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Stock market volatility and jumps in times of uncertainty

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Abstract

In this paper we examine the predictive power of latent macroeconomic uncertainty on US stock market volatility and jump tail risk. We find that increasing macroeconomic uncertainty predicts a subsequent rise in volatility and price jumps in the US equity market. Our analysis shows that the latent macroeconomic uncertainty measure of Jurado *et al*. (2015) has the most significant and long-lasting impact on US stock market volatility and jumps in the equity market when compared to the respective impact of the VIX and other popular observable uncertainty proxies. Our study is the first to show that the latent macroeconomic uncertainty factor outperforms the VIX when forecasting volatility and jumps after the 2007 US Great Recession. We additionally find that latent macroeconomic uncertainty is a common forecasting factor of volatility and jumps of the intraday returns of S&P 500 constituents and has higher predictive power on the volatility and jumps of the equities which belong to the financial sector. Overall, our empirical analysis shows that stock market volatility is significantly affected by the rising degree of unpredictability in the macroeconomy, while it is relatively immune to shocks in observable uncertainty proxies.

Keywords: *Jumps, Bipower variation, Realized volatility, Macroeconomic Uncertainty*

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1. Introduction

What are the key drivers of volatility and jumps in stock market prices? Historically, stock prices exhibit large swings during periods of heightened uncertainty in the economy. For example, the S&P500 index lost approximately 20% of its market value during the first quarter of 2020, while the VIX index jumped from 12.5% on 2nd January 2020 to 82.7% on 16th March 2020, in response to the COVID-19 pandemic uncertainty episode. The recent history contains many examples of rising stock price volatility and jumps in times of significant macro-oriented uncertainty shocks like the COVID-19 pandemic, the Great Recession and the Euro Area debt crisis. Despite the wealth of descriptive evidence, there is only limited empirical evidence in the literature showing the impact of economic uncertainty shocks on stock market volatility and jumps.[1] Moreover, while some recent empirical studies show that stock price volatility is positively correlated with several different measures of financial and macroeconomic uncertainty (Baker *et al*., 2020; Bloom, 2009; Bekaert and Hoerova, 2014; among others), little attention has been given to the dynamic impact and the predictive power of macroeconomic uncertainty shocks on stock market volatility and price jumps.[2] In this study, we fill this gap in the literature by empirically examining the impact and the predictive power of macroeconomic uncertainty on stock market volatility and jumps.

The extant empirical literature suggests that short-term volatility and jumps in the equity market are predictable to a degree using variables such as lagged realized volatility and implied volatility (Andersen et al., 2007; Bekaert and Hoerova, 2014; Corsi, 2009; Canina and Figlewski, 1993; Christensen and Prabhala, 1998; Fleming *et al*., 2007). Moreover, another strand of the literature shows that a large part of the time variation of equity market volatility can be explained by a single common factor. For example, Engle and Susmel (1993) demonstrate that the international stock markets have the same time varying volatility, while Anderson and Vahid (2007) show that a common factor which is constructed using the lagged volatility series of equity prices

[1] To the best of our knowledge, Amengual and Xiu (2018) and Liu and Zhang (2015) are the only studies showing the positive effect of Economic Policy Uncertainty (EPU) on US stock market volatility. In this paper, the primary focus is on the impact of macroeconomic uncertainty (measured as unpredictability regarding future macroeconomic outcomes) and not of EPU on stock market volatility.

[2] For example, Bekaert and Hoerova (2014) show that the US stock market volatility and the VIX index coincide with major uncertainty shocks like the 2007-2009 Great Recession, the Russian Crisis and the European sovereign debt crisis. Baker *et al*. (2020) in their study show that no other disease has influenced the US stock market as strongly as the recent COVID-19 pandemic.

explains a large part of the aggregate time varying stock market volatility. A third strand of the literature shows that equity market volatility is related to business cycle fluctuations (Engle *et al.,* 2013; Hamilton and Lin, 1996; Paye, 2012; Schwert, 1989; Wachter, 2006; among others). For instance, Schwert (1989) finds that the yearly volatility of industrial production and interest rates forecasts aggregate stock market volatility, while Wachter (2013) shows that the time-varying probability of rare-disaster risk in the macroeconomy is an important early warning signal of rising volatility in the equity market. Other studies concentrate on equity price jumps instead of volatility and examine their relationship to macroeconomic news (Evans, 2011; Faust and Wright, 2018; Lahaye *et al*., 2011; Miao *et al*., 2014).

Motivated by the empirical findings that identify the significant impact of macroeconomic news releases and economic policy uncertainty on stock market volatility (Amengual and Xiu, 2018; Brenner *et al*., 2009; Engle, *et al*., 2013; Kaminska and Roberts-Sklar, 2018; Liu and Zhang, 2015; among others), we investigate the stock market effect of unobservable (latent) macroeconomic uncertainty which captures the unforecastable (by economic agents) variations in key macroeconomic indicators. We base our analysis on a discounted cash-flow model in which we attribute the unexplained part of stock price volatility (the non-fundamental driven volatility) to macroeconomic uncertainty. As a proxy for macroeconomic uncertainty, we use the unobservable Macroeconomic Uncertainty measure of Jurado *et al*. (2015) (MU henceforth), which captures the time variation in the degree of unpredictability of US macroeconomic fluctuations. MU is defined as the squared forecast error of a multivariate factor model used for forecasting US business cycles.[3] The results presented in the paper clearly show that latent macroeconomic uncertainty has significant predictive power on US stock market volatility and contains information which is different to the predictive information content of the VIX and other uncertainty proxies based on observable macroeconomic news. The fact that the MU factor has incremental predictive power when included into a multivariate forecasting regression model which includes the VIX, US Industrial Production and the Baa corporate default

[3] Jurado *et al*. (2015) support the view that some popular and widely accepted uncertainty proxies like the Economic Policy Uncertainty may fluctuate for several other reasons which are not related to uncertainty. According to Jurado *et al*. (2015), observable macroeconomic indicators can fluctuate over time even if there is no change at all in uncertainty about economic fundamentals.

spread, shows that the MU factor indeed explains the part of stock market volatility which cannot be attributed to changes in fundamentals. Moreover, our VAR analysis reveals that a positive latent macroeconomic uncertainty shock has larger and more long-lasting positive effect on stock market volatility compared with the respective impact of VIX shocks and shocks to other popular observable economic uncertainty proxies. For example, the response of stock market volatility to MU shocks is more than 3 times larger in magnitude and persistence when compared with the respective response of stock market volatility to VIX or Economic Policy Uncertainty (EPU) shocks. Hence, our second and more significant contribution in the literature is that we show for the first time that the latent macroeconomic uncertainty outperforms the VIX and EPU when forecasting volatility in the US equity market.

When we decompose the realized variance of equity returns into its continuous and discontinuous part, we find that the latent MU factor does not perform well in forecasting equity price discontinuities (jumps). This result is puzzling, as previous literature (see Akhtar *et al.*, 2017) has successfully linked unanticipated macroeconomic news and stock market jumps. Motivated by a strand in the literature that identifies tighter linkages between the macroeconomy and financial markets during the post-2007 crisis era (Abbate *et al*., 2016, Caldara *et al*., 2016), we split our sample to before and after the 2007 US recession period and re-estimate our models. Our econometric analysis identifies a spectacular rise in the forecasting performance of MU on both stock market volatility and jumps in the post-crisis period. Moreover, when estimating our VAR model for the post-2007 period, we find that the dynamic effect of MU shocks on stock market volatility and price jumps increases tremendously in magnitude. Importantly, our post-crisis VAR analysis identifies the MU shock as the most significant (in terms of magnitude and persistence) type of uncertainty shock affecting the time varying volatility and jump tail risk in the US equity market. Our findings provide further empirical insights to the findings of Abbate *et al.* (2016), Caldara *et al.* (2016) and Ellington *et al*. (2017) who investigate the time variation in macro-financial linkages and find that the impact of financial shocks to US real business cycles has exponentially increased after the Great Recession. Our results are in line with this strand of literature since we also show that the impact of macroeconomic uncertainty shocks on US stock market volatility has exponentially increased during the post-2007 crisis period. Our analysis identifies an increasing effect of all macroeconomic uncertainty shocks (e.g. macro-uncertainty and monetary policy uncertainty) on stock market volatility and jumps after the 2007 US recession. Nevertheless, it is the latent MU factor that has the highest predictive power in the post-crisis period, when compared to that of observable economic uncertainty proxies like Economic Policy Uncertainty (EPU) and Monetary Policy Uncertainty (MPU).

Our findings are also broadly in line with those of Akhtar *et al.* (2017), Bernanke and Kuttner (2005) and Rangel (2011) who find that the unanticipated component of Fed fund's rate and of macroeconomic announcements has the most significant effect on stock market price jumps and jump intensities. While the relevant literature so far shows that jumps and co-jumps in stock market prices are attributed to scheduled releases of macroeconomic news (Bollerslev, Law and Tauchen, 2008; Evans, 2011; Lahaye *et al.*, 2011; Miao *et al.,* 2014), our contribution in this strand of macro-finance literature is that we show that the key driver of stock market price volatility and jumps is the rising uncertainty about the future state of the economy, and not the uncertainty about economic policy which is based on macroeconomic news.[4] Hence, the economic interpretation of our findings, is that, what matters most for equity price stability, is not the numerous large fluctuations in macroeconomic indicators which are relatively more predictable by financial market participants, but the relatively fewer unanticipated (difficult to be predicted ex ante) changes in macroeconomic outcomes.

In order to gain further insights on our results at the aggregate market level, we also examine the predictive power of the MU factor on the volatility and price jumps of individual US equities (S&P500 constituents), so as to identify the market sectors that have the highest sensitivity to macroeconomic uncertainty. Our forecasting regressions show that the latent macroeconomic uncertainty factor constitutes a common volatility and jump tail risk forecasting factor in the equity market (it enters significantly in predictive regressions on volatility and jumps of the S&P 500 constituents). Moreover, we empirically show for the first time in the literature that the MU factor outperforms

[4] For example, the Economic Policy Uncertainty (EPU) index of Baker *et al*. (2016) is constructed using newspaper articles which refer to policy uncertainty. Similarly, the US long-term bond yield volatility quantifies the dispersion of expectations of economic agents about the future path of short-term interest rates. Hence, both these uncertainty proxies are strongly related with (and quantify in some degree) the changes in the macroeconomic environment and market expectations in response to macroeconomic news releases.

the VIX when used as predictor of volatility and price jumps of individual stocks. Interestingly, we find that, although the MU factor performs well as a predictor of the volatility and price jumps of stocks belonging to many sectors of US stock market, it performs the best when predicting the volatility and price jumps of financial firms (with the weakest performance exhibited on the Technology and Healthcare sectors). It appears that the instability and turbulence in the US financial sector is, to a significant extent, driven by the rising uncertainty about the future state of the US economy.

The rest of the paper is organized as follows: Section 2 discusses the theoretical stock price volatility model and the channels linking macroeconomic uncertainty with stock market volatility. Section 3 describes the data and outlines the empirical methodology. Section 4 presents the empirical results and Section 5 reports the various robustness checks. Finally, Section 6 concludes.

2. The discounted cash-flow model under uncertainty

We postulate that the main channel through which economic uncertainty affects the volatility of stock prices is by increasing the uncertainty about future cash flows (dividends). The discounted cash flow model specifies that the fair value of a firm's stock is equal to the sum of the discounted expected cash flows to its stockholders (Fama, 1990; Schwert, 1989; among others). Nevertheless, most related studies show that stock price fluctuations are too high to be entirely attributed to fluctuations of their discounted dividend yields. For example, Fama (1990) shows that approximately 40% of stock price changes cannot be explained by changes in fundamentals like expected dividends and economic activity. Shiller (1981) comes to the same conclusion by showing that stock market volatility (which, according to the efficient market hypothesis, has to be roughly equal to the volatility of expected cash flows to stockholders) is many times larger than the volatility of expected cash flows (dividends plus capital gains). The more recent empirical findings of Schmeling (2009) show that investor sentiment (measured as consumer confidence) is a statistically significant predictor of stock market returns in 18 industrialized economies, while Berger and Turtle (2015) find that the changes in investor sentiment are followed by periods of increasing overvaluation in the equity market. Overall, the consensus in the literature is that there is a significant percentage of stock market fluctuations which cannot be explained by fundamentals. To address this issue, we introduce a stock pricing model with time varying latent macroeconomic uncertainty (which can be viewed as uncertainty about future dividend yields, see Schwert, 1989) representing the component of stock market volatility which is 'unexplained' by economic fundamentals. Following Schwert (1989), we assume that the stock price is equal to the sum of the expected discounted cash flows of the stock to its stockholders:

$$P_t = E_{t-1}(DCF_t) \tag{1}$$

Hence, in **Equation (1)** DCF_t represents the sum of expected discounted dividends plus capital gains as shown in **Equation (2)** below:

$$DCF_t = \sum_{k=1}^{\infty} \frac{D_{t+k}}{(1+r_{t+k})^k} \tag{2}$$

In **Equation (2)** above, D_{t+k} is the capital gain plus the dividend yield which is paid to stockholders and r_{t+k} is the expected discount rate for the dividends which are distributed to stock owners during the period $t+k$. Without loss of generality, we assume that the sum of expected discounted cash flows $E_{t-1}(DCF_t)$ shown in **Equation (1)** is equal to the actual sum of discounted cash flows to investors (DCF_t) plus the forecast error e_t about future cash flows being made by stock market participants. Hence, **Equation (1)** becomes:

$$P_t = DCF_t + e_t \tag{3}$$

In **Equation (3)**, different assumptions can be made about the distributional properties of the forecast error e_t. For example, in models with rational expectations the main assumption is that economic agents do not make systematic mistakes and their forecast errors are identically and independently distributed (i.i.d) variables following the normal distribution with zero mean and constant finite variance (Muth, 1961). These assumptions can be relaxed by allowing economic agents to have both rational and irrational expectations. Investors can behave rationally by making very negligible and non-systematic forecast errors, and irrationally by making persistent mistakes and forecast errors when for example their expectations are driven by non-fundamental factors like market sentiment (Baker and Wurgler, 2007; Shiller, 1981; Schmeling, 2009).[5] A corollary of **Equation (3)** is that the variance of the stock price will be the sum of the variance of discounted cash-flows (DCF_t) plus the variance of the forecast error (e_t) as shown in **Equation (4)** below:[6]

$$VAR(P_t) = VAR(DCF_t) + VAR(e_t) \tag{4}$$

From **Equation (4)** we observe that if there is no uncertainty (or sentiment driven dispersion in expectations) regarding the future dividends and discount rates (when the forecast error is equal to zero), then the volatility of the stock price will be equal to the volatility of discounted expected cash flows. **Equation (4)** can be equivalently written as below:

$$VAR(P_t) = \sigma_t^2 + u_t^2 \tag{5}$$

In **Equation (5)**, σ_t^2 is the fundamental volatility and u_t^2 is the squared forecast error which is linked to uncertainty. Our main hypothesis is that the latent macroeconomic uncertainty is a sound proxy for uncertainty regarding the level of expected dividend yields, and therefore, it is a major driver of fluctuations in stock market volatility. Following Schwert (1989) we postulate that uncertainty about future macroeconomic conditions causes a proportional increase in the volatility of stock prices. Our proxy for macroeconomic uncertainty is the Jurado *et al.* (2015) measure which is defined as the squared forecast error of a large set of predictors on future economic activity. More specifically, according to Jurado *et al.* (2015), the *h*-period ahead uncertainty about a macroeconomic indicator $Y_{i,t}$ is the purely unforecastable component (the squared forecast error) of the $Y_{i,t}$ series using all available information up to time *t*, as shown below:

$$u_t(h) = \sqrt{E\left[(y_{t+h} - E[y_{t+h} / I_t])^2 / I_t \right]} \tag{6}$$

Where I_t is the information set, containing all the information available to economic agents at time *t*. In order to remove all the forecastable component, Jurado *et al*. (2015)

[5] Another strand of the literature attributes the deviation of stock prices from their fundamental (intrinsic) values to the existence of rational bubbles (Blanchard and Watson, 1982; Diba and Grossman, 1988; among others).
[6] In **Equation (4)** we do not include the covariance term. Following the fundamental principle of optimal forecasts, (see for example Shiller, 1981), we assume that forecast errors and the forecasted variable are uncorrelated, hence the covariance term COV(DCF_t,e_t)=0.

choose a large set of predictors of economic activity so that they span as close to the information set I_t as possible. The aggregation of individual uncertainty series for a large set of US economic indicators is the Jurado *et al*. (2015) measure of latent macroeconomic uncertainty. Then, from **Equation (5)** it follows that rising $u_t(h)$ is associated with rising stock market volatility h-periods ahead.

3. Data-Methodology

3.1 Data

We estimate monthly realized variance and jump tail risk, using high-frequency (5-minute) price observations for the S&P 500 index for the period between 1st January 1990 and 31st December 2017. We additionally use 5-minute price observations of the 501 stocks that comprise the S&P500 stock market index for the period covering November 2002 to December 2017.[7] The intraday stock market prices for the S&P500 index and its constituents are obtained from Pi Trading. The analytical methodology for the estimation of realized variance and jump tail series is presented in **Subsection 3.2**. The main macroeconomic variable we consider for forecasting stock market volatility and jumps is the latent macroeconomic uncertainty measure of Jurado *et al.* (2015). More specifically, we include the monthly Macroeconomic Uncertainty (MU) variable which quantifies the time-varying unpredictability of future macroeconomic outcomes for the next 1-month (MU1), the next 3-month (MU3) and the next 12-month period respectively. The MU1, MU3 and MU12 variables have all monthly frequency and are estimated as the squared forecast error of a large-scale Factor Augmented VAR (FAVAR) model on future economic activity. As a result, the dataset we use for our econometric estimations has monthly frequency. Therefore, we cannot include the daily and weekly lagged realized variance and jump series (as in the HAR-RV model, see for example Bekaert and Hoerova, 2014) to our analysis, as the highest frequency used is dictated by the frequency of the dependent variable, which is in monthly frequency. For robustness, we also include in the analysis the monthly US Economic Policy Uncertainty (EPU) measure of Baker *et al*. (2016) and its component which measures

[7] The S&P 500 index is comprised from 505 stocks. Due to data availability issues, we include 501 out of the 505 stocks currently reported as constituents of the S&P500 index. The list of the 501 S&P500 constituents that are included in our analysis as well as the 4 missing S&P500 stocks, are reported in the on-line Appendix. Moreover, unlike the data series for the S&P500 index which starts from January 1990, due to data availability issues, the respective high-frequency (5-minute) price series for the 501 constituents of S&P500 cover the period from 1st November 2002 to 31st December 2017.

uncertainty about US monetary policy (Monetary Policy Uncertainty (MPU) index).[8] We also use monthly time series for the Baa corporate bond spread (the monthly spread between Moody's Baa corporate bond and the 10-year constant maturity US Treasury Bond yield) which also covers the January 1990 till December 2017 period. The Baa corporate bond spread (BAA) time series is downloaded from the FRED database. The monthly VIX index data cover the period from January 1990 till December 2017 and are downloaded from Datastream. Finally, the 90 day and 360-day maturity S&P500 monthly implied volatility series are obtained from the Option-metrics database.[9]

3.2 Realized Variance and jump tail risk estimation

The time series of realized volatilities is estimated as in Andersen *et al.* (2001) by calculating the sum of squared 5-minute logarithmic returns filtered through an MA(1) process as shown in **Equation (7):**

$$RV_t = \sum_{i=1}^{n} r_i^2 \tag{7}$$

where $r_i = \log(p_i/p_{i-1})$, with p denoting the filtered price series and n the number of intraday (5-minute) observations in each monthly period.[10]

To construct the time series that captures stock price variation due to jumps ($JUMP_t$), we use the methodology of Barndorff-Nielsen and Shephard (2006), according to which the jump component of the intraday returns is the difference between realized variance (which captures quadratic variation) and realized bi-power variation (which captures the continuous component of RV) calculated using 5-minute returns:

$$JUMP_t = RV_t - RBV_t \tag{8}$$

with

$$RBV_t = \mu_1^{-2} \sum_{i=2}^{n} |r_i||r_{i-1}| \tag{9}$$

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[8] The uncertainty measures of Jurado et al. (2015) are available at: https://www.sydneyludvigson.com/data-and-appendixes while the Economic Policy Uncertainty measures can be found on the EPU website at: http://www.policyuncertainty.com

[9] The VIX index corresponds to the constant (interpolated) 30-day S&P500 index implied volatility. In order to include the implied volatilities which are backed-out from 3-month and 12-month maturity S&P500 option contracts, we include the respective implied volatility series with constant (interpolated) 90-day and 360-day maturity. The Option-metrics implied volatility data cover the period from January 1996 till December 2017.

[10] Since we estimate the monthly realized variance, the value of (n) is equal to the number of intra-day (5-minute) observations during each monthly time series period. The average number (n) of 5-minute observations (intra-day returns) for all months in our data sample is equal to 1,646 observations

where $\mu_1 = \sqrt{2/\pi}$ and $r,\ n$ are defined as previously. We obtain a more robust estimator for RBV_t by averaging between skip-0 through skip-4 realized bi-power variation (for more details see Patton and Shephard, 2015).[11]

3.3 OLS Predictive Regression models

We estimate a set of bivariate and multivariate regression models on the Realized Variance (RV) and the price jumps (JUMP) of the intra-day returns of the S&P500 equity index. For the bivariate OLS forecasting regressions the *MU(k)* latent uncertainty is the only predictor of S&P500 Realized Variance. The bivariate time-series forecasting regression model is given in **Equation (10)** below:

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + \varepsilon_t \tag{10}$$

Where *MU(k)* is the latent macroeconomic uncertainty with *k*-month ahead forecasting horizon. Since the *MU(k)* is the squared forecast error of a multivarite dynamic factor model on US economic activity having *k*-month forecasting horizon (Jurado *et al.*, 2015), it can only be observable *k*-months after the initial forecast period (when the actual forecast error materializes). In order to avoid this look-ahead bias issue in our forecasting regression models, we include one more lag on the MU(k) variable so that it can be available to the predictive modeler at the time the stock market volatility forecast takes place.[12] Motivated by the results of the literature on equity volatility and jump tail risk forecasting which identify the VIX index (Canina and Figlewski, 1993; Fleming *et al.*, 2007; among others), the lagged Realized Variance and jump tail risk (Bekaert and Hoerova, 2014; Corsi, 2009; among others), Economic Policy Uncertainty (Liu and Zhang, 2015) and monetary policy uncertainty (Bekaert *et al.*, 2013; Bernanke

[11] Andersen *et al.* (2007) show that skip versions of various estimators possess statistical properties superior to those computed using adjacent returns. The "skip-q" bi-power variation estimator is defined as

$$RBV_{q,t} = \mu_1^{-2} \sum_{i=q+2}^{n} |r_i||r_{i-1-q}|$$

with μ_1, r and n defined as previously. The usual RBV estimator is obtained when q = 0. As noted by Patton and Shephard (2015), averaging the skip-0 through skip-4 estimators "…represents a trade-off between locality (skip-0) and robustness to both market microstructure noise and jumps that are not contained in a single sample (skip-4)."

[12] For example, for one-month horizon predictive regressions (*k=1*), we include two lags on the *MU1* factor in the predictive regression, in order for the *MU1* variable to be available to the predictive modeler on month *t-1* to make the volatility forecast for month *t*.

and Kuttner, 2005; Kaminska and Roberts-Sklar, 2018; among others), we estimate the same type of bivariate regression models on stock market volatility using the VIX, the lagged RV, the Economic Policy Uncertainty (EPU) and Monetary Policy Uncertainty (MPU) in the right-hand side of the regression equation. Our baseline multivariate forecasting regression model on stock market Realized Variance (*RV*) is given in **Equation (11)** below:

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + \varepsilon_t \quad (11)$$

We also empirically examine the predictive power of the latent macroeconomic uncertainty measures on the jump component of stock market volatility (the stock market variation due to jumps). Our baseline jump tail risk forecasting regression model is presented in **Equation (12)** below:

$$JUMP_t = b_0 + b_1 MU(k)_{t-k-1} + \varepsilon_t \quad (12)$$

We additionally estimate identical bivariate regression models on JUMPS using the *VIX*, the lagged RV, EPU and MPU instead of the MU(k) factor. We run an identical (to **Equation (11)**) multivariate forecasting regression model when predicting stock market price jumps (JUMP).

3.4 VAR Model

Following Bekaert *et al.* (2013), we estimate a multivariate VAR model for stock market volatility (RV) in which we control for latent macroeconomic uncertainty (MU), the VIX index and US Economic Policy Uncertainty (EPU). Therefore, we estimate a 4-factor VAR model in which we include as endogenous variables the observable economic uncertainty shocks (VIX, lagged RV and EPU, see Baker *et al.* (2016), Bloom (2009)) as well as the unobservable (latent) economic uncertainty shocks. In this way, we control for the interaction between various types of observable and unobservable uncertainty and stock market volatility. Our reduced form VAR model is given in **Equation (13)** below:

$$Y_t = A_0 + A_1 Y_{t-1} + \ldots + A_k Y_{t-k} + \varepsilon_t \quad (13)$$

Where A_0 is a vector of constants, A_1 to A_k are matrices of coefficients and ε_t is the vector of serially uncorrelated disturbances, with zero mean and variance-covariance matrix $E(\varepsilon_t, \varepsilon_t^{'}) = \sigma_\varepsilon^2 I$. Y_t is the vector of endogenous variables. The lag-length (*k*) for the VAR model is selected using the Schwarz (*SBIC*) optimal-lag length information criterion which suggests the inclusion of two lags in the VAR model (*k=2*).[13] The ordering of our baseline 4-factor VAR model is shown in **Equation (14)** below.[14]

$$Y_t = [RV_t \; VIX_t \; EPU_t \; MU1_t] \tag{14}$$

where *RV, EPU, VIX* and *MU1* are the monthly endogenous variables of the VAR model.[15] We base our analysis on the estimated Orthogonalized Impulse Response Functions (OIRFs) using the Cholesky identification method for the orthogonalization of shocks in the VAR model.

4. Econometric analysis

4.1 Descriptive statistics

In this section we present some descriptive statistics of our time series variables. **Table 1** below shows the descriptive statistics and **Table 2** shows the correlation matrix of our explanatory variables.

[Insert Tables 1 and 2 Here]

From **Table 1** we observe that the standard deviation of the MU series is much smaller compared to observable uncertainty proxies like EPU and MPU. According to Jurado *et al.* (2015), the reason for the significantly lower volatility of the MU series compared with other observable economic uncertainty proxies is that macroeconomic uncertainty episodes (in the form of increasing unpredictability in the economy) are less frequent

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[13] Our VAR estimates remain robust to the choice of lags that are included in the VAR model. More specifically, our VAR results remain unaltered when using the Akaike or the Hannan-Quinn information criteria for selecting the optimal lag-selection of the VAR model. These additional VAR results are available upon request.

[14] Our findings remain robust to alternative VAR orderings. For example, following Bekaert *et al.* (2013) we also place macroeconomic variables first and stock market variables last in the VAR model and our main findings remain unaltered. These additional VAR results can be provided upon request.

[15] In our paper we choose to present the VAR model in which we include the MU1 variable as our proxy for latent macro-uncertainty. Our VAR results remain unaltered when choosing the MU3 or MU12 variable instead for the MU1 variable to estimate our 4-factor VAR model. These results which provide robustness to our findings, can be found in our on-line Appendix.

compared to the observable fluctuations of EPU or MPU, which may not be entirely related to uncertainty. According to Jurado *et al.* (2015), the observable proxies for uncertainty like EPU can change over time even if there is no change in uncertainty about fundamentals. Moreover, the correlation matrix shown in **Table 2** reports low values for the correlations between the explanatory variables used in the empirical analysis. **Figures 1** and **2** below show the synchronous time series variation of the latent Macroeconomic Uncertainty (MU), the VIX index and the realized volatility and jumps, respectively.

[Insert Figures 1 and 2 Here]

We observe from **Figure 1** that realized volatility significantly rises after large macroeconomic uncertainty episodes. Moreover, the large volatility spike in the US financial crisis of 2008 was not captured by the VIX since the VIX increased only as an overreaction of investors linked with the aftermath of the Lehman Brothers collapse.[16] On the other hand, the latent macroeconomic uncertainty started rising many months prior to the large October 2008 stock market volatility episode. This is a first indication that the rising economic uncertainty can act more efficiently as an early warning signal of rising stock market turbulence.[17] **Figure 2** reveals a similar story for the relationship between high levels of the MU index and price jumps in the stock market.

4.2 Forecasting regression models on stock market volatility and jumps

4.2.1 In sample evidence

In this section we present the results of our forecasting regression models on the jumps (JUMP) and the Realized Variance (RV) of S&P500 returns. We firstly perform

[16] The VIX rose in value not before, but after the October 2008 volatility spike. We see from **Figure 1** that the VIX jumped from 20% in August 2008 to approximately 60% in October 2008 in response (as an overreaction) to the Lehman Brothers collapse. Unlike Bates (1991) who finds that the stock market crisis of 1987 had been anticipated by option-markets (option-implied tail-risk measures increased many months prior to the 1987 stock market crash), we find that the 2008 financial crash was not anticipated by equity option markets.

[17] Apart from these elementary descriptive statistics showing the timely increase of the MU factor prior to several large stock market volatility episodes, we estimate a probit model in which we use MU as predictor of US stock market crises when defining the crisis months as local peaks in the S&P500 RV series (see Candelon *et al*., 2008). Our probit regression on the incidence of large volatility spikes shows that the estimated probability spikes many months before the occurrence of many large jumps in stock market volatility, including the market crash of October 2008 which is related to the Lehman Brothers collapse.

bivariate forecasting regressions of various uncertainty proxies on US stock market volatility (RV) and price jumps (JUMP). The respective regression models and the variables used are analytically described in Subsection 2.3 (**Equations (5-6)).** The regression results of our bivariate regression models on RV and JUMPS respectively are shown in **Tables 3** and **4** below.

[Insert Tables 3 and 4 Here]

The results presented in **Table 3** indicate that the *MU(k)* factor produces statistically significant forecasts when forecasting the monthly Realized Variance (RV) of S&P 500 index returns: rising macroeconomic uncertainty is associated with rising volatility in the US equity market. More specifically, we find that the *MU(k)* factor enters significantly into forecasting regressions of stock market volatility for both short and long-term forecasting horizons ranging from 1 up to 12 months. For example, when running forecasting regressions using the MU1, MU3 and MU12 factor as predictor of stock market volatility having one-, three- and twelve-month forecasting horizon respectively, we report positive and statistically significant coefficients for the MU series and R^2 values of 23.2%, 14.9% and 3.5%, respectively.

In addition, the results presented in **Table 3** show that the MU factor outperforms the VIX for medium and long-term volatility forecasts.[18] For example, when using the VIX as the only predictor of S&P500 index volatility, we get an R^2=11% for 3-month forecasting horizon and R^2=3% for a twelve-month horizon. Our bivariate regression analysis also indicates that the latent macroeconomic factor explains a larger part of the time variation of stock market volatility than other popular uncertainty proxies like the EPU and monetary policy uncertainty (MPU). The results of **Table** 4 which report the regression results on JUMP indicate that the MU factor does not provide significant forecasts regarding the discontinuous (jump) component of stock market volatility. On the other hand, as expected, the VIX and the lagged JUMP variables are the most

[18] The VIX index is implied volatility with one-month horizon. So, in order to examine more accurately the predictive information content of S&P500 option implied volatility for medium and long-term forecasting horizons, we use 3-month (IV3) and 12-month (IV12) horizon implied volatility (instead of the VIX) for the 3- and 12-month horizon forecasting regression models, respectively. We provide the regression results in the on-line appendix showing that the predictive power of IV3 and IV12 is very similar with that of the VIX index for 3- and 12-month horizon. Consequently, our argument on the increased predictive power of the MU index when compared with the VIX remains valid when replacing the VIX index with its longer-term counterparts.

significant predictors of JUMP in the US stock market. Following the recent literature on the role of the 2007 Great Recession to the time varying macro-finance linkages (Caldara *et al*., 2016; Hubrich and Tetlow, 2015; Prieto *et al*., 2016), we estimate the same bivariate forecasting regression models (presented in **Equations (5)-(6)**) using two subsamples, one before the occurrence of the financial crisis (Jan/1990-Dec/2006), and one after the financial crisis (Jan/2007-Dec/2017). **Tables 5** and **6** report the regression results of our bivariate forecasting models on RV and JUMPS respectively for the dataset covering the post-2007 crisis period.

[Insert Tables 5 and 6 Here]

The subsample (post-crisis) regression results shown in **Table 5** indicate an increase in the predictive power of all economic uncertainty proxies on stock market volatility during the post-crisis era. More specifically, the R^2 value of the post crisis predictive regression of MU(k) on RV raises from 23.2% to 32.4% for one-month horizon predictive regressions and from 14.9% to 19.5% for 3-month horizon when we run the regressions using the post-crisis dataset. Moreover, our analysis is the first to show that the MU factor outperforms the VIX for volatility forecasts during the post-crisis era for both short and long-term forecasting horizon. Additionally, the EPU and MPU also have higher predictive power in the post-crisis especially in a mid-term and long-term predictions.[19] These results provide further empirical insights to the findings of the relevant literature which identifies a positive and significant relationship between monetary policy uncertainty and equity return volatility (Kaminska and Roberts-Sklar, 2018). Overall, our findings regarding the role of the financial crisis on the linkages between macro-uncertainty and stock market volatility is broadly in line and provides further empirical insights on the findings of the macro-finance literature according to which the macro-financial linkages have exponentially increased after the 2007 US credit crash (Abbate *et al*., 2016; Caldara *et al.,* 2016; Ellington *et al*., 2017; Hubrich and Tetlow, 2015; Prieto *et al*., 2016).

[19] We additionally perform the same regression analysis for the pre-crisis (Jan 1987-Dec 2006) period and we show that the predictive power of MU and MPU deteriorates in the pre-crisis period, while the predictive power of VIX is relatively higher during the pre-crisis era. These results provide further support and robustness to our findings according to which the Great Recession has increased the linkages between uncertainty in the macroeconomy and stock market turbulence. To conserve space, we do not report the bivariate regression results in the paper, but they can be found in our on-line Appendix.

The post-crisis regression results on JUMP (reported in **Table 6**) show that the predictive power of macroeconomic uncertainty on the price jumps in US stock market increases significantly in the post-crisis period. More specifically, when regressing MU on the stock price jumps, we get positive and statistically significant coefficients for MU for forecasting horizon ranging from 1 up to 12 months. The predictive power of MU on JUMP is impressive as we get R^2 values equal to 18.1% and 18.0% for the bivariate forecasting models with 1 and 3 months jump tail risk forecasting horizon, respectively. Our regression analysis shows for the first time that the latent macroeconomic uncertainty has predictive power comparable to the VIX on equity jump tail risk. Moreover, the predictive power of Monetary Policy Uncertainty (MPU) on JUMP also increases during the post-crisis period. Overall, our findings provide further empirical insights on the relevant literature which identifies the role and the significant impact of macroeconomic news releases on stock market price jumps (Evans, 2011; Miao *et al.,* 2014; Lahaye *et al*., 2011). We contribute to this literature by showing that the predictive power of latent uncertainty (or rising unpredictability) has significant explanatory power on stock market price jumps and that the predictive power of macro-uncertainty increases exponentially in the post-crisis era. We continue the regression analysis by presenting the results of our multivariate regression models which are analytically described in Subsection 3.3 (**Equation 11**). **Tables 7-10** present estimation results of multivariate forecasting models for stock market volatility and jumps for the full sample and for the pre-crisis and post-crisis sample respectively.

[Insert Tables 7-10 Here]

Surprisingly, our results are the first to identify that, while the predictive power of the MU factor is absorbed by the VIX and RV when running the regressions using the pre-crisis data (Jan 1987-Dec 2006), exactly the opposite is the case for the post-crisis regression estimation. More specifically, the post-crisis multivariate regression results show that the MU is a statistically significant predictor of stock market volatility and price jumps for forecasting horizon ranging from 1 up to 12 months, with the VIX performing worse in most instances when forecasting volatility and jumps in a multivariate regression setting. Our findings are in line and provide further insights on the strand of the macro-finance literature which identifies the significant impact and predictive power of macroeconomic fundamentals and macroeconomic news surprises on stock market price jumps and volatility (Becker *et al*., 1995; Bomfim, 2003; Engle *et al*., 2013; Schwert, 1989, Paye, 2012).

Overall, our multivariate predictive regressions show that the Great Recession has turned macroeconomic uncertainty shocks into the most significant indicator and early warning signal of rising volatility and tail risk in the US equity market. Our findings are in line with those of Caldara *et al*. (2016) who empirically show that the 2007-2009 US Great recession is the results of the 'toxic' interaction between financial and macroeconomic uncertainty shocks.[20] One possible explanation for the increased impact of macro-uncertainty shocks on stock market volatility after the Great recession, is the stronger correlation between variation in global economic activity and stock prices during the post-2007 crisis period (Foroni *et al*., 2017; Kang *et al*., 2015). For example, Kang *et al.* (2015) show that the positive reaction of US stock prices to aggregate demand (global economic activity) shocks has increased significantly during the 2007-2009 period and has remained high since then. Consequently, equity price volatility has become more sensitive to macroeconomic uncertainty shocks in the post-Great recession period, as we empirically show in our paper. One other possible channel explaining the increased significance of macro-uncertainty shocks for the stock market, is the rising degree of risk aversion after the 2008 financial crisis (Bekaert and Hoerova, 2014; Guiso *et al*., 2018; among others).[21]

4.2.2 Out of sample evidence

Following the econometric approach of Corsi (2009) and Bekaert and Hoerova (2014), we repeat the regression analysis for our baseline bivariate and multivariate regression models on predicting the volatility and jumps of the S&P 500 index in an out-of-sample setting. We use a recursive estimation scheme where we obtain forecasts for the period

[20] In order to show that our econometric findings for the post-crisis (post-2007) period are not driven by the increased correlation between MU and stock return volatility during the Great recession, we perform a subsample analysis for the post-crisis period in which we exclude the turbulent 2007-2008 Great recession period. Our econometric findings for the 2009-2017 period remain qualitatively the same. These additional regression results can be found in our on-line Appendix. We thank an anonymous referee for suggesting this robustness test.

[21] Guiso *et al.* (2018) show that both quantitative and qualitative measures of investors' risk aversion have increased after the 2008 crisis, while Bekaert and Hoerova (2014) find a persistent and massive increase in investors' risk aversion (proxied by the time varying variance risk premium) which resulted in the post-2008 period due to the Lehman Brothers collapse in 2008 and the subsequent Euro area crisis during the 2009-2010 period.

t+h (where h is the forecasting horizon) using available data up to month *t*, with an initial 10-year (120-month) window. The estimation window is then extended by one monthly period in order to obtain a new out-of-sample forecast. We estimate the forecasting regression models described in **Subsection 3.3** of the paper (**Equations (11)** and **(12)**) and compute the respective out-of-sample R^2 values. **Table 11** presents the out-of-sample R^2 for the bivariate and multivariate regression models on the S&P 500 realized volatility and its components.

[Insert Table 11 Here]

From **Table 11** we observe that the MU factor produces significantly better out-of-sample realized volatility forecasts when compared with EPU and MPU. More specifically, when using MU as our only predictor of SP500RV for one-month horizon, we obtain out-of-sample adjusted R^2 values of 17.8% as opposed to 0.5% and 2.6% when using EPU and MPU instead. These results show that the latent MU factor has the highest predictive power on stock market volatility when compared to popular macroeconomic uncertainty proxies like EPU. On the other hand, our out-of-sample analysis reveals that the MU factor cannot outperform the VIX in real-time out-of-sample stock market volatility forecasting, since the respective out-of-sample R^2 value for our VIX bivariate model is 26.4%.

When we turn our attention to out-of-sample forecasts of decomposed realized variance, it is clear that the forecasting performance of most factors is driven by the continuous part (realized bi-power variation, RBV) of realized variance, whereas the jumps are more difficult to anticipate in an out-of-sample setting and indeed only in the short term. For bi-power variation, MU performs very close to the VIX, whereas EPU and MPU do not perform particularly well. The multivariate out-of-sample estimations show that our multivariate volatility regression model is not able to outperform the historical mean in most cases, a fact that is probably attributed to the poor out-of-sample performance of EPU and MPU. An exception to this rule appears to be the case of short-term forecasting of jumps, where the multivariate model produces the best results. Overall, the out-of-sample analysis confirms the fact that the MU factor contains useful information for predicting the realized variance of the S&P 500 index.

4.3 Forecasting regressions on the volatility and jumps of S&P500 constituents

In this section we present the results of our time series regression models on the volatility and the price jumps of the constituents of the S&P500 index. This allows us to investigate whether, in addition to the aggregate stock market, the latent macroeconomic uncertainty is a common volatility and jump tail risk predictor for the S&P500 constituents. The purpose of this exercise is to better understand our results at the aggregate market level, by examining the sectoral decomposition of the S&P500 index. To this end, in this section we perform a sectoral (industry-specific) analysis to examine the sectors of the US equity market which are most significantly affected by latent macroeconomic uncertainty shocks. More specifically, instead of reporting the sorted adjusted R^2 values and t-statistics of the individual forecasting regressions on the volatility and jumps on S&P500 constituents, we report the average values of adjusted R^2 and t-statistics for the forecasting regressions on the US equities which belong to each sector.[22] We follow ICB industry classification,[23] which defines 10 categories: Utilities, Telecommunications, Technology, Oil and Gas, Industrials, Health Care, Financials, Consumer Services, Consumer Goods and Basic Materials. **Figure 3** below reports the average adjusted R^2 coefficients and t-statistics when forecasting volatility of S&P500 constituents having one-month forecasting horizon for each of the previously mentioned broad industry categories.

[Insert Figure 3 Here]

Figure 3 clearly shows that the MU factor does not only explain the largest part of time variation in the volatility of S&P500 constituents, but also that this relationship holds for most sectors of the US equity market. More specifically, the average t-statistics show that the estimated coefficients of VIX, RV and MU are statistically significant for volatility predictions of stocks belonging to all possible different sectors of the equity market. On the other hand, the EPU and MPU are not statistically significant in most cases. Hence, the latent macroeconomic uncertainty is the only macroeconomic factor

[22] The detailed (sorted) R^2 values and t-statistics for the regressions on the volatility and price jumps of S&P500 constituents can be found in our on-line Appendix. Overall, for the bivariate regression models of the MU factor on US stock market volatility, the estimated coefficient of MU is positive and statistically significant for more than 450 stocks currently belonging to S&P500 and the respective R^2 values for those regressions is more than 15%.

[23] ICB classification data are obtained from Thomson Reuters DataStream.

which provides robust volatility predictions, not only at the aggregate market level, but for sectoral equity price volatility forecasting as well. **Figure 3** also shows that the mean of R^2 values for predictive regressions on individual stocks is more than 20% for half of the sectors in the US stock market and more than 10% for all the rest. This means that the MU factor alone explains a large part of the time-varying volatility in almost all the sectors in the US stock market. Our analysis also shows that the MU factor outperforms (in terms of explanatory power on the volatility of equity prices) the VIX factor across all sectors.

Interestingly, the maximum predictive power of the MU factor occurs for the Financials sector. It appears that the rising stock price volatility of financial firms is primarily driven by latent macroeconomic shocks. The higher explanatory power of the MU factor on stock return volatility of the firms belonging to the financial sector shows that macroeconomic uncertainty has higher impact on the firms which are hardest to value and to arbitrage, like banks and financial services firms. The fact that banking stocks are hard to value is owed to their tendency to not distribute dividends to their shareholders. This happens because financial institutions have a strict preference, instead of distributing part of their profits to their shareholders, to keep them as retained earnings for solvency and regulatory purposes (Kanas, 2013; Mayne, 1980; among others). According to the expected cash flow model shown in **Equations (1)** and **(2)**, the shares of the firms who choose not to distribute dividends are hard to value since it is difficult to estimate their expected discounted cash flows, and as a consequence, the price volatility of these firms will be more heavily impacted by changes in macroeconomic uncertainty and much less by variations in economic fundamentals. A similar argument is made by Baker and Wurgler (2007), who point out that the stock valuations of hard to value firms (like banks and insurance firms) are also more heavily affected by changes in sentiment. We also estimate the same type of bivariate regression models (shown in **Equation (6)**) for forecasting the intra-day price jumps (JUMP) of the S&P500 constituents. We undertake the same analysis by averaging the R^2 values and t-statistics across the 500 bivariate regressions on JUMP on S&P500 constituents using the MU, EPU, MPU, VIX and lagged RV as predictors of jumps in the S&P500 constituents. **Figure 4** below reports the average R^2s and t-statistics of the bivariate regressions on the jump tail risk of S&P500 constituents.

[Insert Figure 4 Here]

Figure 4 shows that the MU factor explains the largest part of the time variation in the stock market price jumps of different stock market sectors when compared to EPU, MPU and the VIX. Again, the MU factor performs best on stock market price jumps of the financial sector, with the average adjusted R^2 reaching almost 15.5%. Thus, except from forecasting return volatility of the equities which belong to the financial sector, the MU factor has the highest explanatory power when used as a predictor of price jumps of financial and banking stocks. Our analysis is the first to show that the instability and turbulence in the US financial services industry (measured as rising market volatility and price jumps in the US financial services sector) is most significantly affected, not by financial uncertainty shocks (as someone would reasonably expect), but by the rising uncertainty about the future state of the US economy. One policy recommendation behind these results is that, reduced uncertainty in the macroeconomy (which may be achieved through a more transparent monetary policy) may also lead to less instability in the financial and banking sector.[24] Moreover, the average t-statistics for the MU factor coefficient show that the MU factor coefficient is significant at the 1% level for most sectors except Telecommunications and Health Care sector that is significant at the 5% level.

4.4 Responses of stock market volatility and jump tail risk to uncertainty shocks

In this section we present the impact of the dynamic effect of economic uncertainty shocks on stock market volatility and price jumps. We base our analysis on the estimated Orthogonalized Impulse Response Functions (OIRFs) derived by the baseline 4-factor VAR model analytically described in Subsection 2.4. **Figures 5-6** below show the estimated OIRFs of stock market volatility (RV) and jumps (JUMP) to their own innovations and to different types of financial and macroeconomic uncertainty shocks.

[Insert Figures 5 and 6 Here]

[24] Our predictive regressions do not necessarily imply causality, but they provide initial empirical evidence showing that the MU factor is positively correlated with rising volatility and jumps in the market prices of stocks of financial firms subsequently observed. Much more empirical work is needed to empirically examine the existence and the possible channels constituting a robust causal relationship running from macroeconomic uncertainty to instability and turbulence in the banking sector.

Several interesting conclusions emerge from observing the results regarding the empirical behavior of OIRFs. **Figure 5** shows that a positive latent uncertainty shock has a significant positive effect on stock market volatility which reaches its maximum (nearly 7 basis points increase) two months after the initial latent macro-uncertainty shock and remains positive and statistically significant for 16 months after the initial shock. The persistent effect of macroeconomic uncertainty shocks on stock market volatility is in line with the findings of Engle *et al*. (2013) who find that the inclusion of macroeconomic fundamentals into volatility forecasting models improves the predictability of these models for long-term forecasting horizons. On the other hand, a positive VIX or EPU shock increases stock market volatility by 2 and 3 basis points respectively with the effect remaining positive and significant for the first two months after the respective shocks. Hence, our VAR estimates show for the first time that the MU shocks have a significant and long-lasting impact on stock market volatility which is more than 2 times larger in magnitude and more than 6 times larger in persistence, when compared to the dynamic effect of VIX and EPU shocks. More importantly, the MU shocks have a more long-lasting impact even when compared to the response of RV to its own innovations. This is an interesting and unexpected finding given the fact that stock market volatility is a highly persistent series (see for example evidence on the persistence of equity volatility and volatility clustering, e.g. Choudhry, 1996). The estimated OIRFs of **Figure 6** show that the JUMP and VIX shocks have the most significant and long-lasting effect on equity jump tail risk (JUMP), while the MU shock has a rather transitory impact on the jump tail risk in the US equity market.

In order to empirically examine the dynamic effect of macroeconomic uncertainty shocks on price jumps in the post-crisis period, we estimate our VAR model using the post-2007 dataset (Jan 2007-Dec 2017). The respective estimated OIRFs for the post-recession VAR model are shown in **Figures 7** and **8**.

[Insert Figures 7 and 8 Here]

The estimated responses of the price jumps to uncertainty shocks after the US Great Recession, show that the Great recession has played a significant role on the dynamic interactions between macroeconomic uncertainty and stock market turbulence. More specifically, from **Figure 7** we observe that the dynamic response of RV to MU shocks has increased in magnitude during the post-crisis period. Moreover, from **Figure 8** we observe that, unlike the pre-crisis period, in the post-crisis period the MU shock has the largest and more long-lasting impact on time varying equity tail risk when compared to the other types of shocks included in the analysis. Overall, our VAR estimates show that during the recent post-crisis era, the latent macroeconomic shocks have become the most significant types of uncertainty shocks affecting the time varying volatility and jump tail risk in the US equity market.

4.5 Macro-finance implications

Our results provide further empirical insights on the findings of the macro-finance literature which shows that macroeconomic news surprises have a positive effect on stock market volatility (Brenner *et al.*, 2009; Rangel, 2011; among others). For example, Brenner *et al.* (2009) find that the unanticipated information releases about macroeconomic fundamentals (macroeconomic news surprises) have a significant positive impact on stock market volatility. Our findings are in line with this strand of the macro-finance literature, while they provide further empirical insights to it, by showing that when there is higher uncertainty regarding future macroeconomic outcomes (and consequently expected dividends), this results in rising stock market volatility. A rough generalization of our findings when combined with those of the literature on the role of unanticipated monetary policy and macro-news shocks, is that any macroeconomic policy which results in positive or negative surprises to economic agents, can also lead to large volatility and jump tail risk episodes in the stock market. Thus, a hidden policy recommendation of our results is that policymakers can achieve the dual target of macro and financial stability when moving towards more transparent and time-consistent (less discretionary) macroeconomic policy.

Our findings have important implications for the macro-finance literature, since we show that when the forecast errors of investors regarding the future state of the macroeconomy are reduced, this results in decreasing stock market volatility. This reduction in stock market volatility comes not through less fluctuations in the real economy, but through less ambiguity (or uncertainty) about these cash flows. The rising macroeconomic uncertainty represents the component of stock market volatility which cannot be explained by fundamentals. These results show that the excess volatility of stock prices (which cannot be attributed to the volatility of expected dividends) apart from being related to non-fundamental factors like investor sentiment (Chiu *et al.*, 2018; Shiller, 1981), can also be explained by changes in macroeconomic uncertainty. Lastly, our empirical analysis shows that the MU is associated with rising volatility for most of the S&P500 constituents. To the best of our knowledge, our paper is the first in the literature to show that latent macroeconomic uncertainty has significant explanatory power on the time varying volatility of the majority of the firms belonging to the S&P500 index and can outperform the VIX in terms of its explanatory power.

5. Robustness

In this section we provide robustness to the results presented in the previous section by varying different elements of our empirical design. All our robustness checks and their relevant discussion can be found in the on-line Appendix. Firstly, we perform the same forecasting regression analysis on the continuous component of stock market volatility (namely the bi-power variation (RBV) shown in **Equation (9)** of the paper), and we show that the MU factor is a robust predictor of RBV. Moreover, we include a set of alternative macroeconomic variables like US industrial production, unemployment and short-term interest rates which have already been proven significant predictors of stock market volatility (Bekaert *et al*., 2013; Engle *et al.,* 2013; Schwert, 1989; Paye, 2012; among others) and our main findings showing the significant predictive power and the long-lasting effect of macroeconomic shocks on stock market volatility and price jumps, remain robust to the inclusion of these macroeconomic factors on the multivariate OLS and VAR settings. Furthermore, in order to provide robustness to our regression results for the post-crisis period, we estimate the same set of regression models using different subsamples for the post-crisis period (starting from either June 2007 or January 2008) and our findings remain unaltered. We also re-estimate our models on a sample that completely excludes the 2007-2008 US financial crisis period and the results remain qualitatively the same. This shows that the stronger predictive power and dynamic impact of macroeconomic uncertainty on stock market volatility and jumps during the post-crisis period is not driven by the inclusion of the crisis period in the post-crisis data sample.

We additionally empirically examine the predictive power of latent Financial Uncertainty (FU) (also introduced by Jurado *et al.* (2015)) on stock market volatility and jumps. We find that the FU factor is also a significant predictor of stock market volatility, with its predictive power being higher in the pre-crisis period while it deteriorates significantly during the recent post-crisis period. We also provide additional robustness checks and more analytical results for our regression models on the volatility and tail risk of individual equity prices. Our additional forecasting regressions on S&P constituents clearly show that the MU factor is a robust common volatility and jump tail risk predictor for individual equity prices belonging to different sectors-industries, with the highest predictive power still remaining for the stocks which belong to the financial and banking sector. We lastly provide additional robustness to our VAR results. In more detail, we estimate identical VAR models in which we use MU3 and MU12 instead of MU1 as endogenous variables in the 4-factor VAR model and our results also remain unaltered. Hence, our findings are independent of the choice of Jurado *et al.* (2015) macroeconomic uncertainty series.

6. Conclusions

We find that the latent macroeconomic uncertainty measure of Jurado *et al*. (2015) is a robust predictor of equity market volatility and jumps. Our analysis is the first to show that latent macroeconomic uncertainty outperforms the VIX when forecasting volatility and jump tail risk in the US equity market. Moreover, our VAR models reveal for the first time that the latent MU shocks have three to five times larger and more long-lasting effect on stock market volatility when compared to the respective effect of VIX shocks and shocks in other popular observable economic uncertainty proxies. Overall, we show that the US stock market is heavily impacted by changes in unpredictability of the US macroeconomy, while it is relatively immune to observable (more predictable) changes in macroeconomic fluctuations. While Jurado *et al*. (2015) show that the latent macroeconomic uncertainty, which captures the time varying unpredictability of the US macroeconomy, is mostly correlated with US economic activity, we additionally show that it is the most significant determinant of stock market volatility for forecasting horizons ranging from one up to twelve months. Our analysis also shows that the predictive power of MU on stock market volatility and price jumps is significantly increased in the post-2007 crisis period. Particularly in the case of jumps, whereas in the pre-crisis sample the MU factor does not perform at all well, in the post-crisis period it exhibits the best performance out of all other factors. Our findings provide further empirical insights on the strand of literature which identifies the increasing interaction between financial markets and the macroeconomy in the post-2007 period (Abbate *et al.*, 2016; Caldara *et al.*, 2016; Ellington *et al.*, 2017; Prieto *et al.,* 2016; Hubrich and Tetlow, 2015).

Our findings are also in line with those of the relevant literature which shows that the surprise component (unexpected macro-shocks) of macroeconomic news announcements is an important driver of equity market volatility and price jumps (Bomfim, 2003; Rangel, 2011; among others). When forecasting the volatility of individual stock market prices, we find that the latent macroeconomic uncertainty is a common volatility and jump tail risk forecasting factor across different sectors of the US stock market. More specifically, the latent uncertainty factor enters significantly in forecasting regressions on the volatility and the jumps of the returns of S&P 500 constituents, with adjusted R^2 values exceeding 15% for most of the S&P 500 constituents. Surprisingly, the predictive power of MU outperforms the VIX when forecasting volatility and price jumps of individual US stocks. Interestingly, the predictive power of the MU factor is significantly higher when forecasting the return volatility of stocks belonging in the financial industry. This result provides an initial indication to policy makers that reducing uncertainty in the macroeconomy through a more transparent monetary policy may have beneficial effects on the stability of the financial and banking sectors. Further research is needed to investigate the possible existence of a causal relationship behind this linkage.

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Table 1. Descriptive statistics

The time series sample covers the period from January 1990 till December 2017.

	MU1	MU3	MU12	RV	JUMP	VIX	EPU	MPU	BAA
Mean	0.645	0.782	0.911	0.002	0.001	0.194	106.795	89.014	0.024
Median	0.631	0.768	0.905	0.001	0.000	0.175	98.702	73.460	0.022
Maximum	1.063	1.214	1.153	0.049	0.007	0.626	245.127	407.941	0.060
Minimum	0.544	0.676	0.846	0.000	0.000	0.101	57.203	16.575	0.013
Std. Dev.	0.084	0.088	0.051	0.004	0.001	0.076	33.193	56.143	0.008
Skewness	2.311	2.331	2.183	7.995	3.576	1.971	1.036	1.812	1.609
Kurtosis	10.309	10.549	9.660	94.378	19.858	9.420	3.761	8.120	7.536

Table 2. Correlation matrix

The time series sample covers the period from January 1990 till December 2017. The correlation matrix presents the contemporaneous correlations between the explanatory variables.

	MU1	MU3	MU12	RV	JUMP	VIX	EPU	MPU	BAA
MU1	1.00								
MU3	0.98	1.00							
MU12	0.98	0.99	1.00						
RV	0.57	0.58	0.57	1.00					
JUMP	0.07	0.07	0.09	0.42	1.00				
VIX	0.62	0.63	0.64	0.79	0.54	1.00			
EPU	0.33	0.32	0.29	0.32	0.09	0.43	1.00		
MPU	0.19	0.18	0.20	0.30	0.41	0.43	0.51	1.00	
BAA	0.66	0.66	0.64	0.55	0.17	0.66	0.62	0.23	1.00

Table 3. Forecasting stock market volatility for the full time period (Jan 1990- Dec 2017)

Panel A

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.011**	-2.42	0.021***	2.77	23.2
3m	-0.010**	-2.14	0.016**	2.47	14.9
12m	-0.009	-1.59	0.013*	1.85	3.5

Panel B

$$RV_t = b_0 + b_1 VIX_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.003***	-3.98	0.025***	5.42	30.3
3m	-0.001***	-2.66	0.015***	5.65	11.0
12m	0.0004	0.71	0.008**	2.31	3.00

Panel C

$$RV_t = b_0 + b_1 RV_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.001***	5.20	0.626***	11.57	39.2
3m	0.001***	5.16	0.300***	6.94	9.0
12m	0.002***	5.69	0.082	1.39	0.7

Panel D

$$RV_t = b_0 + b_1 EPU_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.001	-0.63	0.0002*	1.73	6.8
3m	0.001**	2.08	0.00006	0.98	0.4
12m	0.003***	3.76	-0.00005	-1.07	0.3

Panel E

$$RV_t = b_0 + b_1 MPU_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.001**	2.18	0.0001**	2.34	5.7
3m	0.001***	5.49	0.000003	1.40	0.3
12m	0.001***	5.23	0.00005	1.26	0.8

Note: *, ** and *** denote statistical significance at 10%, 5% and 1% respectively. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

Table 4. Forecasting stock market price jumps for the full time period (Jan 1990- Dec 2017)

Panel A

$$JUMP_t = b_0 + b_1 MU(k)_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.0003	0.88	0.0005	0.95	0.2
3m	0.0003	0.82	0.0004	0.73	0.1
12m	-0.0001	-0.11	0.0008	0.57	0.2

Panel B

$$JUMP_t = b_0 + b_1 VIX_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.0002	-1.08	0.004***	2.68	17.9
3m	-0.0001	-0.06	0.003***	2.94	7.9
12m	0.0006	0.28	0.002*	1.84	5.6

Panel C

$$JUMP_t = b_0 + b_1 JUMP_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.0002***	6.03	0.640***	10.72	40.9
3m	0.0003***	5.57	0.377***	5.07	14.2
12m	0.0004***	6.37	0.260**	2.50	8.2

Panel D

$$JUMP_t = b_0 + b_1 EPU_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.0005***	2.97	0.0001	0.44	0.1
3m	0.0008***	3.83	-0.0002	-1.33	0.6
12m	0.0008***	4.08	-0.0002	-1.39	1.2

Panel E

$$JUMP_t = b_0 + b_1 MPU_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.0002**	2.12	0.0004***	3.54	9.2
3m	0.0004***	4.36	0.0002**	2.03	0.9
12m	0.0004***	2.90	0.0001	1.21	2.2

Note: *, ** and *** denote statistical significance at 10%, 5% and 1% respectively. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

Table 5. Forecasting stock market volatility during the post-crisis period (Jan 2007- Dec 2017 period)

Panel A

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.015**	-2.60	0.026***	2.83	32.4
3m	-0.013**	-2.13	0.019**	2.33	19.5
12m	-0.008	-1.20	0.011	1.48	2.5

Panel B

$$RV_t = b_0 + b_1 VIX_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.003***	-3.76	0.029***	4.49	28.1
3m	-0.001	-1.65	0.017***	4.38	9.2
12m	0.002*	1.69	0.004	0.98	0.5

Panel C

$$RV_t = b_0 + b_1 RV_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.001***	2.82	0.619***	9.15	38.4
3m	0.002***	2.69	0.276***	6.21	7.6
12m	0.002***	2.91	0.011	0.30	0.0

Panel D

$$RV_t = b_0 + b_1 EPU_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.002	-1.06	0.0004	1.65	8.4
3m	0.002	1.25	0.0003	0.35	0.1
12m	0.005*	1.86	-0.0002	-1.28	2.1

Panel E

$$RV_t = b_0 + b_1 MPU_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.001***	3.98	0.0004	1.62	16.6
3m	0.002***	4.78	0.0001*	1.98	2.9
12m	0.002***	3.35	0.0002*	1.66	5.1

Note: *, ** and *** denote statistical significance at 10%, 5% and 1% respectively. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

Table 6. Forecasting stock market price jumps during the post-crisis period (Jan 2007- Dec 2017)

Panel A

$$JUMP_t = b_0 + b_1 MU(k)_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.0004***	-4.05	0.001***	6.94	18.1
3m	-0.0005***	-3.44	0.001***	5.21	18.0
12m	-0.0005	-1.31	0.001*	1.94	5.6

Panel B

$$JUMP_t = b_0 + b_1 VIX_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.0002	0.37	0.001***	3.70	19.0
3m	0.0002	0.56	0.001***	7.45	19.3
12m	0.0002***	3.47	0.0003	1.26	1.2

Panel C

$$JUMP_t = b_0 + b_1 JUMP_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.0001***	5.23	0.267***	3.08	7.2
3m	0.0002***	5.43	0.249**	2.39	6.2
12m	0.0003***	7.51	0.028	0.32	0.1

Panel D

$$JUMP_t = b_0 + b_1 EPU_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.0006	0.67	0.0001**	2.15	5.3
3m	0.0002	0.27	0.0001**	2.32	7.3
12m	0.0003***	3.32	-0.0003	-0.47	0.2

Panel E

$$JUMP_t = b_0 + b_1 MPU_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.0001***	4.15	0.0001*	1.67	2.5
3m	0.0001***	2.63	0.0001**	2.37	8.2
12m	0.0002***	3.59	0.0001	1.50	3.5

Note: *, ** and *** denote statistical significance at 10%, 5% and 1% respectively. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

Table 7. Forecasting stock market volatility (RV) -multivariate OLS model

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.006	-0.008	-0.0093
	t-stat	(-1.30)	(-1.31)	(-1.41)
MU(k)	Coef.	0.012	0.012	0.012
	t-stat	(1.22)	(1.38)	(1.55)
RV	Coef.	0.497***	0.074	-0.14**
	t-stat	(5.85)	(1.18)	(-2.43)
JUMP	Coef.	0.487	0.29	-0.22
	t-stat	(0.89)	(0.85)	(-0.53)
VIX	Coef.	-0.003	0.003	0.013**
	t-stat	(-0.28)	(0.48)	(2.49)
EPU	Coef.	0.0006	-0.0001*	-0.0002 **
	t-stat	(0.54)	(-1.89)	(-2.31)
MPU	Coef.	0.0001	-0.0001	0.0001
	t-stat	(0.28)	(-0.31)	(1.34)
BAA	Coef.	-0.028	0.026	-0.04
	t-stat	(-0.59)	(0.67)	(-0.69)
% adj. R^2		44.3	18.6	9.2

Table 8. Forecasting stock market jumps (S&P 500 Jumps) -multivariate OLS model

$$JUMP_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	0.0004*	0.0006*	0.0008
	t-stat	(1.87)	(1.77)	(0.79)
MU(k)	Coef.	-0.009**	-0.001	-0.006
	t-stat	(-2.15)	(-1.10)	(-0.50)
RV	Coef.	-0.048***	-0.027	-0.047**
	t-stat	(-4.78)	(-1.55)	(-2.10)
JUMP	Coef.	0.477***	0.306**	0.15*
	t-stat	(4.85)	(2.07)	(1.66)
VIX	Coef.	0.005***	0.003**	0.005***
	t-stat	(4.45)	(2.07)	(3.84)
EPU	Coef.	-0.0004***	-0.0005**	-0.0001***
	t-stat	(-2.90)	(-2.05)	(-2.90)
MPU	Coef.	0.0004	-0.0004	0.0002
	t-stat	(0.88)	(-0.49)	(1.09)
BAA	Coef.	0.005	0.004	-0.003
	t-stat	(0.43)	(0.28)	(-0.25)
% adj. R^2		43.4	28.4	19.8

Note: *, ** and *** denote statistical significance at 10%, 5% and 1% respectively. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

Table 9. Forecasting stock market volatility (RV) – stability of coefficients before and after the financial crisis for the multivariate OLS model

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
		Panel A: pre-crisis period (Jan 1990-Dec 2006)		
Const	Coef.	-0.0004	-0.001	-0.0012
	t-stat	(-0.53)	(-0.70)	(-0.19)
MU(k)	Coef.	-0.001	0.001	0.002
	t-stat	(-0.90)	(0.40)	(0.38)
RV	Coef.	0.520	-0.097	0.401
	t-stat	(1.02)	(-0.33)	(1.52)
JUMP	Coef.	-0.369	0.413	-0.933***
	t-stat	(-0.33)	(0.60)	(-2.80)
VIX	Coef.	0.011***	0.010*	0.014***
	t-stat	(4.02)	(1.85)	(3.96)
EPU	Coef.	-0.0001	-0.0001*	-0.0003***
	t-stat	(-1.34)	(-1.79)	(-4.53)
MPU	Coef.	-0.0006	-0.0004	0.0006
	t-stat	(-0.29)	(-1.36)	(1.55)
BAA	Coef.	0.056	0.109*	0.019
	t-stat	(1.04)	(1.68)	(0.32)
% adj. R^2		57.2	28.4	27.3
		Panel B: post-crisis period (Jan 2007-Dec 2017)		
Const	Coef.	-0.013*	-0.016	-0.010
	t-stat	(-1.88)	(-1.62)	(-1.36)
MU(k)	Coef.	0.028*	0.028*	0.021*
	t-stat	(1.92)	(1.72)	(1.88)
RV	Coef.	0.653***	0.095	-0.325**
	t-stat	(4.91)	(1.12)	(-2.1)
JUMP	Coef.	5.467	-0.862	-1.161
	t-stat	(1.18)	(-0.79)	(-1.01)
VIX	Coef.	-0.044	-0.013	0.026*
	t-stat	(-1.53)	(-1.02)	(1.81)
EPU	Coef.	0.0004	-0.0001	-0.0005**
	t-stat	(0.45)	(-1.03)	(-2.58)
MPU	Coef.	0.0002	0.0002	0.0005***
	t-stat	(1.27)	(1.44)	(2.96)
BAA	Coef.	-0.031	-0.062	-0.300*
	t-stat	(-0.55)	(-0.8)	(-1.83)
% adj. R^2		56.6	23.9	28.7

Note: *, ** and *** denote statistical significance at 10%. 5% and 1% respectively. t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

Table 10. Forecasting stock market price jumps (Jumps) – stability of coefficients before and after the financial crisis for the multivariate OLS model

$$JUMP_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Panel A: pre-crisis period (Jan 1990-Dec 2006)				
Const	Coef.	-0.0004	-0.0002	-0.0007
	t-stat	(-0.11)	(-0.36)	(-0.23)
MU(k)	Coef.	-0.001*	-0.0002	0.0012
	t-stat	(-1.79)	(-0.21)	(0.35)
RV	Coef.	0.056	-0.19312	0.101
	t-stat	(0.26)	(-1.28)	(0.83)
JUMP	Coef.	0.151	0.457452	-0.256
	t-stat	(0.32)	(1.23)	(-1.26)
VIX	Coef.	0.005***	0.004*	0.006***
	t-stat	(4.13)	(1.86)	(3.18)
EPU	Coef.	-0.0002	-0.0005	-0.0001***
	t-stat	(-0.5)	(-0.94)	(-3.50)
MPU	Coef.	-0.0001	-0.0003	-0.0004***
	t-stat	(-0.56)	(-1.54)	(1.74)
BAA	Coef.	0.026	0.052	0.007
	t-stat	(0.89)	(1.58)	(0.24)
% adj. R^2		43.3	22.6	19.7
Panel B: post-crisis period (Jan 2007-Dec 2017)				
Const	Coef.	-0.0003	-0.0004**	-0.0009*
	t-stat	(-1.42)	(-2.55)	(-1.92)
MU(k)	Coef.	0.0003	0.001**	0.001***
	t-stat	(0.77)	(2.47)	(2.81)
RV	Coef.	-0.024***	0.0003	-0.015***
	t-stat	(-3.84)	(0.09)	(-2.86)
JUMP	Coef.	-0.003	0.0003	-0.050
	t-stat	(-0.04)	(0)	(-0.58)
VIX	Coef.	0.002**	0.0004	0.0004
	t-stat	(2.25)	(1.01)	(0.86)
EPU	Coef.	0.0002	0.0007	-0.0001
	t-stat	(0.27)	(0.91)	(-1.17)
MPU	Coef.	-0.0002	0.0005	0.0002**
	t-stat	(-0.42)	(1)	(2.33)
BAA	Coef.	0.001	-0.003	-0.005
	t-stat	(0.2)	(-0.68)	(-1.17)
% adj. R^2		28.9	22.4	17.1

Note: *, ** and *** denote statistical significance at 10%. 5% and 1% respectively. t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

Table 11. Out-of-sample R^2 of forecasting regressions – forecasting S&P 500 realized volatility (REALVAR), bi-power variation (RBV) and the jump component of realized variance (JUMP)

	Panel A - Dependent Variable: *REALVAR*					**Panel B - Dependent Variable: *JUMP***					**Panel C - Dependent Variable: RBV**				
Horizon (k)	*EPU*	*MPU*	*VIX*	*MU(k)*	*Multivariate model*	*EPU*	*MPU*	*VIX*	*MU(k)*	*Multivariate model*	*EPU*	*MPU*	*VIX*	*MU(k)*	*Multivariate model*
1m	0.5%	2.6%	26.4%	17.8%	-154.7%	-2.0%	7.0%	6.0%	-5.6%	34.6%	-0.5%	0.4%	18.1%	17.3%	-16.4%
3m	-5.2%	-3.7%	7.1%	2.5%	-89.4%	-5.0%	-4.0%	-1.0%	-7.8%	-1.9%	-4.7%	-3.9%	3.0%	1.4%	-16.5%
12m	-7.5%	-5.4%	-4.8%	-13.7%	-191.9%	-23%	-14%	-26.0%	-33.7%	-88.6%	-7.1%	-6.4%	-4.9%	-1.3%	-16.3%

Note: The *EPU, MPU, VIX* and *MU(k)* columns show the out-of-sample R^2s for the bivariate regression models presented in Equation (10) and (12). The *Multivariate model* columns show the respective out-of-sample R^2s for the baseline multivariate regression model presented in Equation (11).

Figure 1. Latent macroeconomic uncertainty, the VIX index and stock market volatility

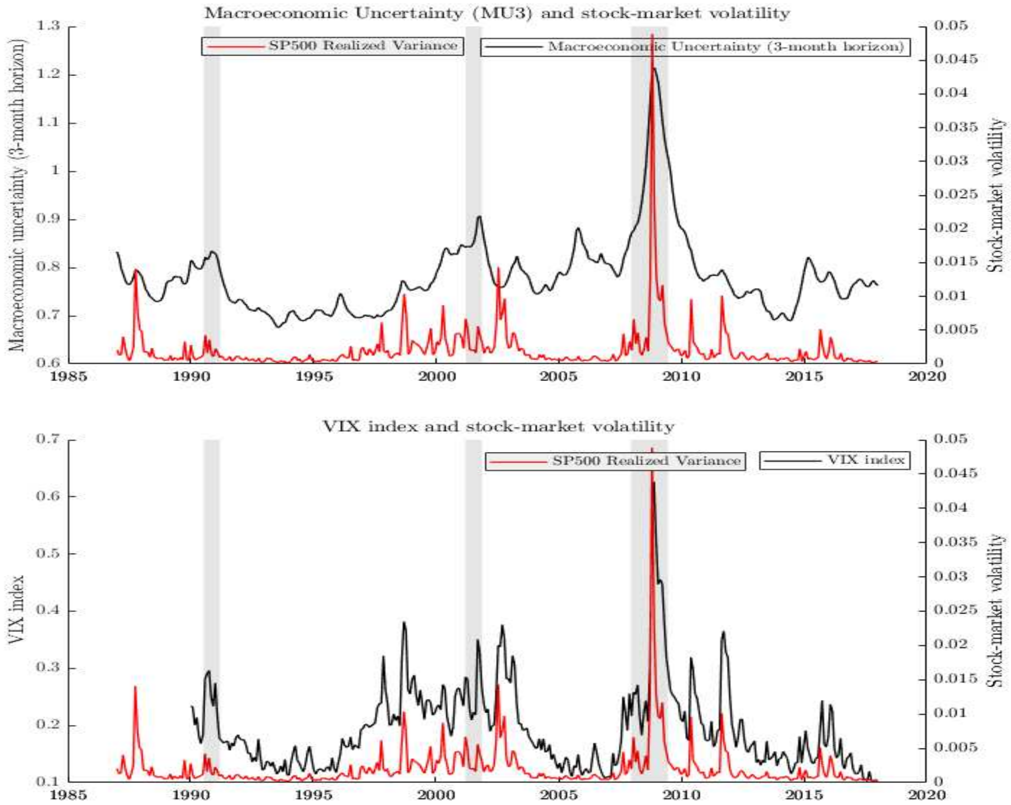


Figure 2. Latent macroeconomic uncertainty, VIX index and stock market price jumps

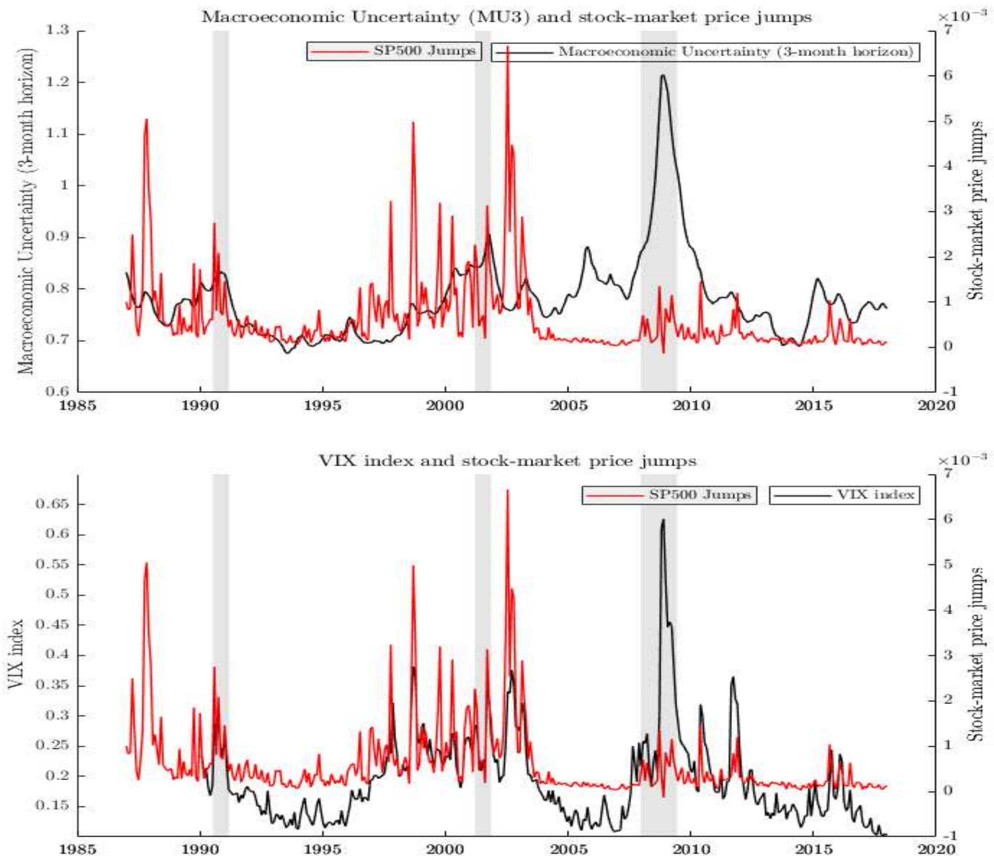
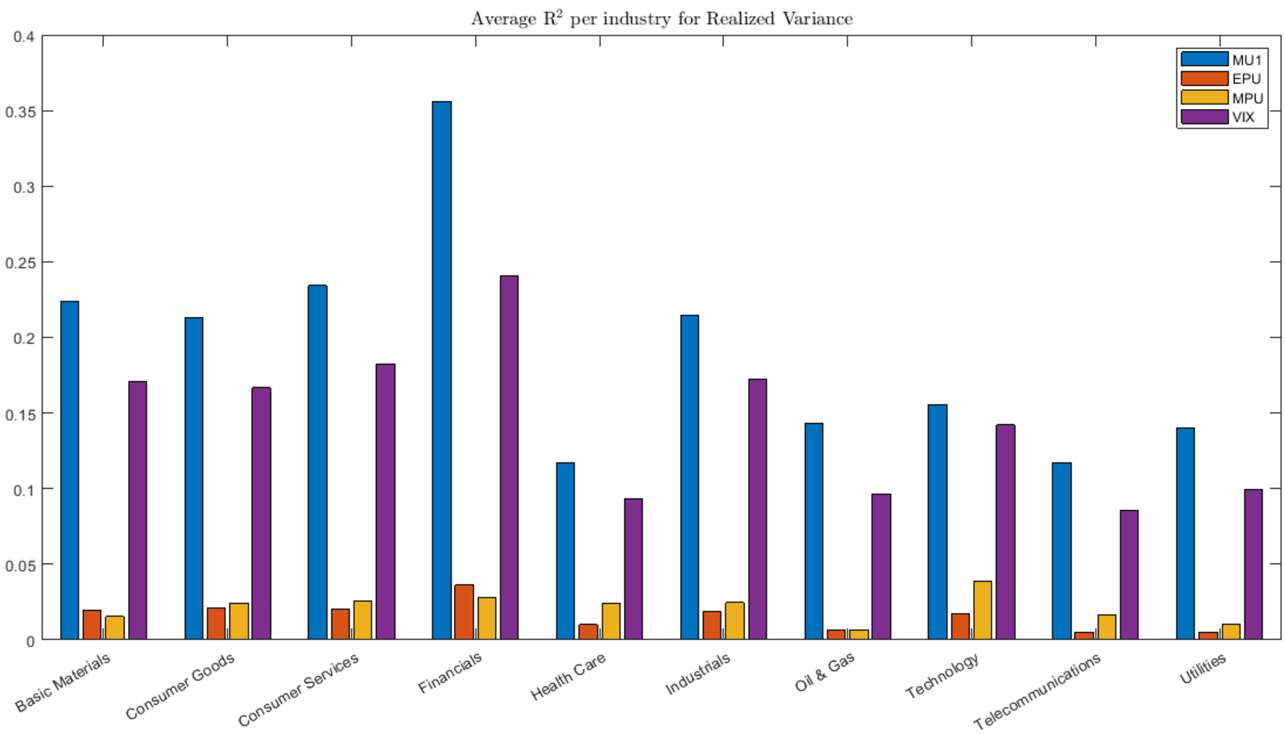


Figure 3. Average R^2 values and t-statistics per sector for the bivariate regression models on the Realized Variance of S&P500 constituents.

This figure shows the average sectoral R^2 values and t-statistics when forecasting the Realized Variance (RV) of the returns of S&P 500 constituents using MU1, VIX index, EPU and MPU as predictors. In more detail, the bar chart shows the average R^2s and t-statistics for the univariate regressions on the RV of the stocks which belong to different sectors. The forecasting horizon of the bivariate regressions on the RV of S&P500 constituents is always one-month. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.



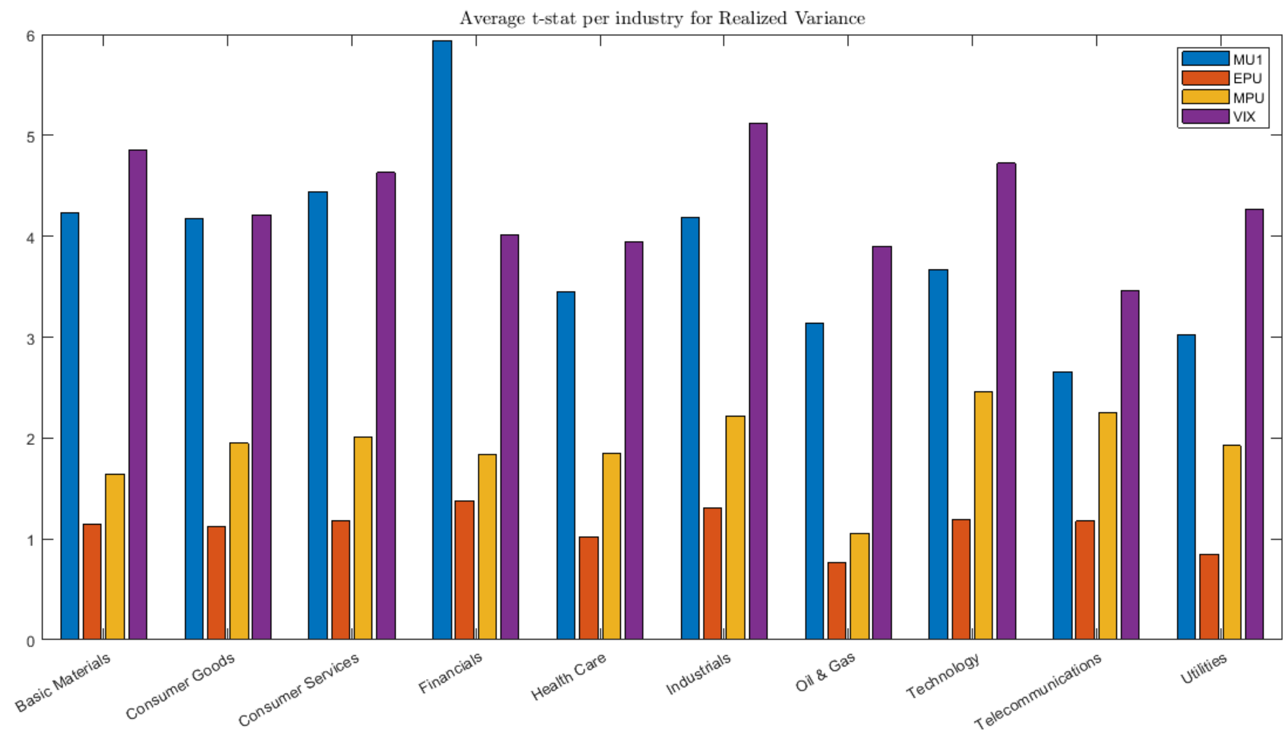


Figure 4. Average R^2 values and t-statistics per sector for bivariate regression models on the price jumps of S&P500 constituents.

This figure shows the average sectoral R^2 values and t-statistics of the univariate regression models on stock market price jumps when using MU1, VIX index, EPU and MPU as predictors. In more detail, the bar chart shows the average R^2s and t-statistics for the univariate regressions on the price jumps of the stocks which belong to different sectors. The forecasting horizon of the bivariate regressions on JUMPS of S&P500 constituents is always one-month. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

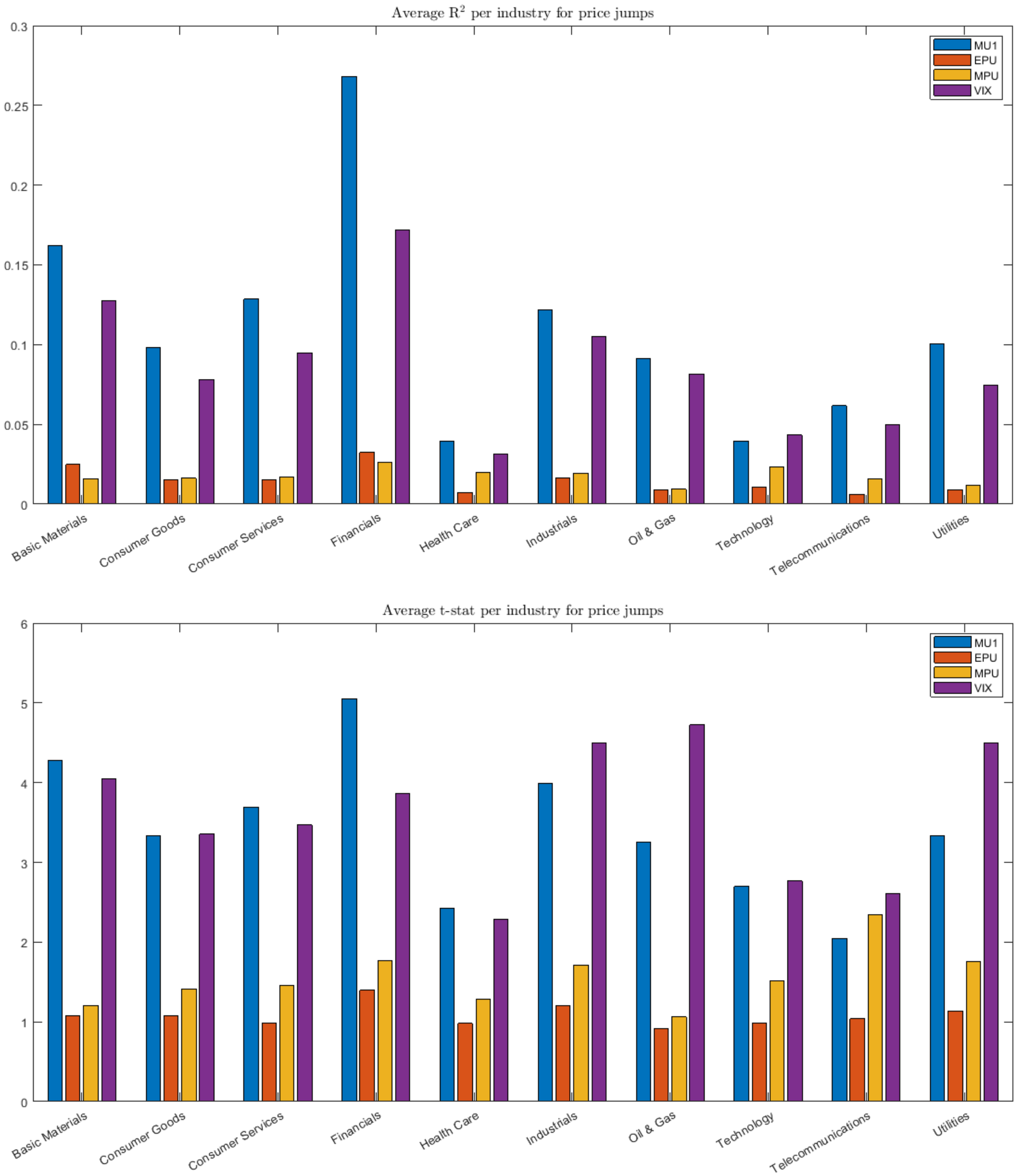


Figure 5. Orthogonalized Impulse Response Functions (OIRFs) of stock market volatility to uncertainty shocks.

The figure below shows the OIRFs the S&P500 Realized Variance (RV) to its own RV shock, VIX index (VIX) shock, Economic Policy Uncertainty (EPU) shock and latent Macroeconomic Uncertainty with one-month forecasting horizon (MU1) shock.The estimated responses are obtained from the baseline 4-factor reduced form VAR model and they are expressed in percentages (%). The VAR model is estimated using monthly time series for the full period (January 1987 till December 2017).

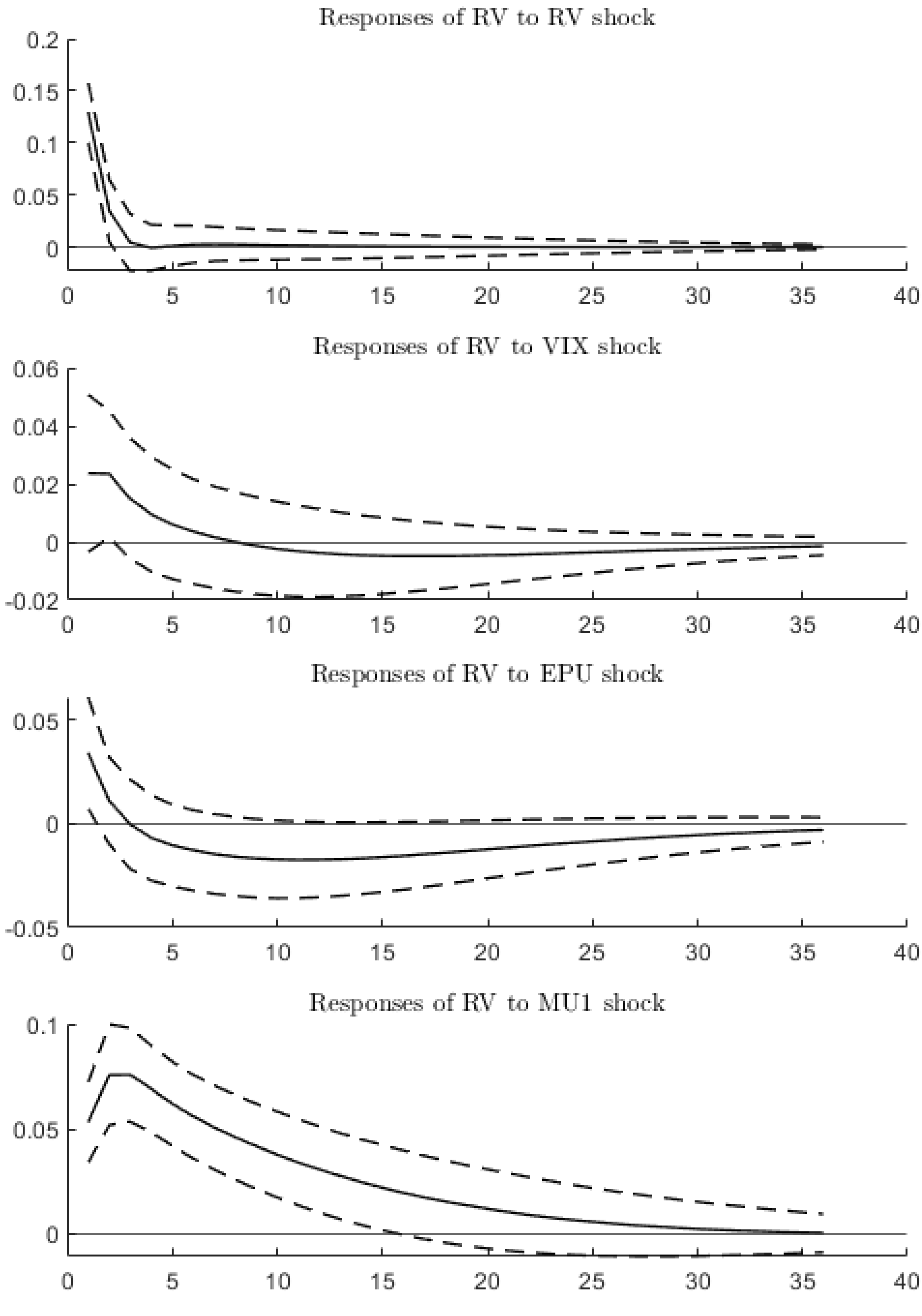


Figure 6. Orthogonalized Impulse Response Functions (OIRFs) of stock market price jumps (JUMP) to uncertainty shocks.

The figure below shows the OIRFs the the jump component (JUMP) of the Realized Variance of S&P500 to its own JUMP shock, VIX index (VIX) shock, Economic Policy Uncertainty (EPU) shock and latent Macroeconomic Uncertainty with one-month forecasting horizon (MU1) shock.The estimated responses are obtained from the baseline 4-factor reduced form VAR model and they are expressed in basis points (the original IRFs are multiplied by 10000). The VAR model is estimated using monthly time series for the full sample (January 1987 till December 2017).

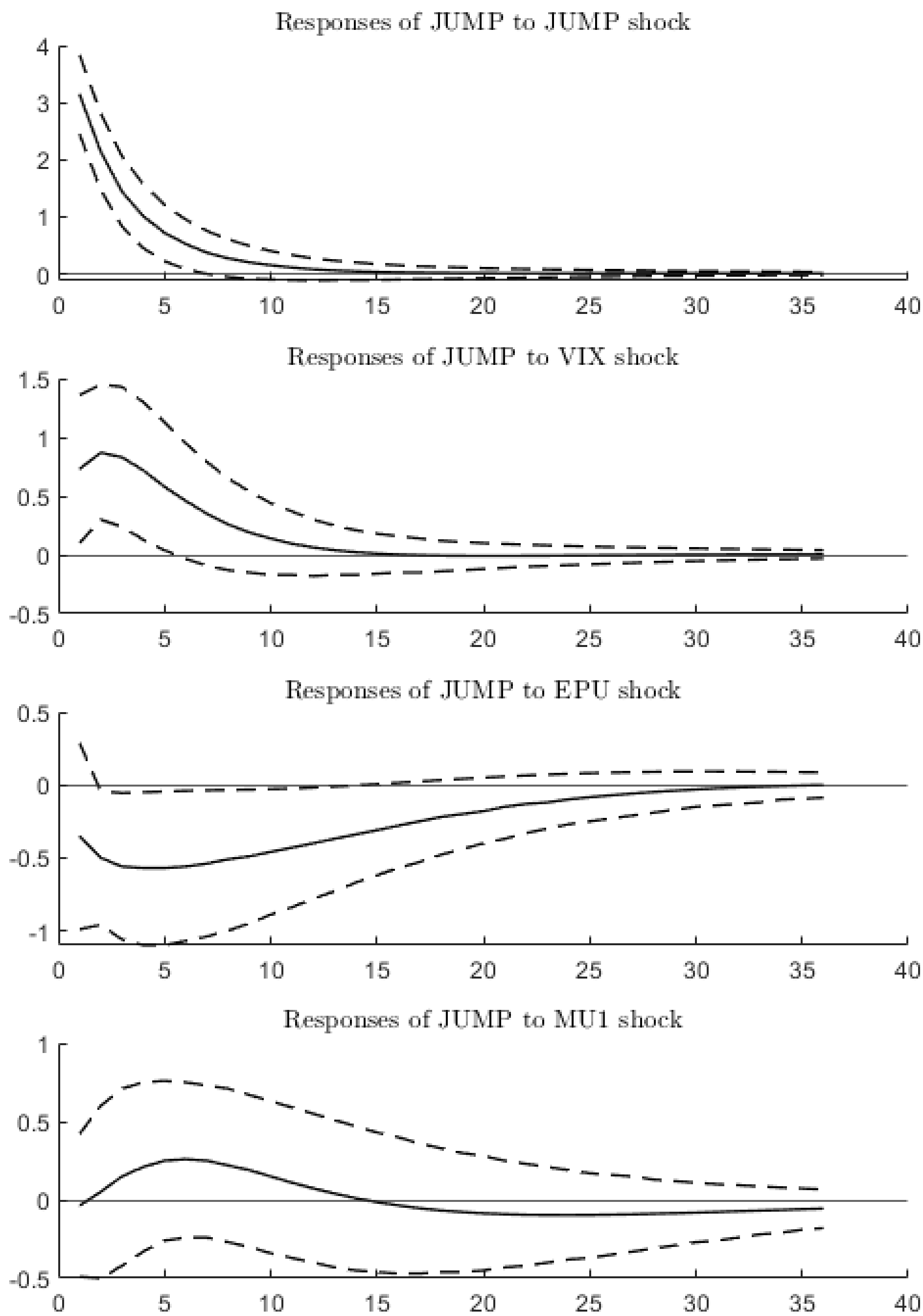


Figure 7. Orthogonalized Impulse Response Functions (OIRFs) of stock market volatility to uncertainty shocks in the post-crisis period.

The figure below shows the OIRFs the S&P500 Realized Variance (RV) to its own RV shock, VIX index (VIX) shock, Economic Policy Uncertainty (EPU) shock and latent Macroeconomic Uncertainty with one-month forecasting horizon (MU1) shock.The estimated responses are obtained from the baseline 4-factor reduced-form VAR model and they are expressed in percentages (%). The VAR model is estimated using monthly time series for the post-crisis period (January 2007 till December 2017).

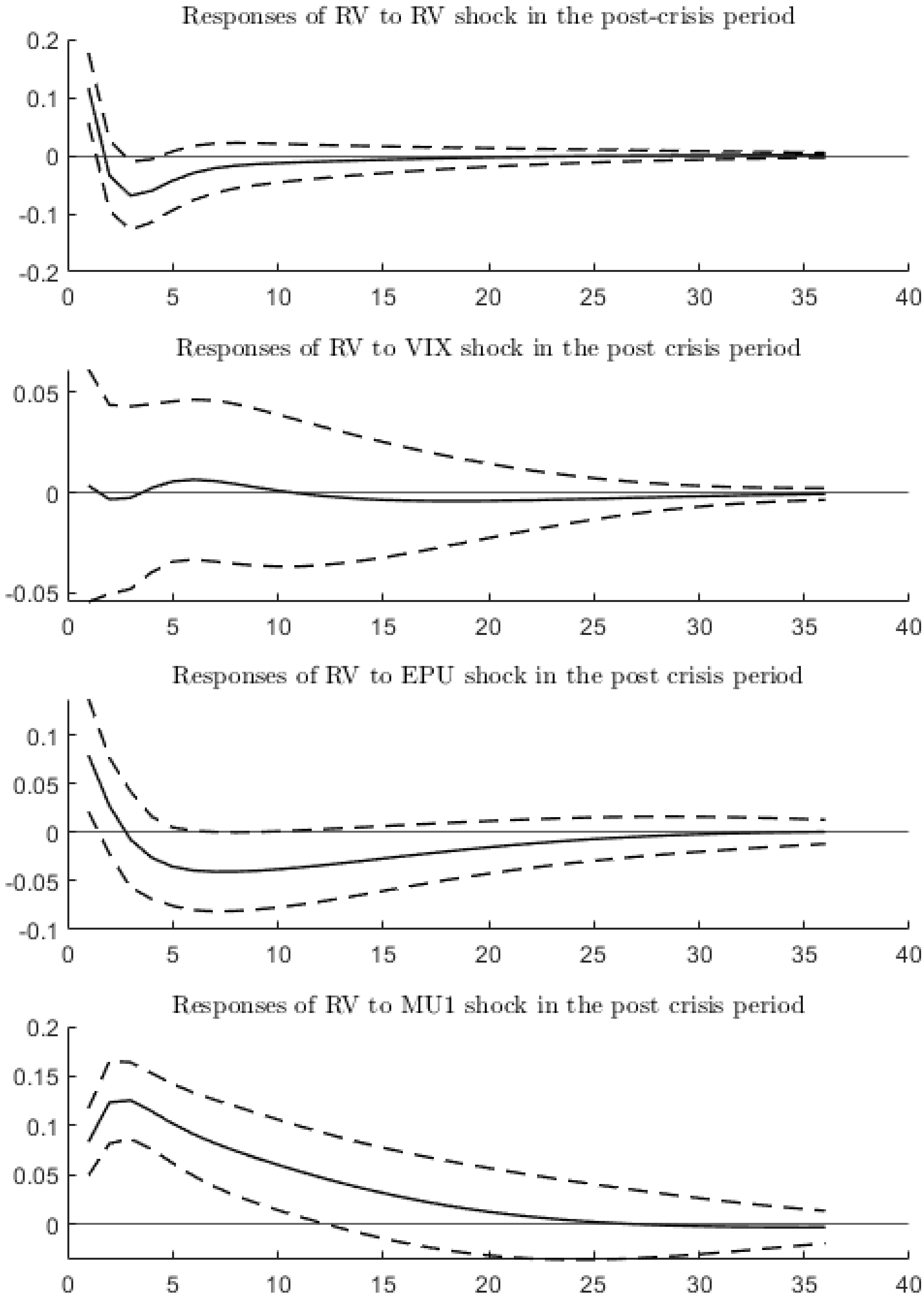


Figure 8. Orthogonalized Impulse Response Functions (OIRFs) of stock market price jumps (JUMP) to uncertainty shocks in the post-crisis period.

The figure below shows the estimated OIRFs of the jump component (JUMP) of S&P500 Realized Variance to its own JUMP shock, VIX index (VIX) shock, Economic Policy Uncertainty (EPU) shock and latent Macroeconomic Uncertainty (MU1) shock.The estimated responses are obtained from the baseline 4-factor reduced-form VAR model and they are expressed in basis points (the original IRFs are multiplied by 10000). The VAR model is estimated using monthly time series for the post-crisis period (January 2007 till December 2017).