.035)	(0.032)	(0.034)	(0.034)
R^2	57.42	55.29	57.26	54.70	55.93	56.74	60.08	59.66	60.44	59.89	59.84	59.79
	T-Note						HYB					
β	0.507***	0.511***	0.564***	0.563***	0.472***	0.468***	0.412***	0.398***	0.513***	0.513***	0.426***	0.319***
	(0.063)	(0.059)	(0.057)	(0.063)	(0.064)	(0.068)	(0.060)	(0.064)	(0.078)	(0.070)	(0.055)	(0.057)
ϕ	0.206***	0.211***	0.126**	0.098*	0.232***	0.255***	0.313***	0.325***	0.186***	0.152	0.278***	0.409***
	(0.052)	(0.052)	(0.059)	(0.059)	(0.047)	(0.050)	(0.048)	(0.052)	(0.067)	(0.060)	(0.061)	(0.054)
R^2	38.50	38.76	36.48	35.84	38.93	39.91	40.42	40.68	36.39	35.25	38.80	43.40
	Dollar						GSCI					
β	0.511***	0.539***	0.608***	0.591***	0.516***	0.488***	0.519***	0.661***	0.722***	0.739***	0.663***	0.612***
	(0.055)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.055)	(0.052)	(0.047)	(0.045)	(0.052)	(0.057)
ϕ	0.245***	0.191***	0.117***	0.126**	0.228***	0.269***	0.320***	0.159***	0.069**	0.012	0.151***	0.211***
	(0.044)	(0.050)	(0.042)	(0.061)	(0.068)	(0.054)	(0.052)	(0.045)	(0.032)	(0.037)	(0.042)	(0.044)
R^2	44.16	42.38	40.87	40.99	43.43	44.76	60.34	56.96	55.51	55.08	56.72	57.81

Note: This table reports the results of the predictive regression of realized volatility on economic uncertainty. All of the variables are standardized prior to estimation and, consequently, the intercept α is omitted from the specification. Newey-West standard errors are provided in parentheses. ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels, respectively. The reported R^2 are the true values multiplied by 100. The sample period is from 1990:01 to 2014:07.

Table 5: In Sample Regression (Structure Change)

	$\log RV_{t+1} = \alpha + \theta I_t^{rec} + \beta \log RV_t + \gamma I_t^{rec} \log RV_t + \phi U_t + \delta I_t^{rec} U_t + e_{t+1}$					
	S&P 500	NAS100	T-Note	HYB	Dollar	GSCI
β	0.643***	0.766***	0.508***	0.338***	0.496***	0.680***
	(0.049)	(0.047)	(0.067)	(0.062)	(0.065)	(0.049)
γ	-0.376**	-0.194	-0.463**	-0.305	-0.065	-0.722***
	(0.159)	(0.142)	(0.200)	(0.193)	(0.227)	(0.143)
ϕ	0.099**	-0.011	0.142***	0.264***	0.175***	0.096**
	(0.049)	(0.032)	(0.054)	(0.067)	(0.057)	(0.042)
δ	0.369**	0.062	0.378**	0.364**	0.239	0.510***
	(0.147)	(0.138)	(0.184)	(0.170)	(0.210)	(0.109)
R^2	57.48	60.72	41.55	44.72	44.78	61.40

Note: This table reports the results of the predictive regression of realized volatility on economic uncertainty when considering the structural changes during the recession periods. The uncertainty measure used here is the first principal component of the five uncertainty indexes (PC). I_t^{rec} is an indicator that takes the value of one when month t is in an NBER recession period. All of the parameters are transferred to make the results comparable with those in Table 2 and, consequently, the interaction term measures the difference of the impact of a one standard deviation change in the predictor on the standard deviation of the realized volatility between the expansion and recession periods. Newey-West standard errors are provided in parentheses. ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels, respectively. The reported R^2 are the true values multiplied by 100. The full sample period is from 1990:01 to 2014:07.

Table 6: Out of Sample Results

	$\widehat{RV_{t+1}} = \widehat{\alpha_t} + \widehat{\beta_t} RV_t + \widehat{\phi_t} U_t$							
	R^2_{OS}	CW	$R^2_{OS,exp}$	$R^2_{OS,rec}$	R^2_{OS}	CW	$R^2_{OS,exp}$	$R^2_{OS,rec}$
	S&P 500				NAS100			
MacUnc	6.00***	2.53	2.73	19.7	-0.05*	1.53	-0.09	0.17
SMU	1.49**	2.30	1.34	2.09	-1.32	-1.09	-0.35	-7.56
VRP	3.12***	3.67	8.72	-20.4	-1.50	1.25	-0.24	-9.60
EPU	-1.47	-0.75	-1.80	-0.12	-1.54	-0.29	-0.44	-8.63
SUI	3.62***	2.72	2.80	7.03	-0.06	1.09	0.47	-3.44
PC	5.86***	2.42	3.95	13.9	-0.51	0.52	-0.26	-2.12
KS	6.24***	3.20	7.33	1.64	-3.73**	1.93	-2.64	-10.7
	T-Note				HYB			
MacUnc	6.43**	1.77	-3.34	32.9	10.4**	2.20	-5.10	54.3
SMU	7.46**	1.93	-1.46	31.6	11.0**	2.06	-1.84	47.4
VRP	3.02***	2.93	5.39	-3.38	5.45***	2.82	8.64	-3.61
EPU	-0.13*	1.50	-4.26	11.03	1.10**	1.78	-1.59	8.74
SUI	9.30**	2.26	2.77	26.9	8.33**	1.93	-0.88	34.5
PC	9.91**	2.15	0.30	35.9	14.8**	2.33	2.90	48.4
KS	6.28**	2.24	1.99	17.9	13.8***	2.39	5.06	38.4
	Dollar				GSCI			
MacUnc	11.9**	1.81	-1.40	49.9	17.6***	3.24	12.4	33.7
SMU	7.25*	1.60	-0.82	30.3	6.87***	2.44	2.47	20.3
VRP	0.95*	1.28	-0.07	3.86	-1.30	0.34	-2.74	3.08
EPU	-7.06	0.80	-9.06	-1.34	-1.58	-0.95	-1.49	-1.88
SUI	5.19*	1.53	-4.31	32.4	4.10**	2.21	-0.03	16.7
PC	9.09**	1.70	-1.44	39.2	9.04***	2.43	3.03	27.4
KS	-3.31*	1.30	-12.99	24.4	13.2***	2.94	7.03	32.2

Note: This table reports the out-of-sample performances of various economic uncertainty measures in predicting realized volatility. All of the out-of-sample forecasts are estimated recursively using data available at the forecast formation time t. The out-of-sample evaluation period is 2000:01-2014:07. R^2_{OS} is the Campbell and Thompson (2008) out-of-sample R^2 measuring the reduction in the mean squared forecast error (MSFE) for the competing predictive regression forecast relative to the AR(1) benchmark forecast. CWstat is the Clark and West (2007) statistic for testing the null hypothesis that the AR(1) forecast MSFE is less than or equal to the competing predictive regression forecast MSFE against the one-sided (upper-tail) alternative hypothesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. We also report the R^2_{OS} statistics separately for NBER-dated business-cycle expansions ($R^2_{OS,exp}$) and recessions ($R^2_{OS,rec}$).

Table 7: Utility-based Economic Value

	ΔUtility(%) (All)	DM	ΔUtility(%) (exp)	ΔUtility(%) (rec)	ΔUtility(%) (All)	DM	ΔUtility(%) (exp)	ΔUtility(%) (rec)
		S&P 500				NAS100		
MacUnc	0.84*	1.38	0.20	4.47	0.21	0.95	0.11	0.76
SMU	0.07*	1.34	0.06	0.12	-0.13	-1.17	-0.02	-0.78
VRP	0.17	0.42	0.68	-2.70	-0.01	-0.05	0.04	-0.29
EPU	-0.05	-0.69	-0.07	0.04	-0.16	-0.87	-0.08	-0.57
SUI	0.38**	1.74	0.24	1.17	0.08	0.69	0.04	0.28
PC	0.69**	1.90	0.40	2.31	0.06	0.65	0.02	0.27
KS	1.20**	1.93	0.68	4.14	0.18	0.38	0.11	0.54
		T-Note				HYB		
MacUnc	0.45**	1.82	-0.04	3.29	2.87*	1.33	-0.34	21.22
SMU	0.45**	2.09	-0.01	3.10	2.57*	1.40	-0.17	18.32
VRP	0.06	0.45	0.14	-0.44	0.00	0.00	1.14	-6.53
EPU	0.08	0.51	-0.06	0.93	0.86	0.79	0.90	0.62
SUI	0.45***	2.47	0.10	2.47	2.00**	1.64	0.42	11.02
PC	0.61**	2.14	0.06	3.73	3.90**	1.73	1.09	19.97
KS	0.34**	1.95	0.08	1.83	3.62**	1.87	0.94	18.92
		Dollar				GSCI		
MacUnc	0.50*	1.44	-0.07	3.79	1.01***	2.35	0.48	4.08
SMU	0.33*	1.54	-0.03	2.41	0.38***	2.78	0.15	1.73
VRP	0.04	0.21	0.02	0.12	0.02	0.15	-0.11	0.79
EPU	-0.03	-0.12	-0.21	0.99	-0.09	-1.18	-0.05	-0.31
SUI	0.32	1.17	-0.08	2.62	0.20*	1.31	-0.03	1.54
PC	0.46*	1.27	-0.04	3.37	0.54***	2.28	0.15	2.83
KS	0.21	0.49	-0.29	3.06	0.82**	1.83	0.25	4.05

Note: This table reports the portfolio performance measures developed by Bollerslev et al. (2018) for a mean-variance investor with a constant Sharpe ratio SR of 0.4 and risk aversion degree θ of 2, who makes monthly allocations between risky and risk-free assets. The utility measures the fee, on average, that investor would be willing to pay for trading the risky asset instead of the risk-free asset. We multiply this difference in utility ΔUtility by 12 so that it can be interpreted as the annual portfolio management fee that an investor would be willing to pay to have access to the model with economic uncertainty instead of the benchmark model. The out-of-sample evaluation period is 2000:01-2014:07. We use DM stat to test the null hypothesis that the utility generated by the benchmark model is larger than or equal to the model with an uncertainty measure against the one-sided alternative hypothesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. We also report ΔUtility separately for NBER-dated business-cycle expansions (ΔUtility(exp)) and recessions (ΔUtility(rec)).