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"Anastasios Megaritis, Nikolaos Vlastakis, Athanasios Triantafyllou"

Essex Business School, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ
Web site: http://www.essex.ac.uk/ebs/

Stock market volatility and jumps in times of uncertainty

Anastasios Megaritis[a], Nikolaos Vlastakis[a] and Athanasios Triantafyllou[a,b†]

[a] *Essex Business School, University of Essex, UK*
[b] *SC Johnson College of Business, Cornell University, USA*

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*
JEL Classification: C22, G12, G17, E32

† Corresponding Author, Essex Business School, University of Essex, Wivenhoe Park, Colchester, Essex, CO4 3SQ, UK (a.triantafyllou@essex.ac.uk), tel: +44 (0) 1206 876635

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; Kozeniauskas *et al.*, 2018; 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., 2007a; Bekaert and Hoerova, 2014; Corsi, 2009; Canina and Figlewski, 1993; Christensen and Prabhala, 1998; Fleming *et al.*, 2007; Jiang and Tian, 2005). 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

[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.

Vahid (2007) show that a common factor which is constructed using the lagged volatility series of equity prices 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 (Barro 2006; Engle *et al.,* 2013; Errunza and Hogan, 1998; 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 Barro (2006) and Wachter (2013) show 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. One such case is Evans (2011), who finds that approximately one third of the price jumps in US stock and bond futures markets take place after macroeconomic news announcements and that the announcement effect causes a large increase in the absolute size of these price jumps. Lahaye *et al*. (2011) estimate the jumps in stock index futures and find that the co-jumping behavior is related to macroeconomic news and monetary policy announcements. Miao *et al*. (2014) show that macroeconomic news announcements explain more than three-fourths of the intra-day S&P500 index futures price jumps which occur during the morning hours when macroeconomic news are released. Faust and Wright (2018) come to similar conclusions regarding the role of macroeconomic news announcements on equity risk premia and find that the excess returns in equity markets accrue around scheduled macro-news announcement hours.

Some researchers focus on proxies of macroeconomic uncertainty other than news announcements. Amengual and Xiu (2018) for example find that the downward volatility jumps in the S&P 500 index coincide with drops in Economic Policy Uncertainty (EPU), while Liu and Zhang (2015) show that Economic Policy Uncertainty results in a rapid rise in stock market volatility. Beltratti and Morana (2006) use deviations in the Fed funds rate and in money supply (M1) growth to measure monetary policy uncertainty and find that it causes a subsequent increase in stock market volatility. Gospodinov and Jamali (2012) provide further support to the findings of Beltratti and Morana (2006) by showing that the unanticipated changes in monetary policy (measured as the surprise component of daily changes in the Fed funds target rate) predict significant increases in stock market volatility. Kaminska and Roberts-

Sklar (2018) find that the option-implied monetary policy uncertainty helps in predicting the return volatility of international equity indices. Beber and Brandt (2009) identify significant structural linkages between macroeconomic uncertainty derived by the prices of economic derivatives and the implied volatility of equity option indices, attributing the sudden drops of implied volatility in equity markets to the resolution of macroeconomic uncertainty which is associated with macroeconomic news releases. Gu *et al*. (2018) provide further support to the findings of Beber and Brandt (2009), by reporting significantly positive average stock market returns after the scheduled FOMC meetings and attributing these positive returns to the resolution of uncertainty which takes place right after the FOMC announcements. Finally, Pastor and Veronesi (2012) and Kim and Mei (2001) show that the rising political uncertainty results in a sudden rise in the volatility of stock market returns.

Motivated by the empirical findings that identify the significant impact of macroeconomic news releases and policy uncertainty on stock market volatility (Amengual and Xiu, 2018; Asgharian and Hou, 2013; Brenner *et al*., 2009; Conrad and Loch, 2015; Corradi *et al.*, 2013; Engle, *et al*., 2013; Kaminska and Roberts-Sklar, 2018; Liu and Zhang, 2015; Pastor and Veronesi, 2012; 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

[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.

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 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, for example 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 (or difficult to be predicted ex ante by economic agents) 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

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[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.

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 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, the majority of 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 as a consequence, 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

[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.

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) 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

[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.

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 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]

[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

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

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

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:

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

[11] Andersen et al. (2007a) 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)."

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 (Antonakakis *et al*., 2015; Liu and Zhang, 2015; among others) and monetary policy uncertainty (Bekaert *et al*., 2013; Bernanke 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

[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*.

(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:

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

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]

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

[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.

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 Table 1 Here]

[Insert Table 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 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]

[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.

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 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

[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.

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 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.

[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.

[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).

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

[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.

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]

The results of our multivariate regression models for the full sample and for the post-crisis and pre-crisis period clearly show that the predictive power of MU on stock market volatility and jumps, while absorbed by the VIX and the lagged RV when forecasting volatility and jumps in the pre-crisis period, it becomes statistically significant and provides incremental predictive power when included into the right-hand side of the multivariate regression equation. 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.

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. Caldara *et al*.

(2016) show that in recessionary times stock-return volatility comoves strongly with macro-uncertainty and thus they attribute the Great recession in the 'toxic' interaction between financial and macroeconomic uncertainty shocks. Hence, their findings implicitly reveal the reason why macroeconomic uncertainty is the most significant indicator of stock-market volatility during the 2007-2009 Great Recession period.[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]

Our analysis is also the first to show that latent macroeconomic uncertainty outperforms the VIX for short and long-term volatility and jump tail risk predictions during the recent post-2007 period. 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; Corradi *et al*., 2013; Engle *et al*., 2013; Errunza, and Hogan, 1998; Schwert, 1989, Paye, 2012).

[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 his suggestion of 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.

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 $t+h$ (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

[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.

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 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 (Brunnermeier *et al*., 2009; 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

[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.

estimated Orthogonalized Impulse Response Functions (OIRFs) derived by the baseline 4-factor VAR model analytically described in Subsection 2.4. **Figures 4-5** 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 4 and 5 Here]

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. Chou, 1988; 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; Gospodinov and Jamali, 2012; 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, while Gospodinov and Jamali (2012) show that unanticipated US monetary policy changes (the surprise component of the Fed funds rate) has a significant positive effect on stock market volatility, while the expected monetary policy changes do not have an analogously significant effect on 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 VAR analysis also shows that the latent macroeconomic uncertainty has a higher impact (in magnitude and persistence) on stock market volatility and jump tail risk, when compared to the respective dynamic impact of VIX, monetary policy uncertainty and EPU shocks. This fact implies that it is not the expectations about future volatility (proxied by the VIX) or the uncertainty about economic policy as proxied by EPU (the frequency of uncertainty related articles in the newspapers, see Baker *et al.*, 2016), but the unexpected component of macroeconomic fluctuations that has the highest impact on stock market volatility.

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 the majority of the S&P500 constituents. To the best of our knowledge, our paper is the first in the literature to show that a macroeconomic uncertainty factor can have statistically 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. 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 statistically significant and robust predictor of RBV. These results show that MU is a robust predictor of both the continuous and the jump component of stock-market RV, with the predictive power being much higher during the recent post-crisis period. As expected, when we compare the forecasting power of the MU factor on the continuous and the jump component of RV, we find that the MU predicts better the continuous component of stock market volatility rather than the discontinuous sudden jumps in the RV series. The relevant discussion and the analytical results of our regression models on RBV can be found in our on-line Appendix.

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 (our subsample covers the period from January 2009 till December 2017) 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. Our additional subsample results for the post-crisis period can be found in the on-line Appendix.

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. These results strengthen our main conclusion in the paper on the increased importance of macro-uncertainty shocks on stock market volatility during the post-Great Recession era. In addition, the high correlation between the FU series and the VIX index shows that financial uncertainty is significantly correlated with changes in the VIX. The relevant discussion and the regression results when using the FU index as predictor of stock-market volatility and jumps can be found in our on-line Appendix.

We also provide additional robustness checks and more analytical results for our regression models on the volatility and tail risk of individual equity prices (presented in **Subsection 4.3)**. 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 the same set of VAR models as in the previous section using alternative VAR orderings and allowing for more lags in the model and our main results remain unaltered. Moreover, 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 the Jurado *et al.* (2015) latent 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 (Andersen *et al.*, 2007b; 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.

References

Abbate, A., Eickmeier, S., Lemke, W., and Marcellino, M. (2016). The changing international transmission of financial shocks: evidence from a classical time-varying FAVAR. *Journal of Money, Credit and Banking,* 48(4), 573-601.

Akhtar, S., Akhtar, F., Jahromi, M., and John, K. (2017). Impact of interest rate surprises on Islamic and conventional stocks and bonds. *Journal of International Money and Finance,* 79, 218-231.

Amengual, D., and Xiu, D. (2018). Resolution of policy uncertainty and sudden declines in volatility. *Journal of Econometrics,* 203(2), 297-315

Antonakakis, N., Chatziantoniou, I., and Filis, G. (2013). Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. *Economics Letters*, 120(1), 87-92.

Arouri, M. E. H., Jouini, J., and Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. *Journal of International Money and Finance,* 30(7), 1387-1405.

Andersen, T. G., Bollerslev, T., and Diebold, F. X. (2007a). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *Review of Economics and Statistics*, 89(4), 701-720.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Labys, P. (2001). The distribution of realized exchange rate volatility. *Journal of the American statistical association*, *96*(453), 42-55.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Vega, C. (2007b). Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of International Economics*, 73(2), 251-277.

Anderson, H. M., and Vahid, F. (2007). Forecasting the volatility of Australian stock returns: Do common factors help? *Journal of Business and Economic Statistics*, 25(1), 76-90.

Asgharian, H., and Hou, A.J. (2013). The Importance of the Macroeconomic Variables in Forecasting Stock Return Variance: A GARCH-MIDAS Approach. *Journal of Forecasting,* 32(7), 600-612

Barro, R.J. (2006). Rare disasters and asset markets in the twentieth century. *Quarterly Journal of Economics*, 121, 823-866

Baker, S.R., Bloom, N., and S.J., Davis (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131(4), 1593-1636.

Baker, S., Bloom, N., Davis, S. J., Kost, K., Sammon, M., and Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. Covid Economics: Vetted and Real-Time Papers, 1(3).

Baker, M., and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2), 129-152.

Barndorff-Nielsen, O. E., and Shephard, N. (2006). Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics*, 4(1), 1-30.

Bates, D. S. (1991). The Crash of ’87: Was It Expected? The Evidence from Options Markets. *Journal of Finance*, 46(3), 1009-1044

Beber, A., and Brandt, M. W. (2008). Resolving macroeconomic uncertainty in stock and bond markets. *Review of Finance*, 13(1), 1-45.

Becker, K. G., Finnerty, J. E., and Friedman, J. (1995). Economic news and equity market linkages between the US and UK. *Journal of Banking and Finance*, 19(7), 1191-1210.

Bekaert, G., Hoerova, M., and Duca, M. L. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, 60(7), 771-788.

Bekaert, G., and Hoerova, M. (2014). The VIX, the variance premium and stock market volatility. *Journal of Econometrics*, 183(2), 181-192.

Beltratti, A., and C. Morana (2006). Breaks and persistency: Macroeconomic causes of stock market volatility. *Journal of Econometrics*, 1(2), 151-177

Berger, D., and Turtle, H. J. (2015). Sentiment bubbles. *Journal of Financial Markets*, 23, 59-74.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *Quarterly Journal of Economics*, 98(1), 85-106.

Bernanke, B. S., and Kuttner, K. N. (2005). What explains the stock market's reaction to Federal Reserve policy?. *Journal of Finance*, 60(3), 1221-1257.

Blanchard, O. J., and Watson, M. W. (1982). Bubbles, rational expectations and financial markets. National Bureau of economic research, (No. w0945).

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3), 623-685.

Bollerslev, T., Law, T. H., and Tauchen, G. (2008). Risk, jumps, and diversification. *Journal of Econometrics*, 144(1), 234-256.

Bomfim, A. N. (2003). Pre-announcement effects, news effects, and volatility: Monetary policy and the stock market. *Journal of Banking and Finance*, 27(1), 133-151

Brenner, M., Pasquariello, P., and Subrahmanyam, M. (2009). On the volatility and comovement of US financial markets around macroeconomic news announcements. *Journal of Financial and Quantitative Analysis*, 44(6), 1265-1289.

Brunnermeier, M., Crockett, A., Goodhart, C. A., Persaud, A., and Shin, H. S. (2009). The fundamental principles of financial regulation (Vol. 11). ICMB, International Center for Monetary and Banking Studies.

Caldara, D., Fuentes-Albero, C., Gilchrist, S., and Zakrajšek, E. (2016). The macroeconomic impact of financial and uncertainty shocks. *European Economic Review*, 88, 185-207.

Candelon, B., Piplack, J., and Straetmans, S. (2008). On measuring synchronization of bulls and bears: The case of East Asia. *Journal of Banking and Finance,* 32(6), 1022-1035.
Canina, L., and Figlewski, S. (1993). The informational content of implied volatility. *Review of Financial Studies,* 6(3), 659-681.
Chiu, C. W. J., Harris, R. D., Stoja, E., and Chin, M. (2018). Financial market volatility, macroeconomic fundamentals and investor sentiment. *Journal of Banking and Finance,* 92, 130-145.
Chou, R. Y. (1988). Volatility persistence and stock valuations: Some empirical evidence using GARCH. *Journal of Applied Econometrics,* 3(4), 279-294.
Choudhry, T. (1996). Stock market volatility and the crash of 1987: evidence from six emerging markets. *Journal of International Money and Finance,* 15(6), 969-981.
Conrad, C., and K. Loch (2015). Anticipating Long-Term Stock Market Volatility. *Journal of Applied Econometrics,* 30(7), 1090-1114
Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, 7(2), 174-196.
Corradi, V., Distaso, W., and Mele, A. (2013). Macroeconomic determinants of stock volatility and volatility premiums. *Journal of Monetary Economics,* 60(2), 203-220.
Christensen, B. J., and Prabhala, N. R. (1998). The relation between implied and realized volatility1. *Journal of Financial Economics*, 50(2), 125-150.
Degiannakis, S., Filis, G., and Kizys, R. (2014). The effects of oil price shocks on stock market volatility: Evidence from European data. *Energy Journal,* 35-56.
Diba, B. T., and Grossman, H. I. (1988). Explosive rational bubbles in stock prices?. *American Economic Review*, 78(3), 520-530.
Ellington, M., Florackis, C., and Milas, C. (2017). Liquidity shocks and real GDP growth: Evidence from a Bayesian time-varying parameter VAR. *Journal of International Money and Finance*, 72, 93-117.
Engle, R. F., and Susmel, R. (1993). Common volatility in international equity markets. *Journal of Business and Economic Statistics,* 11(2), 167-176.
Engle, R.F., Ghysels, E., and Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. *Review of Economics and Statistics,* 95(3), 776-797
Errunza, V., and Hogan, K. (1998). Macroeconomic determinants of European stock market volatility. *European Financial Management,* 4(3), 361-377.
Evans, K. P. (2011). Intraday jumps and US macroeconomic news announcements. *Journal of Banking and Finance,* 35(10), 2511-2527.
Fama, E. F. (1990). Stock returns, expected returns, and real activity. *Journal of Finance,* 45(4), 1089-1108.

Faust, J., and Wright, J. H. (2018). Risk premia in the 8: 30 economy. *Quarterly Journal of Finance*, 8(03), 1850010.

Fleming, J., Ostdiek, B., and Whaley, R. E. (1995). Predicting stock market volatility: A new measure. *Journal of Futures Markets*, 15(3), 265-302.

Foroni, C., Guérin, P., and Marcellino, M. (2017). Explaining the time-varying effects of oil market shocks on US stock returns. *Economics Letters*, 155, 84-88.

Gorspodinov, N., and I., Jamali. (2012). The effects of Federal funds rate surprises on S&P 500 volatility and volatility risk premium. *Journal of Empirical Finance*, 19(4), 497-510

Gu, C., Kurov, A., and Wolfe, M. H. (2018). Relief Rallies after FOMC Announcements as a Resolution of Uncertainty. *Journal of Empirical Finance*, 49, 1-18.

Guiso, L., Sapienza, P., and Zingales, L. (2018). Time varying risk aversion. *Journal of Financial Economics*, 128(3), 403-421.

Hamilton, J. D., and Lin, G. (1996). Stock market volatility and the business cycle. *Journal of Applied Econometrics*, 11(5), 573-593.

Henzel, S. R., and Rengel, M. (2017). Dimensions of macroeconomic uncertainty: A common factor analysis. *Economic Inquiry*, 55(2), 843-877.

Hubrich, K. and Tetlow, R.J. (2015). Financial stress and economic dynamics: The transmission of crises. *Journal of Monetary Economics*, 70, pp.100-115.

Jiang, G. J., and Tian, Y. S. (2005). The model-free implied volatility and its information content. *Review of Financial Studies*, 18(4), 1305-1342.

Jurado, K., Ludvigson, S.C., and S., Ng (2015). Measuring uncertainty. *American Economic Review*, 105(3), 1177-1216.

Kang, W., Ratti, R. A., and Yoon, K. H. (2015). Time-varying effect of oil market shocks on the stock market. *Journal of Banking and Finance*, 61, S150-S163.

Kaminska, I., and Roberts-Sklar, M. (2018). Volatility in equity markets and monetary policy rate uncertainty. *Journal of Empirical Finance*, 45, 68-83

Kanas, A. (2013). Bank dividends, risk, and regulatory regimes. *Journal of Banking and Finance*, 37(1), 1-10.

Keynes J. M. (1936). *The general theory of employment, interest and money*. London Macmillan

Kim, H. Y., and Mei, J. P. (2001). What makes the stock market jump? An analysis of political risk on Hong Kong stock returns. *Journal of International Money and Finance*, 20(7), 1003-1016.

Kozeniauskas, N., Orlik, A., and Veldkamp, L. (2018). What are uncertainty shocks?. *Journal of Monetary Economics*, 100, 1-15.

Lahaye, J., Laurent, S., and Neely, C. J. (2011). Jumps, cojumps and macro announcements. *Journal of Applied Econometrics*, 26(6), 893-921.

Liu, L., and Zhang, T. (2015). Economic policy uncertainty and stock market volatility. *Finance Research Letters*, 15, 99-105.

Mayne, L. S. (1980). Bank dividend policy and holding company affiliation. *Journal of Financial and Quantitative Analysis*, 15(2), 469-480.

Miao, H., Ramchander, S., and Zumwalt, J. K. (2014). S&P 500 Index-Futures Price Jumps and Macroeconomic News. *Journal of Futures Markets,* 34(10), 980-1001.

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica: Journal of the Econometric Society*, 315-335.

Newey, W. K. and K. D., West. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica,* 55(3), 703-708.

Pastor, L., and Veronesi, P. (2012). Uncertainty about government policy and stock prices. *Journal of Finance*, 67(4), 1219-1264.

Patton, A. J., and Sheppard, K. (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics,* 97(3), 683-697.

Paye, B. S. (2012). 'Déjà vol': Predictive regressions for aggregate stock market volatility using macroeconomic variables. *Journal of Financial Economics*, 106(3), 527-546.

Prieto, E., Eickmeier, S. and Marcellino, M., (2016). Time variation in macro-financial linkages. *Journal of Applied Econometrics*, *31*(7), pp.1215-1233.

Rangel, J. G. (2011). Macroeconomic news, announcements, and stock market jump intensity dynamics. *Journal of Banking and Finance,* 35(5), 1263-1276.

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance*, 16(3), 394-408.

Schwert, G. W. (1989). Why does stock market volatility change over time?. *Journal of finance*, 44(5), 1115-1153.

Shiller, R. J. (1981). Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?. *American Economic Review,* 71(3), 421-436.

Summers, L. H. (1986). Does the stock market rationally reflect fundamental values?. *Journal of Finance*, 41(3), 591-601.

Wachter, J.A. (2013). Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock market Volatility? *Journal of Finance,* 68(3), 987-1035

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

*, ** 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

*, ** 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

*, ** 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

*, ** 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

*, ** 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

*. ** 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

*. ** 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%	7%	6%	-5.6%	34.6%	-0.5%	-0,04%	18,1%	17.3%	-16.4%
3m	-5,2%	-3,7%	7,1%	2,5%	-89.4%	-5%	-4%	-1%	-7.8%	-1.9%	-4,7%	-3,9%	3%	1.4%	-16.5%
12m	-7,5%	-5,4%	-4,8%	-13,7%	-191.9%	-23%	-14%	-26%	-33.7%	-88.6%	-7,1%	-6,4%	-4,9%	-11.3%	-16.3%

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

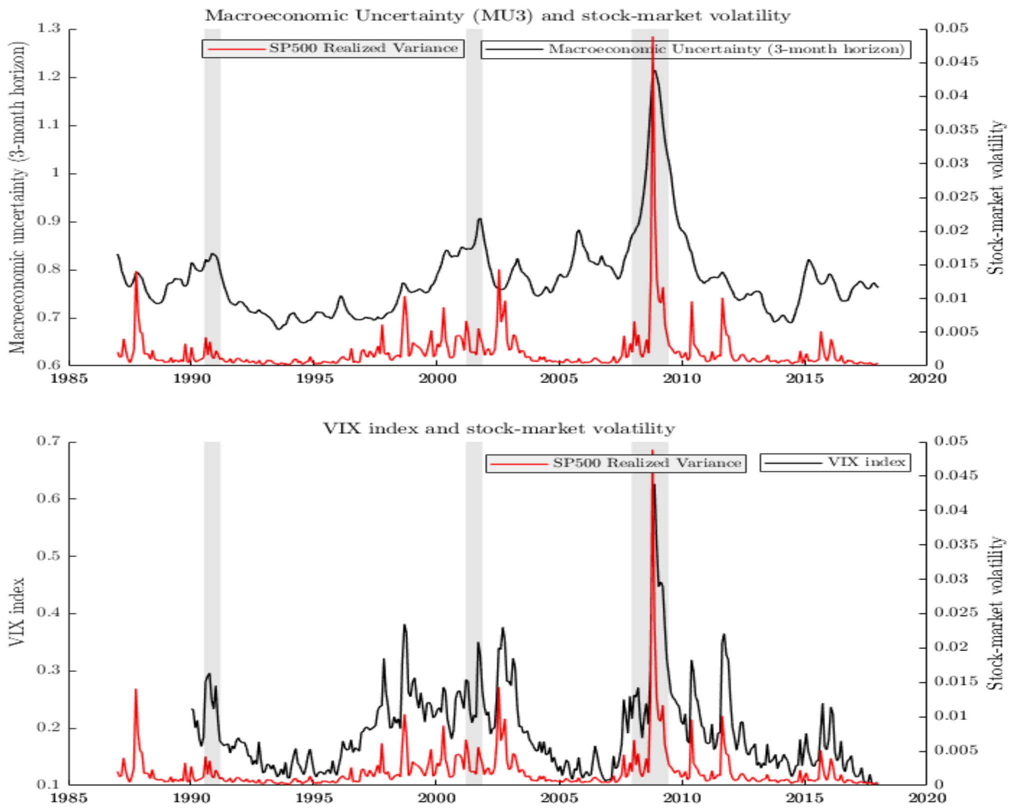


Figure 2. Latent macroeconomic uncertainty, VIX index and stock market price jumps

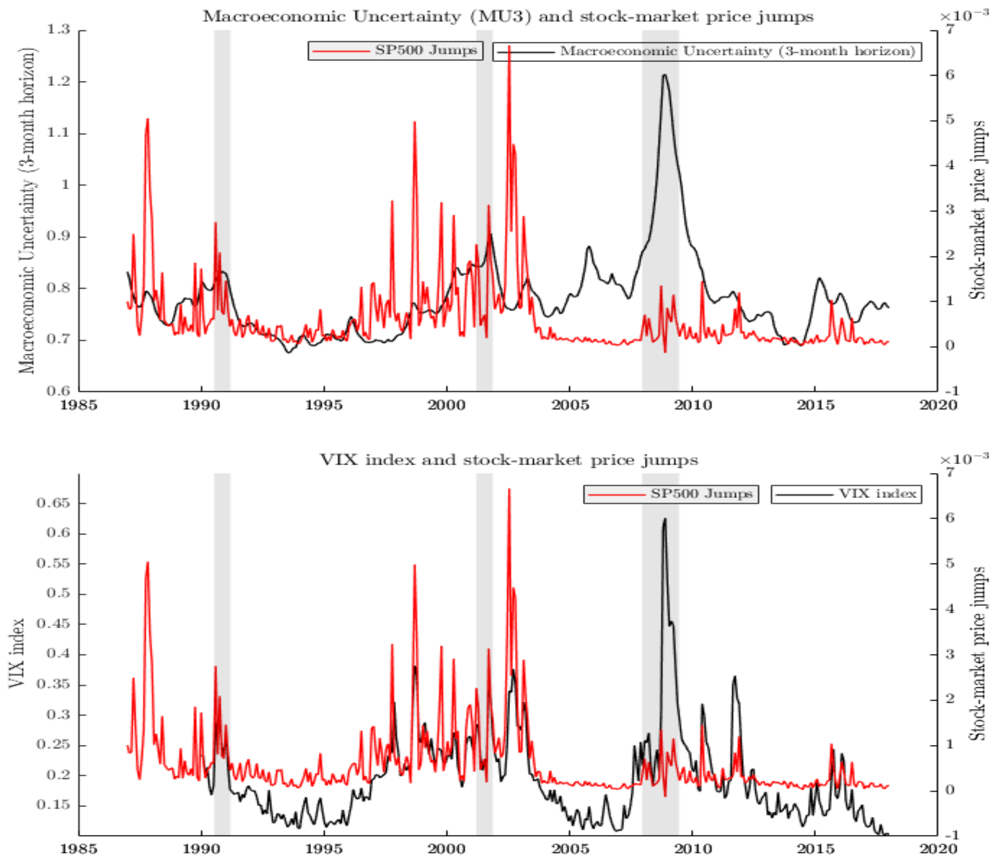
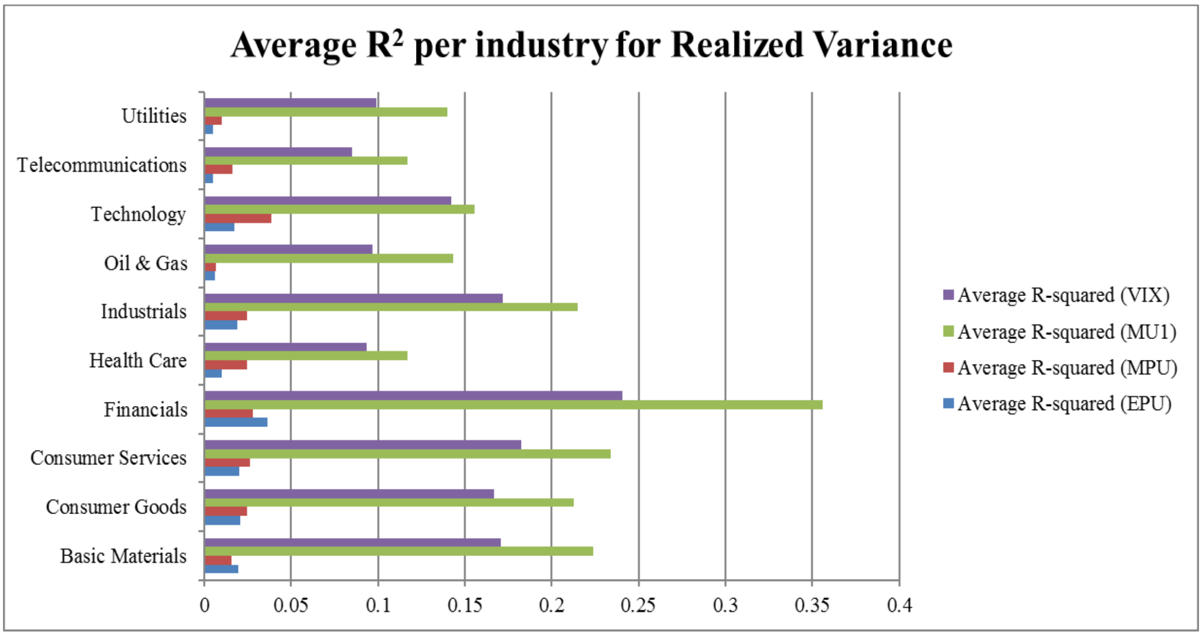


Figure 3. Average R^2 values and t-statistics per sector for the bivariate regression models on the Realized Variance of S&P500 constituents.

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 the MU1, the VIX index, the AR(1) of Realized Variance, 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.



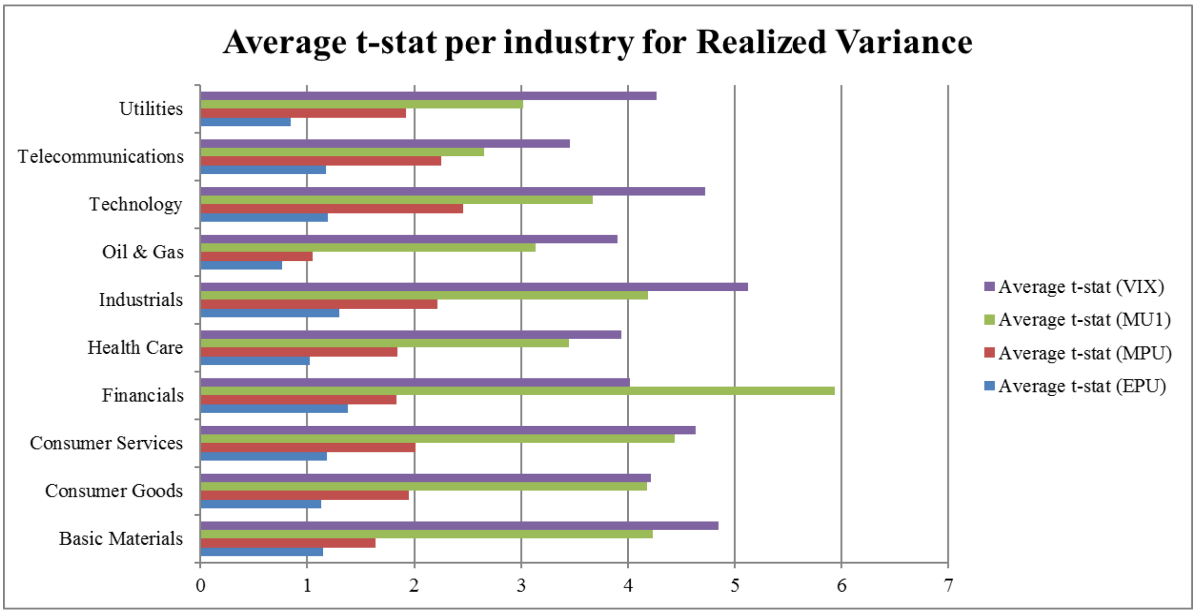
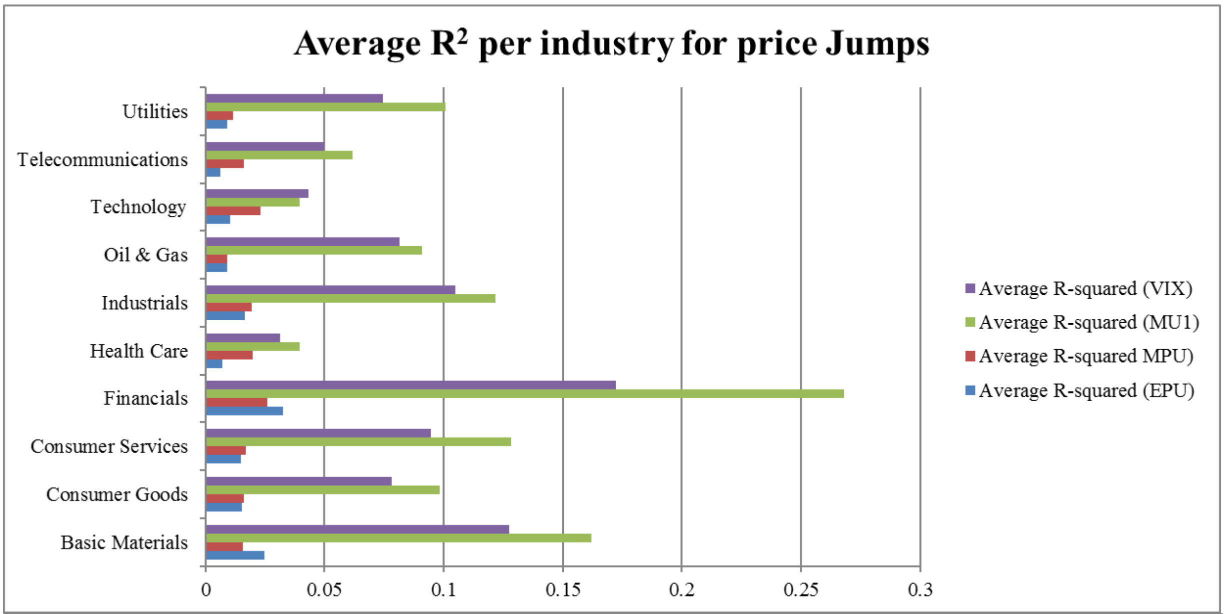


Figure 4. Average R^2 values and t-statistics per sector for bivariate regression models on the price jumps of S&P500 constituents.

This figure shows the average sectoral R^2 values and t-statistics of the univariate regression models on stock market price jumps when using the MU1, the VIX index, the AR(1) of Realized Variance, 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.



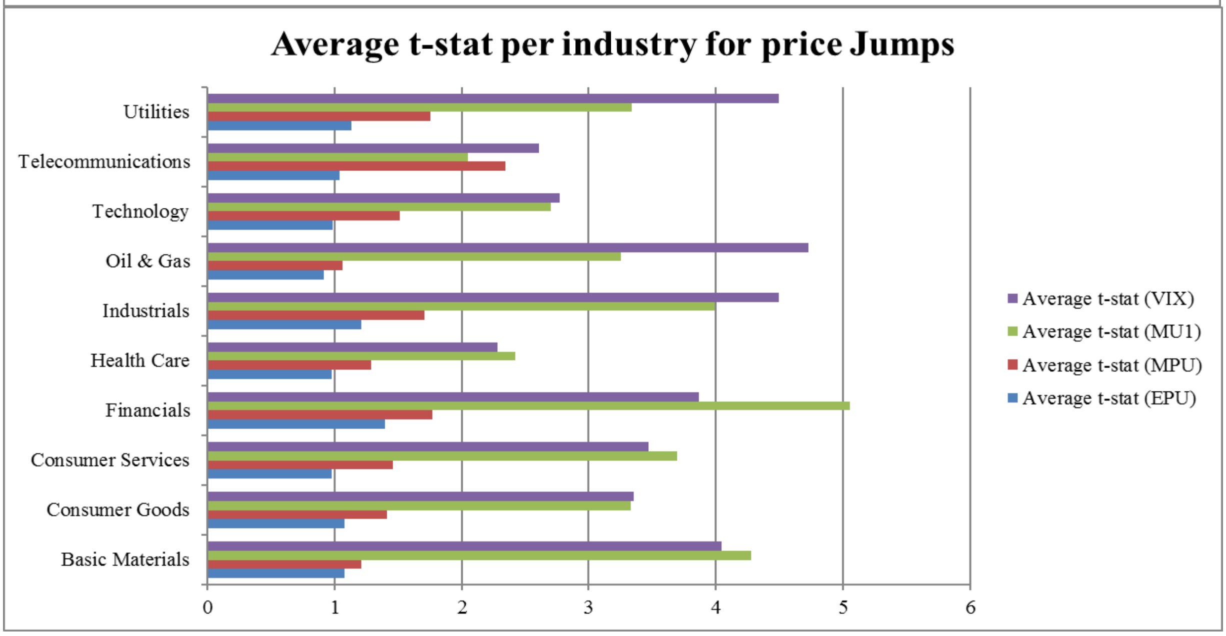


Figure 5. Orthogonalized Impulse Response Functions (OIRFs) of stock market volatility to uncertainty shocks.

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).

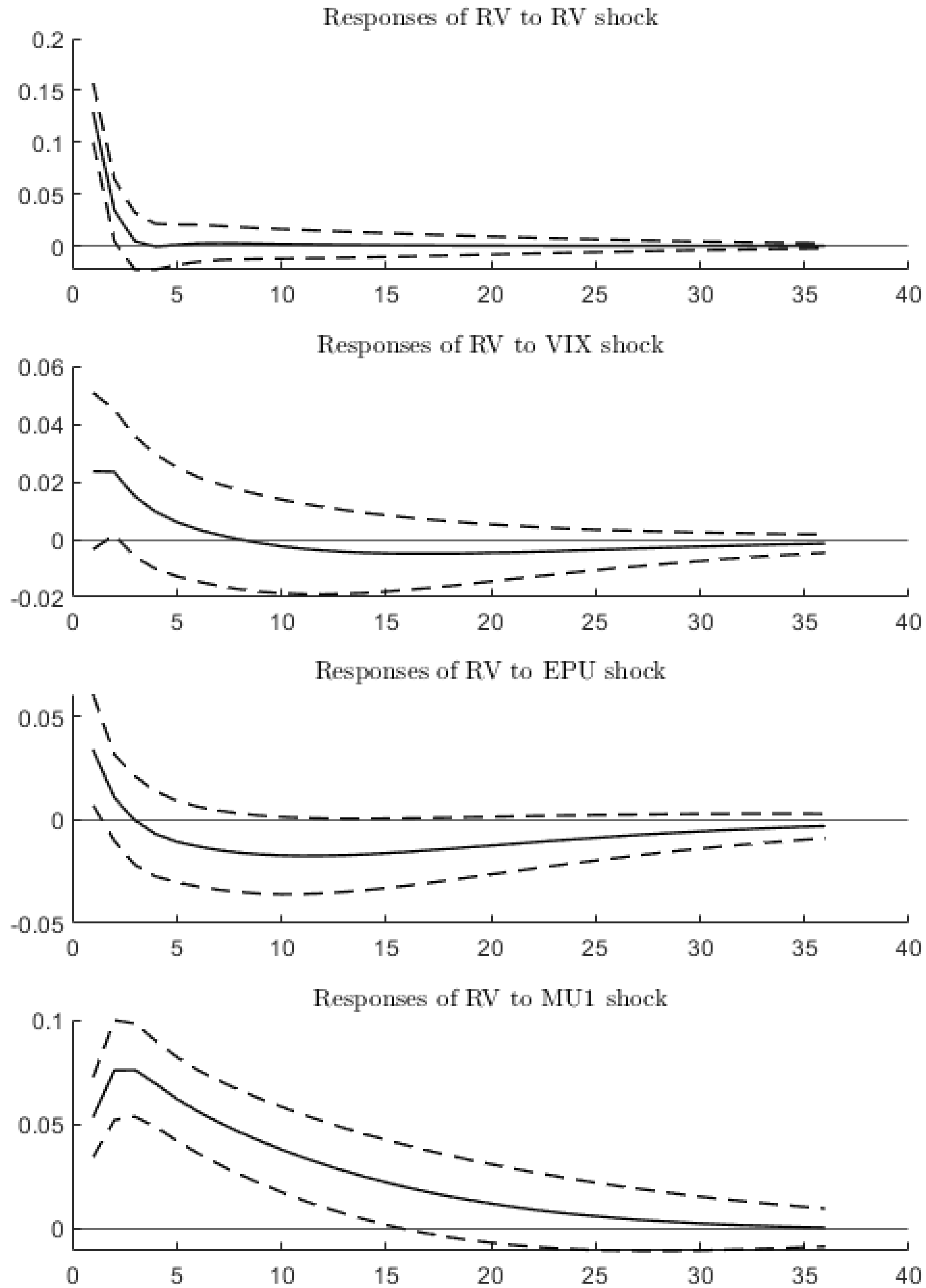


Figure 6. Orthogonalized Impulse Response Functions (OIRFs) of stock market price jumps (JUMP) to uncertainty shocks.

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).

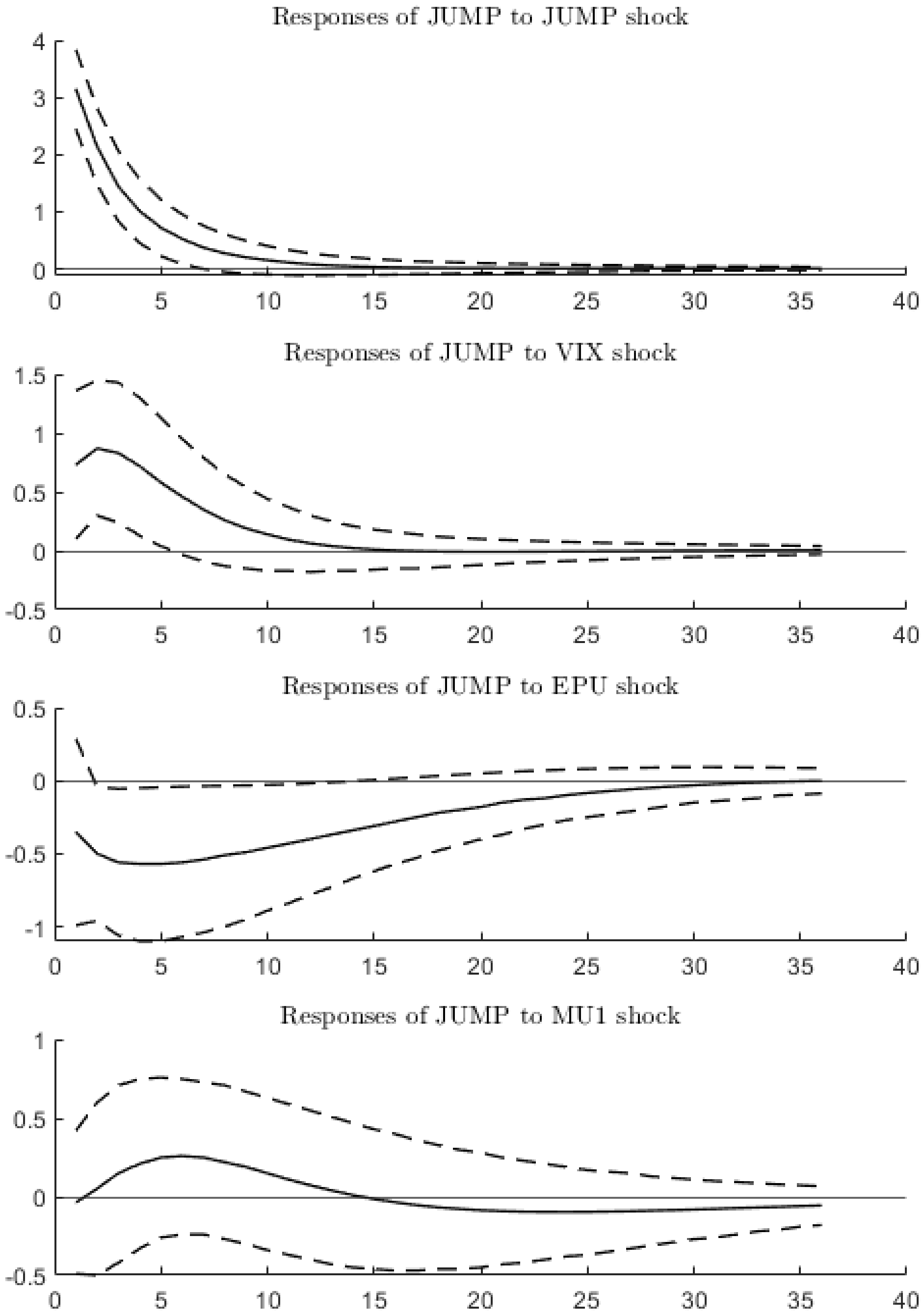


Figure 7. Orthogonalized Impulse Response Functions (OIRFs) of stock market volatility to uncertainty shocks in the post-crisis period.

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).

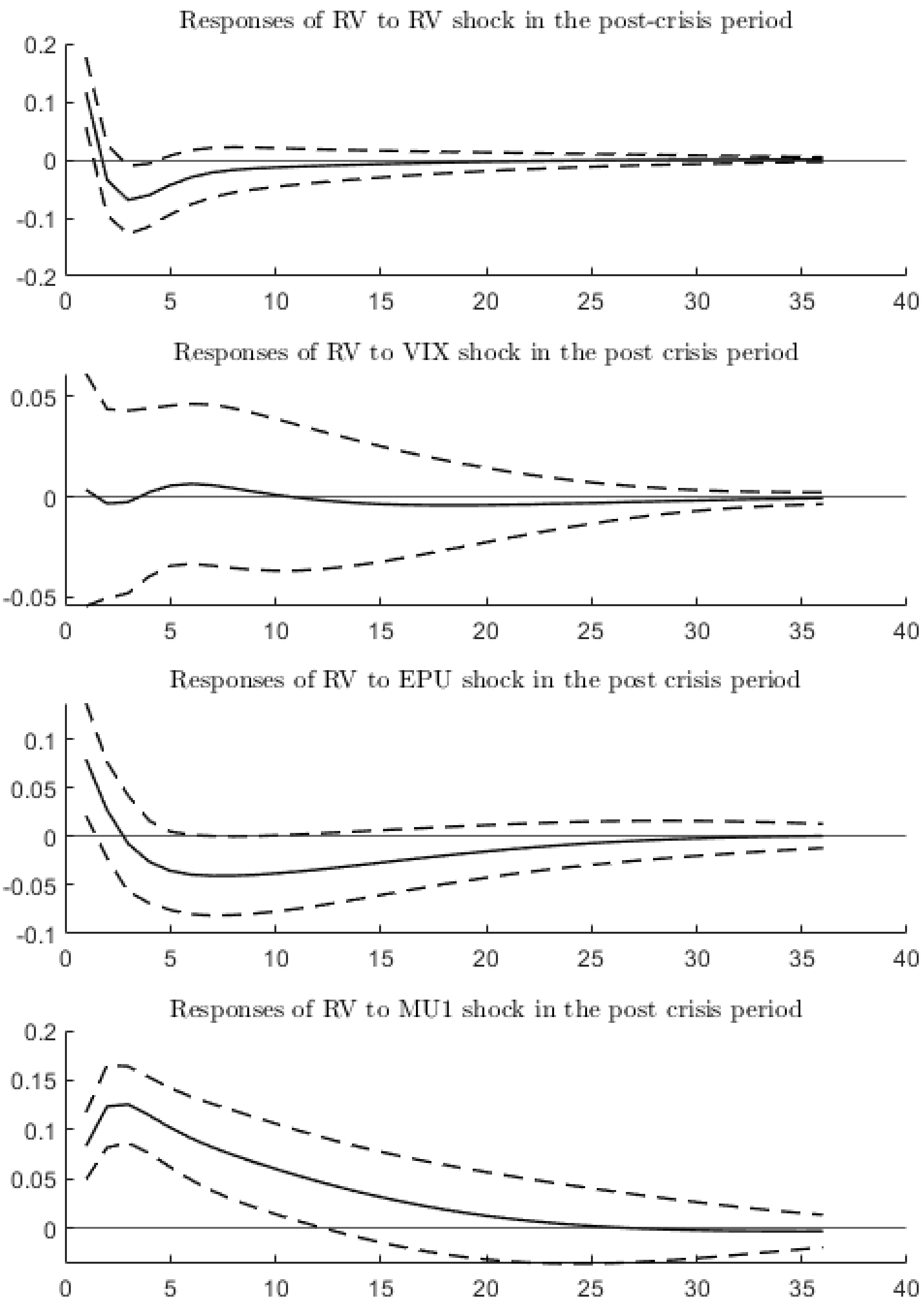
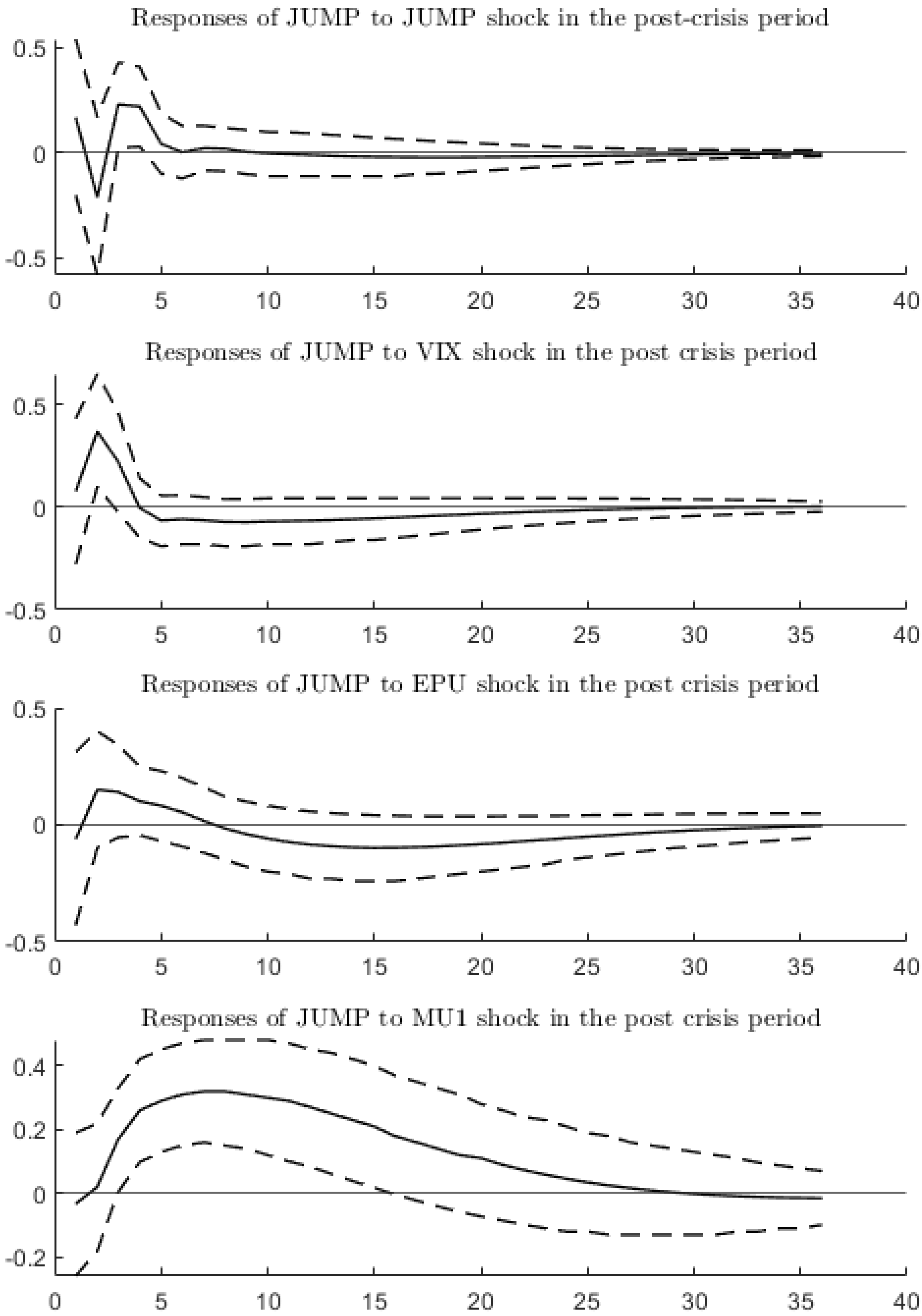


Figure 8. Orthogonalized Impulse Response Functions (OIRFs) of stock market price jumps (JUMP) to uncertainty shocks in the post-crisis period.

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).



On-line Appendix

In our on-line Appendix we provide robustness to our OLS and VAR models presented in the main paper. **Table A1** below shows the results of the Augmented Dickey-Fuller (ADF) tests for our time series variables.

[Insert Table A1 Here]

Our unit root tests shown in **Table A1** reject the hypothesis of a unit root for all our time series variables at the 5% significance level. Moreover, **Tables A2** and A**3** below show the results of our univariate regression models (shown in **Equations (10), (11)** and (**12)** of the paper) on stock-market volatility and jumps for the pre-2007 (January 1990-December 2006) period.

[Insert Tables A2-A3 Here]

The regression results shown in **Tables A2** and A**3** clearly show that the forecasting power of our MU factor has deteriorated in the pre-crisis period (when compared with the respective forecasting power on the post-2007 period). Our additional results on the forecasting regression models for the pre-crisis period show that, while the MU factor outperforms the VIX when forecasting volatility and price jumps in the post-2007 Great recession period, exactly the opposite holds for the pre-crisis period. Moreover, **Tables** A**4** to **A7** show the regression results of the multivariate regression models in which we additionally control for macroeconomic determinants of stock-market volatility and price jumps like the Fed fund rate (Bekaert *et al*., 2013; among others), the US Industrial Production Index growth (IPI) and the US unemployment rate (UNEMP) (Schwert, 1989; Paye, 2012; among others).

[Insert Tables A4-A7 Here]

The results shown in **Tables A4** to **A7** show that our main findings regarding the predictive power of the MU factor on stock-market volatility and jumps remain robust to the inclusion of industrial production, Fed fund rate and unemployment rate into the right-hand side of the regression equation.

Moreover, we perform a sensitivity analysis in our post-crisis regression results for the regression models shown in **Equations (10), (11)** and **(12)** of the paper, by estimating the regression models for different crisis periods. Since our choice of choosing January 2007 as the beginning month of 2007 US financial crisis is somewhat arbitrary, we perform the post-crisis analysis using two additional subsamples for the post-crisis period: one sample starting from June 2007 and another subsample starting from January 2008. The respective regression results for the samples covering the periods from June 2007 to December 2017 and from January 2008 to December 2017 are shown in **Tables A8** to **A15** given below:

[Insert Tables A8-A15 Here]

From Tables A8 to A15 we observe that our results showing the increased impact and predictive power of MU on stock-return volatility and jumps is insensitive to the choice of the post-crisis dataset. More specifically, the explanatory power of the MU factor on RV and JUMP remains high when performing the regression analysis for the post-crisis sample starting either from June 2007 or from January 2008.

Additionally, in order to examine whether our post-crisis regression results are driven from the inclusion of the 2007-2008 US financial crisis, we estimate the post-crisis regression models using a sample starting from January 2009 (January 2009-December 2017 data sample). In this way, (by not including in the post-crisis sample the crisis period), we implicitly control whether the extraordinary predictive power of the MU factor is actually driven by the inclusion of the highly uncertain financial crisis period into the econometric analysis. **Tables A16-A19** show the regression results our set of univariate and multivariate regression models (as shown in **Equations (10), (11)** and **(12)** of the paper) for our subsample analysis covering the period from January 2009 till December 2017.

[Insert Tables A16-A19 Here]

The regression results of our bivariate and multivariate regression models shown in **Tables A16** to **A19** show that our main findings regarding the predictive power of MU on stock-market volatility and jumps remain qualitatively the same when estimating the models using the 2009-2017 dataset. These results show that the increased predictive power of MU on stock-market volatility during the post-crisis period, are not driven by the inclusion of the crisis in our post-crisis data sample.

We continue by estimating our set of predictive regression models on the continuous component of stock-market volatility, namely the Realized Bi-power Variation (RBV) as shown in **Equation (9)** of the paper. The respective regression results for our set of bivariate and multivariate regression models on RBV are presented on **Tables A20** to **A25** below.

[Insert Tables A20-A25 Here]

The results of the **Tables A20** to **A25** on the continuous component of stock-market volatility, show that the MU factor is a robust predictor of RBV as well. Interestingly, the MU factor outperforms the VIX when used for forecasting RBV for 3-month and 12-month forecasting horizon. In conclusion, our results show that except for the jump component, the MU factor is a statistically significant predictor of the continuous component of stock-market volatility and it outperforms the VIX for medium and long-term forecasts.

Moreover, we perform an additional robustness check on the relative performance of the MU(k) factor when compared with the VIX. Since the VIX represents the option-implied volatility which corresponds to the 30-day maturity S&P500 option contracts (hence represents the uncertainty and risk-aversion of equity option writers over the next monthly period), we believe that, while it is comparable with MU1, it is not directly comparable with MU3 and MU12 (the latent macro-uncertainty for the next 3-month and 12-month horizon respectively). For this reason, we estimate our set of regression models which are presented in the paper using the IV3 (3-month S&P500 implied volatility) and the IV12 (12-month S&P500 implied volatility) instead of the VIX, when forecasting volatility and jumps having 3-month and 12-month forecasting horizon respectively. Tables **A26** to **A30** show the regression results of our bivariate and multivariate models in which we include IV3 and IV12 (instead of VIX) when forecasting stock-market volatility and jumps with 3- and 12-month horizon respectively.

[Insert Tables A26-A30 Here]

From **Tables A26** we observe that the IV3 and IV12 series do not perform better than the VIX when used as predictors of 3-month and 12-month ahead equity price volatility and jump tail risk. Consequently, our main finding on the superior long-term forecasting power of MU when compared to S&P500 option-implied volatility remains valid when we replace the VIX (1-month option-implied volatility) with its 3-month and 12-month maturity (horizon) counterparts. Moreover, the results of the multivariate models shown in **Tables A27** to **A30** show that the predictive power of the MU index remains robust to the inclusion of the IV3 and IV12 series into the information variable set.

Apart from the latent MU factor, Jurado *et al.* (2015) have deployed a similar methodology for the estimation of their latent Financial Uncertainty (FU). For this reason, we perform an additional robustness check by examining the predictive power of latent Financial Uncertainty (FU1, FU3 and FU12) on stock-market volatility and jumps. More specifically, we perform the same regression analysis using the FU1, FU3 and FU12 instead of the MU1, MU3 and MU12 presented in the paper. Because of the high correlation between the MU and FU series (nearly 70% correlation) we do not include MU and FU simultaneously in the right-hand side of the regression equation, in order to avoid multicollinearity issues. For the same reason, we do not include the VIX index in the right-hand side of the regression equation (as expected, the correlation between VIX and FU1, FU3 and FU12 series very high and lies between 80 and 85%). **Tables A31** to **A39** report the results of our set of bivariate and multivariate models presented in the paper when using FU instead of MU as predictor of stock-market volatility and jumps.

[Insert Tables A31-A39 Here]

From **Tables A31** to **A39** we observe that the FU factor is also a robust predictor of stock-market volatility and jumps. When performing a pre-crisis and post-crisis analysis, we find that the FU factor has higher predictive power during the pre-crisis period when compared with the post-crisis period. This is exactly opposite to what we find for the MU factor. Overall, our analysis on the predictive power of latent financial uncertainty, leads to the same conclusion, according to which, while the financial uncertainty shocks (as quantified by the FU and the VIX) are the key drivers of the stock-market volatility during the pre-2007 period, the macroeconomic uncertainty becomes the most significant determinant of equity price volatility in the post-2007 crisis period.

We additionally estimate the bivariate regressions on the volatility and price jumps of S&P500 constituents (which we present in Subsection 3.3 of the paper) using 3-month and 12-month forecasting horizon. **Figures A1** to **A4** show the respective results (average sectoral R^2s and t-statistics) of our bivariate regression models on the realized variance (RV) and price jumps (JUMPS) of S&P500 constituents for 3-month and 12-month forecasting horizon respectively.

[Insert Figures A1-A4 Here]

From **Figures A1** to A**4** we observe that our main findings and conclusions regarding the predictive power of the MU factor on S&P500 constituents remain robust when having 3-month (instead of one-month) forecasting horizon. For example, the MU factor still outperforms the VIX for volatility and jump tail risk forecasts having a 3-month horizon. Moreover, the forecasting power of the MU factor is higher when forecasting the 3month ahead volatility and price jumps of the stocks which belong to the financial sector. On the other hand, (as expected), the predictive power of the VIX and of the MU factor is significantly diminished for 12-month forecasting horizon. Moreover, in order to provide robustness to our bivariate regression results on the volatility and price jumps of S&P500 constituents, we present the sorted R^2 values and t-statistics for all our bivariate regression models on firm-level volatility risk and price jumps. **Figures A5** to A**10** below plot the respective sorted R^2 values and the Newey-West t-statistics of all our bivariate regression models on the volatility and price jumps of S&P500 constituents.

[Insert Figures A5-A10 Here]

From **Figures A5** to **A10** we observe that the MU factor produces higher R^2 values when compared to the VIX, when forecasting volatility and price jumps having 1 up to 3 month forecasting horizon. Surprisingly, when using the MU factor alone for forecasting volatility and price jumps of S&P500 constituents, we get higher than 10% R^2 values for nearly half of the 501 forecasting regression models. Our results provide robustness to the findings presented in **Subsection 4.3** of the paper in which we present only the sectoral averages of the R^2s and t-statistics.

Finally, we include the detailed list of the companies that are used in the sectoral analysis alongside with the companies that are missing from our dataset. The list is contained in the **Table A40.**

[Insert Table A40 Here]

We provide robustness to our VAR analysis (which is presented in Subsection 3.4 of the paper) by estimating identical 4-factor VAR models using the MU3 and MU12 (instead of the MU1 factor) as our proxy for latent macroeconomic uncertainty on the VAR model. **Figures A11** to A**18** below show the respective OIRFs for these VAR models.

[Insert Figures A11-A18 Here]

Figures A11 to A**18** show that our VAR results remain unaltered when using MU3 or MU12 as endogenous variable in the VAR model. Hence, our estimated OIRFs are independent of the choice of the MU factor in the VAR model.

Finally, we empirically examine the predictive power of the MU factor on the incidence of financial crises, when these are defined as local peaks on the stock-market volatility (RV) series. We follow the methodology of Candelon *et al*. (2008) for the identification of peaks in the evolution of the RV series. A peak occurs if for a given month the Realized Variance reaches a local maximum. Thus, for RV_t we identify a peak when for a given month and a given time window k the following condition holds:

$$RV_t > \max(RV_{t-k}, RV_{t+k}) \quad k \in R^{+} \tag{A1}$$

We choose as time window the 12-months (k=12). In order to forecast stock-market crises, we run predictive probit regressions on the dummy variable using as an explanatory variable the MU factor. The probit predictive regression model on financial crises is given below:

$$P(VOLPEAK_t = 1) = F(a + bMU(k)_{t-k-1}) \tag{A2}$$

Where $VOLPEAK_t$ is the 0-1 dummy variable that takes the value of 1 for the historical peaks in stock-price volatility series and zero otherwise. In **Figure A19** we plot the estimated probabilities for the respective probit model shown in **Equation (A2)** using MU1, MU3 and

MU12 as predictor of stock-market volatility spikes (US stock-market crises) along with the incidence of RV spikes.

[Insert Figure A19 Here]

From **Figure A19** we can observe that the MU factor can act as an early warning signal of large stock-market volatility episodes. We observe that the estimated probability jumps many months before the realization of a peak (financial crisis) in the stock-market volatility series for the majority of the peaks in the RV series. Interestingly, when forecasting the incidence of a financial crisis for short and long-term forecasting horizon, the estimated probability rises almost 1 year before the large US stock-market volatility spike which took place on October 2008 (the aftermath of the Lehman Brothers collapse). On the other hand, we observe that the probabilities falsely rise in 2006 since we do not identify any large volatility spike during this year. Overall, we conclude that the number of false positives (when the probit model predicts a crisis but the crisis does not occur) and the number of false negatives (when the probit model does not predict a crisis and the crisis does occur) is very low (we can also report detailed numbers of false negatives and false positives if requested).

References

Bekaert, G., Hoerova, M., and Duca, M. L. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, 60(7), 771-788.

Candelon, B., Piplack, J., & Straetmans, S. (2008). On measuring synchronization of bulls and bears: The case of East Asia. *Journal of banking and Finance*, 32(6), 1022-1035

Paye, B. S. (2012). 'Déjà vol': Predictive regressions for aggregate stock market volatility using macroeconomic variables. *Journal of Financial Economics*, 106(3), 527-546

Schwert, G. W. (1989). Why does stock market volatility change over time?. *Journal of Finance*, 44(5), 1115-1153.

Table A1. Unit root tests

This table shows the results of the Augmented Dickey-Fuller (ADF) unit roots tests for our explanatory variables, covering the period from January 1990 till December 2017. With *, ** and *** we reject the hypothesis of a unit root at the 10%, 5% and 1% respectively.

Unit root tests (full sample)

Dependent variable	***ADF test-statistic***	***p-value***
SP500RV	-4.111***	0.001
JUMP	-2.980**	0.037
VIX	-3.167***	0.002
EPU	-2.883**	0.047
MPU	-4.139***	0.001
MU1	-2.877**	0.048
MU3	-2.912**	0.044
MU12	-2.977**	0.037
BAA	-3.221**	0.018

Table A2. Forecasting stock market volatility during the pre-crisis period (Jan 1990- Dec 2006)

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	-0.003*	-1.69	0.008**	2.56	4.7
3m	-0.003	-1.52	0.007**	2.18	4.2
12m	-0.014	-1.26	0.014	1.44	5.3

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	-0.002***	-5.32	0.021***	7.61	42.5
3m	-0.0008**	-2.17	0.013***	6.09	17.9
12m	-0.0008	-1.34	0.014***	3.40	17.4

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	0.0005***	4.85	0.669***	12.38	44.7
3m	0.001***	4.44	0.413***	4.52	17.0
12m	0.001***	4.41	0.354**	2.52	12.5

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	0.0005	0.83	0.0001*	1.75	2.4
3m	0.002***	2.81	-0.0001	-0.21	0.0
12m	0.002*	1.92	-0.0001	-0.50	0.7

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	0.0006**	2.60	4.3
3m	0.002***	4.78	-0.0005	-0.02	0.0
12m	0.001***	3.35	0.0002	0.40	0.4

*, ** 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 A3. Forecasting stock market price jumps during the pre-crisis period (Jan 1990- Dec 2006)

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	-0.001	-1.10	0.003*	1.95	2.3
3m	-0.001	-1.00	0.002	1.61	2.0
12m	-0.005	-1.16	0.006	1.32	4.5

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	-0.001***	-5.17	0.009***	7.07	38.7
3m	-0.0004**	-2.01	0.005***	5.55	14.4
12m	-0.0004	-1.23	0.006***	2.91	14.5

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	0.0003***	4.90	0.592***	8.39	35.1
3m	0.0005***	4.46	0.345***	3.28	11.9
12m	0.0005***	4.44	0.272**	2.01	7.5

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	-0.0004	-0.13	0.0001**	2.45	4.3
3m	0.0006**	2.01	0.0001	0.41	0.1
12m	0.0007	1.27	-0.0002	-0.04	0.0

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	0.0004***	3.14	0.0003***	3.19	5.3
3m	0.0007***	4.18	0.0001	0.16	0.0
12m	0.0005**	2.51	0.0001	0.81	1.7

*, ** 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 A4. Forecasting stock market volatility (RV) in the pre-crisis (Jan 1987-Dec 2006) period when controlling for macroeconomic fundamentals

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	0.002	0.009**	0.008
	t-stat	(0.653)	(1.982)	(1.404)
MU(k)	Coef.	-0.002	-0.004	0.001
	t-stat	(-0.983)	(-1.378)	(0.076)
RV	Coef.	0.555	-0.071	0.189
	t-stat	(1.171)	(-0.236)	(0.628)
JUMP	Coef.	-0.439	0.401	-0.423
	t-stat	(-0.423)	(0.622)	(-0.845)
VIX	Coef.	0.008**	0.003	0.009**
	t-stat	(2.436)	(0.565)	(2.171)
EPU	Coef.	-0.001	-0.001	-0.002
	t-stat	(-0.974)	(-1.089)	(-1.586)
MPU	Coef.	0.000	-0.000*	0.000
	t-stat	(-0.256)	(-1.703)	(-0.153)
BAA	Coef.	0.097	0.190**	0.072
	t-stat	(-1.412)	(2.185)	(1.207)
FFR	Coef.	0.010	0.020**	0.011
	t-stat	(-1.477)	(2.014)	(1.051)
IPI	Coef.	0.036	-0.023	-0.005
	t-stat	(-1.279)	(-0.632)	(-0.197)
UNEMP	Coef.	-0.002	-0.023	-0.041**
	t-stat	(-0.247)	(-1.395)	(-2.024)
% adj. R^2		48.9	30.5	31.1

*, ** 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 A5. Forecasting stock market price jumps (JUMP) in the pre-crisis (Jan 1987-Dec 2006) period when controlling for macroeconomic fundamentals

$$JUMP_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	0.001	0.004	0.002
	t-stat	(0.251)	(1.641)	(0.805)
MU(k)	Coef.	-0.001	-0.002	0.001
	t-stat	(-1.291)	(-1.563)	(0.109)
RV	Coef.	0.095	-0.148	0.001
	t-stat	(0.481)	(-1.018)	(0.009)
JUMP	Coef.	0.067	0.382	-0.015
	t-stat	(0.155)	(1.124)	(-0.057)
VIX	Coef.	0.005***	0.002	0.003
	t-stat	(2.881)	(0.740)	(1.563)
EPU	Coef.	0.001	-0.001	-0.001
	t-stat	(-0.857)	(-1.020)	(-1.033)
MPU	Coef.	0.001	0.001	0.001
	t-stat	(-0.152)	(-1.612)	(0.126)
BAA	Coef.	0.051	0.097**	0.040
	t-stat	(1.410)	(2.379)	(1.288)
FFR	Coef.	0.006*	0.012***	0.008
	t-stat	(1.797)	(2.623)	(1.494)
IPI	Coef.	0.022	-0.008	-0.002
	t-stat	(1.462)	(-0.444)	(-0.187)
UNEMP	Coef.	0.007	-0.001	-0.016
	t-stat	(1.315)	(-0.119)	(-1.461)
% adj. R^2		44.8	20.4	18.4

*, ** 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 A6. Forecasting stock market volatility (RV) in the post-crisis (Jan 2004-Dec 2017) period when controlling for macroeconomic fundamentals

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.012*	-0.008	-0.003
	t-stat	(-1.849)	(-1.126)	(-0.315)
MU(k)	Coef.	0.019***	0.027**	0.005
	t-stat	(2.871)	(1.974)	(0.664)
RV	Coef.	0.761***	0.158**	-0.257*
	t-stat	(5.205)	(1.981)	(-1.772)
JUMP	Coef.	3.814	-1.613	-1.512
	t-stat	(1.480)	(-1.050)	(-1.139)
VIX	Coef.	-0.026**	-0.009	0.020
	t-stat	(-2.034)	(-0.892)	(1.460)
EPU	Coef.	0.001	-0.003	-0.002
	t-stat	-0.55	(-1.386)	(-1.169)
MPU	Coef.	0.001	0.002	0.003**
	t-stat	(1.447)	(1.551)	(1.983)
BAA	Coef.	-0.287*	-0.209	-0.160
	t-stat	(-1.729)	(-1.609)	(-1.081)
FFR	Coef.	-0.017	-0.03	0.117
	t-stat	(-0.584)	(-0.675)	(1.363)
IPI	Coef.	-0.341**	-0.159***	-0.027
	t-stat	(-2.201)	(-4.210)	(-0.425)
UNEMP	Coef.	0.035*	0.021	-0.008
	t-stat	(1.756)	(0.973)	(-0.218)
% adj. R^2		68.6	21.6	26.3

*, ** 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 A7. Forecasting stock market price jumps (JUMP) in the post-crisis (Jan 2004-Dec 2017) period when controlling for macroeconomic fundamentals

$$JUMP_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	0.001	-0.001	0.001
	t-stat	(0.787)	(-1.280)	(0.165)
MU(k)	Coef.	0.001	0.001*	0.001**
	t-stat	(0.860)	(1.697)	(1.963)
RV	Coef.	-0.027***	0.003	-0.009*
	t-stat	(-4.224)	(0.875)	(-1.716)
JUMP	Coef.	-0.005	-0.034	-0.038
	t-stat	(-0.054)	(-0.361)	(-0.420)
VIX	Coef.	0.002**	0.001*	0.001
	t-stat	(2.279)	(1.885)	(0.259)
EPU	Coef.	0.001	0.001	0.001
	t-stat	(0.237)	(0.629)	(-1.098)
MPU	Coef.	0.0001	0.0001	0.0001*
	t-stat	(-0.400)	(0.556)	(1.826)
BAA	Coef.	-0.001	-0.011*	-0.002
	t-stat	(-0.179)	(-1.712)	(-0.273)
FFR	Coef.	-0.001	-0.001	0.003
	t-stat	(-0.737)	(-0.743)	(0.779)
IPI	Coef.	0.001	-0.008***	-0.002
	t-stat	(0.005)	(-3.163)	(-0.475)
UNEMP	Coef.	-0.001	0.001	0.002
	t-stat	(-0.751)	(0.698)	(1.046)
% adj. R^2		23.4	18.2	8.4

*, ** 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 A8. Forecasting stock market volatility for the post-crisis period with the post-crisis data sample starting from June 2007 (June 2007- Dec 2017)

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.015**	-2.603	0.026***	2.832	32.4
3m	-0.013**	-2.135	0.019**	2.335	19.5
12m	-0.0083	-1.212	0.011	1.488	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***	-3.829	0.029***	4.536	27.9
3m	-0.0008	-1.637	0.016***	4.501	9.1
12m	0.001	1.416	0.004	1.074	0.7

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	0.0009***	2.779	0.618***	9.146	38.2
3m	0.001**	2.597	0.275***	6.124	7.5
12m	0.002***	2.721	0.014	0.358	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	1.057	0.0004	1.614	8.1
3m	0.002	1.184	0.0002	0.178	0.0
12m	0.005	1.610	-0.0002	1.101	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	0.671	0.00004	1.603	16.4
3m	0.001*	1.753	0.0001**	1.995	2.8
12m	0.0002	0.388	0.0002*	1.764	5.5

*, ** 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 A9. Forecasting stock market price jumps for the post-crisis period with the post-crisis data sample starting from June 2007 (June 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	-0.0003***	-3.936	0.001***	6.830	18.2
3m	-0.0004***	-3.362	0.001***	5.123	18
12m	-0.0005	-1.340	0.001*	1.968	5.8

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	0.00001	0.478	0.001***	3.584	18.1
3m	0.0001	0.764	0.001***	7.119	18.2
12m	0.0002***	3.097	0.0003	1.446	1.8

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***	5.269	0.255***	2.921	6.5
3m	0.0002***	5.450	0.235**	2.227	5.5
12m	0.0002***	6.945	0.042	0.477	0.2

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	0.0008	0.796	0.0001*	1.822	4.1
3m	0.0004	0.398	0.0001**	2.004	5.9
12m	0.0002***	2.632	-0.0001	0.168	0.1

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***	4.243	0.0001	1.463	2.0
3m	0.0001***	2.735	0.0001**	2.205	7.3
12m	0.0001***	3.172	0.0001	1.647	4.3

*, ** 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 A10. Forecasting stock market volatility (RV) for the first alternative post-crisis period (June 2007-Dec 2017) when controlling for macroeconomic fundamentals,

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.049**	-0.124	-0.010
	t-stat	(-2.039)	(-1.629)	(-0.242)
MU(k)	Coef.	0.037**	0.051*	0.005
	t-stat	(2.047)	(1.830)	(0.244)
RV	Coef.	0.617***	0.051	-0.207*
	t-stat	(5.020)	(0.518)	(-1.803)
JUMP	Coef.	5.675	-0.095	-1.012
	t-stat	(1.199)	(-0.0953)	(-1.013)
VIX	Coef.	-0.040*	-0.018	0.013
	t-stat	(-1.679)	(-1.371)	(1.472)
EPU	Coef.	0.0002	-0.0006	-0.0001
	t-stat	(0.703)	(-0.575)	(-1.432)
MPU	Coef.	0.0002	0.0001	0.0002
	t-stat	(1.043)	(1.462)	(1.527)
BAA	Coef.	-0.059	-0.117	-0.059
	t-stat	(-0.573)	(-0.900)	(-0.703)
FFR	Coef.	-0.009	-0.023	0.220*
	t-stat	(-0.203)	(-0.421)	(1.872)
IPI	Coef.	0.0002*	0.0008	0.0004
	t-stat	(1.683)	(1.541)	(0.212)
UNEMP	Coef.	0.035	0.136*	0.027
	t-stat	(1.226)	(1.727)	(0.742)
% adj. R^2		57.7	32.8	39.3

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

Table A11. Forecasting stock market price jumps (JUMP) for the post-crisis period (June 2007-Dec 2017) when controlling for macroeconomic fundamentals.

$$JUMP_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.002	-0.002*	-0.003
	t-stat	(-1.250)	(-1.914)	(-1.611)
MU(k)	Coef.	0.001	0.001***	0.002**
	t-stat	(1.350)	(2.957)	(2.147)
RV	Coef.	-0.028***	-0.0003	-0.011*
	t-stat	(-4.088)	(-0.110)	(-1.866)
JUMP	Coef.	0.001	0.017	-0.021
	t-stat	(0.013)	(0.166)	(-0.241)
VIX	Coef.	0.002**	0.0004	-0.0001
	t-stat	(2.181)	(0.901)	(-0.0212)
EPU	Coef.	0.0005	0.0004	-0.00001
	t-stat	(0.603)	(0.543)	(-1.302)
MPU	Coef.	-0.0002	0.0001	0.0002**
	t-stat	(-0.466)	(0.984)	(2.010)
BAA	Coef.	-0.002	-0.006	-0.001
	t-stat	(-0.315)	(-1.000)	(-0.091)
FFR	Coef.	-0.002	-0.001	0.002
	t-stat	(-0.685)	(-0.676)	(0.645)
IPI	Coef.	0.0001	0.0001	0.0001
	t-stat	(1.075)	(1.558)	(1.186)
UNEMP	Coef.	0.001	0.002	0.005**
	t-stat	(0.549)	(1.247)	(2.139)
% adj. R^2		29.4	23.2	19.8

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

Table A12. Forecasting stock market volatility for the post-crisis period with the post-crisis data sample starting from January 2008 (Jan 2008- 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	-0.015**	-2.606	0.026***	2.819	32.5
3m	-0.013**	-2.138	0.019**	2.320	19.5
12m	-0.006	-1.588	0.008*	1.935	9.2

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***	-4.027	0.029***	4.582	28.5
3m	-0.0008*	-1.701	0.016***	4.462	9.1
12m	0.0007	1.458	0.004	1.603	4.1

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**	2.504	0.622***	9.127	38.8
3m	0.001**	2.398	0.276***	6.151	7.6
12m	0.001***	4.527	0.038	1.254	0.9

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	-0.003	-1.286	0.0004*	1.743	9.2
3m	0.002	0.949	0.0002	0.213	0.2
12m	0.001*	1.673	-0.0001	0.026	0.1

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	-0.783	0.0001	1.614	18.0
3m	0.001*	1.683	0.0001*	1.746	2.6
12m	0.0005	1.039	0.0001*	1.676	9.4

*, ** 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 A13. Forecasting stock market price jumps for the post-crisis period with the post-crisis data sample starting from January 2008 (Jan 2008- 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***	-3.783	0.001***	6.681	18.2
3m	-0.0004***	-3.328	0.001***	5.078	18.2
12m	-0.0005	-1.352	0.001**	2.003	6.7

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	0.0003	0.514	0.001***	3.540	18.4
3m	0.0002	0.634	0.001***	7.179	19.2
12m	0.0001***	3.056	0.0003	1.501	2.2

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	0.0002***	5.130	0.243***	2.761	6.0
3m	0.0002***	5.123	0.235**	2.194	5.7
12m	0.0002***	6.619	0.041	0.509	0.2

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	0.0001	0.698	0.0001*	1.721	3.9
3m	0.0001	0.046	0.0002**	2.182	7.1
12m	0.0002**	2.168	0.0001	0.036	0.1

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***	4.049	0.0001	1.388	2.0
3m	0.0001**	2.598	0.0001*	1.874	6.5
12m	0.0001***	4.007	0.0001	1.228	2.2

*, ** 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 A14. Forecasting stock market volatility (RV) when controlling for macroeconomic fundamentals, for the second alternative post-crisis period (Jan 2008-Dec 2017)

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.058*	-0.114*	-0.0005
	t-stat	(-1.943)	(-1.738)	(-0.0233)
MU(k)	Coef.	0.042*	0.045*	-0.003
	t-stat	(1.933)	(1.894)	(-0.293)
RV	Coef.	0.609***	0.031	-0.098*
	t-stat	(4.953)	(0.290)	(-1.879)
JUMP	Coef.	5.970	-0.561	-0.276
	t-stat	(1.222)	(-0.594)	(-0.797)
VIX	Coef.	-0.044	-0.011	0.008
	t-stat	(-1.597)	(-1.148)	(1.652)
EPU	Coef.	0.0001	-0.00005	-0.0002**
	t-stat	(0.605)	(-0.435)	(-2.147)
MPU	Coef.	0.00002	0.00001	0.0001*
	t-stat	(1.314)	(1.347)	(1.933)
BAA	Coef.	-0.072	-0.112	0.013
	t-stat	(-0.669)	(-0.894)	(0.220)
FFR	Coef.	-0.113	0.0874	0.209***
	t-stat	(-1.062)	(0.447)	(3.810)
IPI	Coef.	0.0003*	0.0007	0.0001
	t-stat	(1.717)	(1.641)	(0.112)
UNEMP	Coef.	0.031	0.135*	0.044**
	t-stat	(1.196)	(1.789)	(2.087)
% adj. R^2		58.9	33.8	47.9

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

Table A15. Forecasting stock market price jumps (JUMP) for the post-crisis period (Jan 2008-Dec 2017) when controlling for macroeconomic fundamentals.

$$JUMP_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.001	-0.003*	-0.001
	t-stat	(-0.886)	(-1.911)	(-0.474)
MU(k)	Coef.	0.001	0.001***	0.001
	t-stat	(0.954)	(2.973)	(0.648)
RV	Coef.	-0.028***	0.001	-0.009**
	t-stat	(-3.719)	(0.215)	(-2.355)
JUMP	Coef.	-0.021	0.030	-0.069
	t-stat	(-0.214)	(0.270)	(-1.058)
VIX	Coef.	0.002**	0.0002	0.0005
	t-stat	(2.124)	(0.474)	(0.868)
EPU	Coef.	0.0003	0.0001	-0.0001
	t-stat	(0.426)	(0.595)	(-0.935)
MPU	Coef.	-0.0002	0.0001	0.0001
	t-stat	(-0.378)	(0.986)	(1.066)
BAA	Coef.	-0.003	-0.007	-0.001
	t-stat	(-0.419)	(-1.002)	(-0.158)
FFR	Coef.	-0.0002	-0.006	0.011**
	t-stat	(-0.0501)	(-1.475)	(2.170)
IPI	Coef.	0.0001	0.0001	0.0001
	t-stat	(0.746)	(1.582)	(0.335)
UNEMP	Coef.	0.0007	0.002	0.004
	t-stat	(0.376)	(1.190)	(1.544)
% adj. R^2		29.4	24.1	20.3

*, ** 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 A16. Forecasting stock market volatility for the post-crisis period when excluding the 2007-2008 crisis period. The sample covers the period from January 2009 till December 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	-0.006***	-3.329	0.013***	3.953	37.2
3m	-0.003***	-3.297	0.006***	4.471	17.3
12m	-0.005*	-1.814	0.007**	2.296	7.0

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	-0.001***	-3.311	0.018***	5.869	45.9
3m	-7.79e-05	-0.199	0.008***	4.845	14.3
12m	0.0004	0.931	0.004*	1.930	5.1

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	0.0005**	2.534	0.635***	5.888	45.8
3m	0.001***	3.979	0.272***	4.817	12.9
12m	0.001***	4.724	0.066	1.221	0.8

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	-1.144	0.0001**	2.253	14.4
3m	0.0002	0.335	0.0001*	1.887	4.4
12m	0.0007	1.071	0.00004	0.811	1.1

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	0.0005	1.102	0.0001*	1.685	8.4
3m	0.001***	3.274	0.00005	1.214	1.7
12m	0.0009**	2.590	0.00005	0.889	1.8

*, ** 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 A17. Forecasting stock market price jumps for the post-crisis period when excluding the 2007-2008 crisis period. The sample covers the period from January 2009 till December 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***	-3.183	0.001***	4.886	18.3
3m	-0.0003**	-2.091	0.001***	3.674	10.1
12m	-0.0004	-1.236	0.001*	1.844	4.5

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	-0.0006	-1.339	0.001***	7.009	28.4
3m	0.0003	0.732	0.001***	3.906	13.1
12m	0.0001**	2.285	0.0004	1.337	1.9

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***	4.443	0.317***	2.897	10.3
3m	0.0002***	5.129	0.161*	1.933	3.1
12m	0.0002***	6.404	0.015	0.270	0.2

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	0.0001	0.016	0.0001**	2.289	8.0
3m	0.0001	0.089	0.0001*	1.958	7.8
12m	0.0001	1.449	0.00003	0.578	0.6

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***	3.166	0.0001	1.255	2.8
3m	0.0001**	2.260	0.0001	1.235	4.5
12m	0.0002***	5.010	0.0002	0.340	0.1

*, ** 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 A18. Forecasting stock market volatility (RV) for post-crisis period (Jan 2009-Dec 2017) when controlling for macroeconomic fundamentals.

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.014	-0.001	-0.024
	t-stat	(-0.861)	(-0.0898)	(-1.103)
MU(k)	Coef.	0.009*	0.007**	0.011
	t-stat	(1.727)	(2.275)	(1.613)
RV	Coef.	0.540**	0.428***	-0.471*
	t-stat	(2.286)	(3.179)	(-1.908)
JUMP	Coef.	-2.151*	-0.933*	0.877
	t-stat	(-1.855)	(-1.663)	(0.872)
VIX	Coef.	0.002	-0.011*	0.012
	t-stat	(0.239)	(-1.794)	(1.525)
EPU	Coef.	0.0004	0.0005	-0.0001*
	t-stat	(0.615)	(0.0950)	(-1.758)
MPU	Coef.	0.0003	0.0002	0.0001*
	t-stat	(0.492)	(0.603)	(1.778)
BAA	Coef.	-0.017	-0.038	-0.012
	t-stat	(-0.451)	(-1.042)	(-0.245)
FFR	Coef.	-0.072	-0.165*	0.048
	t-stat	(-1.150)	(-1.857)	(0.189)
IPI	Coef.	0.00001	-0.0001	0.0001
	t-stat	(0.697)	(-0.150)	(0.787)
UNEMP	Coef.	0.007	0.013	0.045
	t-stat	(0.412)	(0.534)	(1.368)
% adj. R^2		55.6	28.8	20.5

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

Table A19. Forecasting stock market price jumps (JUMP) for the post-crisis period (Jan 2009-Dec 2017) when controlling for macroeconomic fundamentals.

$$JUMP_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	0.002	0.001	-0.001
	t-stat	(1.335)	(0.660)	(-0.627)
MU(k)	Coef.	-0.0003	0.0004	0.001
	t-stat	(-0.598)	(0.771)	(1.582)
RV	Coef.	0.069***	0.070**	-0.037
	t-stat	(3.560)	(2.004)	(-1.654)
JUMP	Coef.	-0.327*	-0.276*	0.052
	t-stat	(-1.974)	(-1.723)	(0.670)
VIX	Coef.	0.0006	-0.0001	0.0006
	t-stat	(0.437)	(-1.196)	(0.691)
EPU	Coef.	0.00001	0.00001	-0.00001
	t-stat	(1.078)	(0.977)	(-0.492)
MPU	Coef.	-0.0001	-0.0001	0.00001
	t-stat	(-1.324)	(-0.0139)	(0.915)
BAA	Coef.	-0.002	-0.006	-0.003
	t-stat	(-0.473)	(-1.282)	(-0.406)
FFR	Coef.	-0.013	-0.024*	-0.012
	t-stat	(-1.372)	(-1.749)	(-0.487)
IPI	Coef.	-0.0001	-0.0001	0.0001
	t-stat	(-1.248)	(-0.742)	(0.283)
UNEMP	Coef.	-0.003	-0.002	0.002
	t-stat	(-1.304)	(-0.402)	(0.748)
% adj. R^2		34.1	24	10.5

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

Table A20. Forecasting the continuous component of stock market volatility (RBV) (Jan 1990-Dec 2017 period)

Panel A

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.011**	-2.452	0.020***	2.678	26.3
3m	-0.011**	-2.230	0.016**	2.442	16.9
12m	-0.010*	-1.764	0.013*	1.961	3.8

Panel B

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.002***	2.873	0.021***	3.776	23.2
3m	-0.0009**	2.281	0.013***	4.209	8.1
12m	0.0004	0.902	0.006**	2.321	1.8

Panel C

$$RBV_t = b_0 + b_1 RBV_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.0006***	4.056	0.620***	9.140	38.5
3m	0.001***	4.063	0.287***	5.753	8.2
12m	0.001***	4.655	0.072	1.275	0.5

Panel D

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.0015	1.025	0.0002*	1.753	8.2
3m	0.0006	1.098	0.0001	1.532	0.8
12m	0.001***	2.853	-0.0002	0.622	0.1

Panel E

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.0005	1.262	0.00001	1.573	3.8
3m	0.001***	4.715	0.00002	1.029	0.2
12m	0.001***	5.594	0.00001	1.202	0.6

*, ** 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 A21. Forecasting the continuous component of stock market volatility (RBV) during the pre-crisis period (Jan 1990- Dec 2006)

Panel A

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

Horizon (k)	*b_0*	*t-stat(b_0)*	*b_1*	*t-stat(b_1)*	*% adj. R^2*
1m	-0.002**	-1.995	0.006***	2.851	6.7
3m	-0.003**	-1.788	0.005***	2.480	5.8
12m	-0.006	-1.382	0.009	1.610	5.4

Panel B

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

Horizon (k)	*b_0*	*t-stat(b_0)*	*b_1*	*t-stat(b_1)*	*% adj. R^2*
1m	-0.001***	-4.915	0.01***	7.640	41.0
3m	-0.0003*	-1.755	0.007***	5.850	18.3
12m	-0.0002	-0.590	0.007***	3.285	14.3

Panel C

$$RBV_t = b_0 + b_1 RBV_{t-k} + \varepsilon_t$$

Horizon (k)	*b_0*	*t-stat(b_0)*	*b_1*	*t-stat(b_1)*	*% adj. R^2*
1m	0.0003***	4.539	0.687***	12.26	47.2
3m	0.0006***	4.419	0.446***	4.901	19.9
12m	0.0006***	4.875	0.4***	3.117	15.1

Panel D

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

Horizon (k)	*b_0*	*t-stat(b_0)*	*b_1*	*t-stat(b_1)*	*% adj. R^2*
1m	0.0005	1.401	0.0001	1.367	1.5
3m	0.001***	3.362	-0.0001	0.528	0.2
12m	0.001***	2.650	-0.0001	0.970	2.2

Panel E

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

Horizon (k)	*b_0*	*t-stat(b_0)*	*b_1*	*t-stat(b_1)*	*% adj. R^2*
1m	0.0007***	4.464	0.0001**	2.222	3.5
3m	0.001***	5.415	-0.0001	0.127	0.2
12m	0.001***	4.192	0.0001	0.099	0.1

*, ** 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 A22. Forecasting the continuous component of stock market volatility (RBV) during the post-crisis period (Jan 2007- Dec 2017)

Panel A

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.015**	-2.501	0.025***	2.699	30.0
3m	-0.013**	-2.064	0.019**	2.245	17.6
12m	-0.008	-1.179	0.011	1.448	2.2

Panel B

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.003***	-3.613	0.020***	4.214	25.4
3m	-0.001	-1.579	0.010***	4.243	7.9
12m	0.001	1.589	0.003	0.974	0.5

Panel C

$$RBV_t = b_0 + b_1 RBV_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.0009***	2.717	0.601***	8.594	36.1
3m	0.001**	2.581	0.248***	5.616	6.1
12m	0.002***	2.756	0.009	0.274	0.1

Panel D

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.002	-1.080	0.0001	1.605	7.9
3m	0.002	1.260	0.0001	0.198	0.5
12m	0.005*	1.788	-0.0002	1.260	2.1

Panel E

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.001	-0.749	0.0001	1.585	16
3m	0.0009*	1.770	0.0001*	1.977	2.5
12m	0.0003	0.535	0.0001	1.657	4.7

*, ** 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 A23. Forecasting the continuous component of the realized variance (RBV) when controlling for macroeconomic fundamentals (Jan 1990 – Dec 2017 data sample)

$$RBV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RBV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.006**	-0.011*	-0.018**
	t-stat	(-2.052)	(-1.954)	(-2.050)
MU(k)	Coef.	0.013	0.013	0.006
	t-stat	(1.248)	(1.313)	(1.045)
RBV	Coef.	0.522***	0.0864	-0.093*
	t-stat	(6.269)	(1.342)	(-1.746)
JUMP	Coef.	0.518	0.076	-0.561
	t-stat	(0.925)	(0.315)	(-1.178)
VIX	Coef.	-0.007	0.0008	0.010*
	t-stat	(-0.700)	(0.185)	(1.745)
EPU	Coef.	0.0001	-0.0001	-0.0001**
	t-stat	(0.954)	(-1.543)	(-2.224)
MPU	Coef.	-0.0001	0.0001	0.0001
	t-stat	(-0.432)	(0.142)	(1.626)
BAA	Coef.	-0.0419	0.00505	-0.0384
	t-stat	(-0.676)	(0.0958)	(-0.535)
FFR	Coef.	-0.00329	0.00494	0.0429**
	t-stat	(-0.229)	(0.352)	(2.352)
IPI	Coef.	-0.0002	0.0002	0.0001**
	t-stat	(-0.118)	(1.475)	(2.370)
UNEMP	Coef.	-0.020	0.009	0.034**
	t-stat	(-0.697)	(0.639)	(2.309)
% adj. R^2		44.3	18.2	14.6

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

Table A24 Forecasting the continuous component of the realized variance (RBV) in the pre-crisis period (Jan 1990 – Dec 2006) when controlling for macroeconomic fundamentals

$$RBV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RBV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.003**	-0.002*	0.004
	t-stat	(-2.260)	(-1.666)	(1.638)
MU(k)	Coef.	-0.002**	-0.004*	-0.002
	t-stat	(-2.358)	(-1.907)	(-0.281)
RBV	Coef.	0.332	0.199	-0.271*
	t-stat	(1.072)	(0.937)	(-1.687)
JUMP	Coef.	0.0188	0.00195	0.00416*
	t-stat	(0.0499)	(0.621)	(1.761)
VIX	Coef.	0.004**	-0.0001	-0.0001***
	t-stat	(2.571)	(-0.0695)	(-2.905)
EPU	Coef.	-0.0001	-0.0001**	0.0001
	t-stat	(-0.0789)	(-2.430)	(1.345)
MPU	Coef.	-0.010	0.109**	0.0396
	t-stat	(-0.976)	(2.588)	(1.106)
BAA	Coef.	0.0495	0.0239***	0.00174
	t-stat	(1.413)	(3.295)	(0.127)
FFR	Coef.	0.015**	0.003**	-0.0001
	t-stat	(2.523)	(2.301)	(-0.260)
IPI	Coef.	0.001**	0.004	-0.038
	t-stat	(2.508)	(0.391)	(-1.489)
UNEMP	Coef.	0.0164	-0.0661	0.236
	t-stat	(1.557)	(-0.421)	(1.472)
% adj. R^2		23.4	18.2	8.4

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

Table A25. Forecasting the continuous component of the realized variance (RBV) in the post-crisis period (Jan 2007 – Dec 2017) when controlling for macroeconomic fundamentals

$$RBV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RBV_{t-k} + b_3 JUMP_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 BAA_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.052**	-0.129	-0.032
	t-stat	(-2.148)	(-1.614)	(-0.975)
MU(k)	Coef.	0.038**	0.052*	0.014
	t-stat	(2.079)	(1.796)	(0.836)
RBV	Coef.	0.608***	0.0140	-0.278
	t-stat	(5.092)	(0.143)	(-1.617)
JUMP	Coef.	6.145	-0.234	-1.140
	t-stat	(1.236)	(-0.228)	(-0.876)
VIX	Coef.	-0.042*	-0.016	0.018
	t-stat	(-1.684)	(-1.252)	(1.313)
EPU	Coef.	0.0001	-0.0001	-0.0002**
	t-stat	(0.690)	(-0.603)	(-2.208)
MPU	Coef.	0.0002	0.0001	0.0003**
	t-stat	(1.155)	(1.434)	(2.588)
BAA	Coef.	-0.063	-0.135	-0.114
	t-stat	(-0.642)	(-1.029)	(-0.984)
FFR	Coef.	-0.021	-0.041	0.112
	t-stat	(-0.553)	(-0.820)	(1.459)
IPI	Coef.	0.0002*	0.001	0.0002
	t-stat	(1.811)	(1.536)	(0.991)
UNEMP	Coef.	0.036	0.137*	0.040
	t-stat	(1.269)	(1.690)	(1.276)
% adj. R^2		56.7	30.8	31.3

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

Table A26. Forecasting stock market volatility (RV) and price Jumps (JUMP) using the implied volatility with 3-month (IV3) and 1-year (IV12) maturity.

PANEL A

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
3m	-0.001	-1.278	0.018***	3.538	8.6
12m	0.001	0.831	0.008*	1.879	1.1

PANEL B

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
3m	-0.001	-0.098	0.003***	3.063	5.9
12m	0.001	0.831	0.008*	1.879	2.0

The IV(3) (3-month maturity S&P500 option-implied volatility) and the IV(12) (12-month maturity option-implied volatility) have been used (instead of the VIX) for forecasting S&P500 stock-market volatility (RV) having 3-month and 12-month forecasting horizon respectively. *, ** 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. The dataset covers the period from January 1996 to December 2017.

Table A27. Forecasting the stock market volatility (RV) when controlling for macroeconomic fundamentals using the three-month implied volatility (IV3) instead of VIX.

$$RV_t = b_0 + b_1 MU(3)_{t-4} + b_2 RV_{t-3} + b_3 JUMP_{t-3} + b_4 IV3_{t-3} + b_5 EPU_{t-3} + b_6 MPU_{t-3} + b_7 BAA_{t-3} + b_8 FFR_{t-3} + b_9 IPI_{t-3} + b_{10} UNEMP_{t-3} + \varepsilon_t$$

Horizon (3 months)		***1/1996-12/2017 dataset***	***1/1996-12/2006 dataset***	***1/2007-12/2017 dataset***
Const	Coef.	0.003**	0.0002	-0.002**
	t-stat	(2.352)	(0.0982)	(-2.017)
MU(3)	Coef.	-0.002**	-0.004*	0.001***
	t-stat	(-2.498)	(-1.972)	(2.981)
RV	Coef.	-0.001	-0.151	0.0001
	t-stat	(-0.075)	(-1.046)	(0.043)
JUMP	Coef.	0.244	0.386	0.016
	t-stat	(1.453)	(1.201)	(0.158)
IV3	Coef.	-0.003	-0.001	0.006
	t-stat	(-0.253)	(-0.264)	(1.144)
EPU	Coef.	-0.0003	-0.0004	0.0001
	t-stat	(-0.982)	(-0.506)	(0.539)
MPU	Coef.	-0.0001	-0.0003	0.0001
	t-stat	(-0.184)	(-1.254)	(1.196)
BAA	Coef.	0.046*	0.147***	-0.007
	t-stat	(1.913)	(2.750)	(-1.172)
FFR	Coef.	0.008**	0.025***	-0.002
	t-stat	(2.182)	(3.797)	(-1.468)
IPI	Coef.	-0.0001**	-0.00002	0.0001*
	t-stat	(-2.161)	(-0.368)	(1.685)
UNEMP	Coef.	-0.001	0.024	0.002
	t-stat	(-0.431)	(1.560)	(1.126)
% adj. R^2		26.0	25.4	24.2

*, ** 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 A28. Forecasting the stock market volatility (RV) when controlling for macroeconomic fundamentals, using the twelve-month implied volatility (IV12) instead of VIX.

$$RV_t = b_0 + b_1 MU(12)_{t-13} + b_2 RV_{t-12} + b_3 JUMP_{t-12} + b_4 IV12_{t-12} + b_5 EPU_{t-12} + b_6 MPU_{t-12} + b_7 BAA_{t-12} + b_8 FFR_{t-12} + b_9 IPI_{t-12} + b_{10} UNEMP_{t-12} + \varepsilon_t$$

Horizon (12 months)		*1/1996-12/2017 dataset*	*1/1996-12/2006 dataset*	*1/2007-12/2017 dataset*
Const	Coef.	0.003**	0.003	-0.003
	t-stat	(2.346)	(0.698)	(-1.548)
MU(12)	Coef.	-0.0005	0.013*	0.002*
	t-stat	(-0.311)	(1.816)	(1.980)
RV	Coef.	-0.030	0.083	-0.011**
	t-stat	(-1.635)	(0.651)	(-2.084)
JUMP	Coef.	0.117	-0.061	-0.025
	t-stat	(1.476)	(-0.248)	(-0.298)
IV12	Coef.	0.0001	-0.0001	0.0001
	t-stat	(0.430)	(-0.148)	(0.114)
EPU	Coef.	0.0001	-0.0001	-0.0001
	t-stat	(0.265)	(-0.439)	(-1.347)
MPU	Coef.	0.0001	0.0002	0.0001**
	t-stat	(0.730)	(0.932)	(2.012)
BAA	Coef.	0.018	0.007	-0.001
	t-stat	(0.971)	(0.200)	(-0.147)
FFR	Coef.	0.008*	-0.018*	0.003
	t-stat	(1.962)	(-1.820)	(1.056)
IPI	Coef.	-0.0003**	-0.0001***	0.0001
	t-stat	(-2.168)	(-3.491)	(1.109)
UNEMP	Coef.	-0.010	-0.074***	0.005*
	t-stat	(-1.622)	(-2.666)	(1.924)
% adj. R^2		28.3	31.6	20.2

*, ** 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 A29. Forecasting the stock market price jumps (JUMP) when controlling for macroeconomic fundamentals, using the three-month implied volatility (IV3) instead of VIX.

$$JUMP_t = b_0 + b_1 MU(3)_{t-4} + b_2 RV_{t-3} + b_3 JUMP_{t-3} + b_4 IV3_{t-3} + b_5 EPU_{t-3} + b_6 MPU_{t-3} + b_7 BAA_{t-3} + b_8 FFR_{t-3} + b_9 IPI_{t-3} + b_{10} UNEMP_{t-3} + \varepsilon_t$$

Horizon (k)		***1/1996-12/2017 dataset***	***1/1996-12/2006 dataset***	***1/2007-12/2017 dataset***
Const	Coef.	0.003**	0.0002	-0.002**
	t-stat	(2.352)	(0.0982)	(-2.017)
MU(3)	Coef.	-0.002**	-0.004*	0.001***
	t-stat	(-2.498)	(-1.972)	(2.981)
RV	Coef.	-0.001	-0.151	0.0001
	t-stat	(-0.0758)	(-1.046)	(0.0432)
JUMP	Coef.	0.244	0.386	0.016
	t-stat	(1.453)	(1.201)	(0.158)
IV3	Coef.	-0.0002	-0.002	0.002
	t-stat	(-0.253)	(-0.264)	(1.144)
EPU	Coef.	-0.0003	-0.0001	0.0001
	t-stat	(-0.982)	(-0.506)	(0.539)
MPU	Coef.	-0.0002	-0.0003	0.0001
	t-stat	(-0.184)	(-1.254)	(1.196)
BAA	Coef.	0.046*	0.147***	-0.007
	t-stat	(1.913)	(2.750)	(-1.172)
FFR	Coef.	0.008**	0.025***	-0.002
	t-stat	(2.182)	(3.797)	(-1.468)
IPI	Coef.	-0.0002**	-0.0001	0.0001*
	t-stat	(-2.161)	(-0.368)	(1.685)
UNEMP	Coef.	-0.001	0.024	0.002
	t-stat	(-0.431)	(1.560)	(1.126)
% adj. R^2		26.0	25.4	24.2

*, ** 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 A30. Forecasting the stock market price jumps (JUMP) when controlling for macroeconomic fundamentals, using the twelve-month implied volatility (IV12) instead of VIX.

$$JUMP_t = b_0 + b_1 MU(12)_{t-13} + b_2 RV_{t-12} + b_3 JUMP_{t-12} + b_4 IV12_{t-12} + b_5 EPU_{t-12} + b_6 MPU_{t-12} + b_7 BAA_{t-12} + b_8 FFR_{t-12} + b_9 IPI_{t-12} + b_{10} UNEMP_{t-12} + \varepsilon_t$$

Horizon (k)		***1/1996-12/2017 dataset***	***1/1996-12/2006 dataset***	***1/2007-12/2017 dataset***
Const	Coef.	0.003**	0.003	-0.003
	t-stat	(2.346)	(0.698)	(-1.548)
MU (12)	Coef.	-0.0005	0.013*	0.002*
	t-stat	(-0.311)	(1.816)	(1.980)
RV	Coef.	-0.030	0.083	-0.011**
	t-stat	(-1.635)	(0.651)	(-2.084)
JUMP	Coef.	0.117	-0.061	-0.025
	t-stat	(1.476)	(-0.248)	(-0.298)
IV12	Coef.	0.0001	-0.0001	0.0001
	t-stat	(0.430)	(-0.148)	(0.114)
EPU	Coef.	0.0001	-0.0001	-0.0001
	t-stat	(0.265)	(-0.439)	(-1.347)
MPU	Coef.	0.0001	0.0002	0.0001**
	t-stat	(0.730)	(0.932)	(2.012)
BAA	Coef.	0.018	0.007	-0.001
	t-stat	(0.971)	(0.200)	(-0.147)
FFR	Coef.	0.008*	-0.018*	0.002
	t-stat	(1.962)	(-1.820)	(1.056)
IPI	Coef.	-0.0001**	-0.0001***	0.0001
	t-stat	(-2.168)	(-3.491)	(1.109)
UNEMP	Coef.	-0.010	-0.074***	0.005*
	t-stat	(-1.622)	(-2.666)	(1.924)
% adj. R^2		28.3	31.6	20.2

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

Table A31. Forecasting stock market volatility (RV) and price jumps (JUMP) using Financial Uncertainty (FU) (Jan 1990-Dec 2017 data sample)

Panel A

$$RV_t = b_0 + b_1 FU_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	% adj. R^2
1m	-0.007***	-3.277	0.011***	3.850	29.7
3m	-0.007***	-3.119	0.011***	3.596	19.6
12m	-0.009***	-2.691	0.012***	3.331	3.5

Panel B

$$JUMP_t = b_0 + b_1 FU_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	% adj. R^2
1m	-0.001***	-2.809	0.002***	3.669	20.9
3m	-0.001***	-3.076	0.002***	3.834	16.5
12m	-0.004***	-2.764	0.005***	3.018	12.2

Table A32. Forecasting stock market volatility (RV) and price jumps (JUMP) using Financial Uncertainty (FU) during the pre-crisis period (Jan 1990- Dec 2006)

Panel A

$$RV_t = b_0 + b_1 FU_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.004***	-6.017	0.007***	7.226	44.4
3m	-0.005***	-6.011	0.008***	6.964	34.7
12m	-0.014***	-4.116	0.016***	4.465	22.7

Panel B

$$JUMP_t = b_0 + b_1 FU_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.002***	-4.725	0.003***	5.646	35.6
3m	-0.002***	-4.814	0.003***	5.580	27.5
12m	-0.006***	-3.906	0.007***	4.158	21.2

Table A33. Forecasting stock market volatility (RV) and price jumps (JUMP) using Financial Uncertainty (FU) during the post-crisis period (Jan 2007- Dec 2017)

Panel A

$$RV_t = b_0 + b_1 FU_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.009**	-2.471	0.014***	2.786	29.0
3m	-0.010**	-1.995	0.013**	2.243	17.2
12m	-0.0003	-0.044	0.003	0.441	0.1

Panel B

$$JUMP_t = b_0 + b_1 FU_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.0003***	-4.706	0.0006***	8.026	24.9
3m	-0.0004***	-3.524	0.0007***	5.635	19.0
12m	-0.0005	-1.237	0.0009*	1.823	3.5

Table A34. Forecasting stock market volatility (RV) when controlling for fundamentals including the Financial Uncertainty (FU) (instead of MU index) (Jan 1990 – Dec 2017)

$$RV_t = b_1 + b_2 FU(k)_{t-k-1} + b_3 RV_{t-k} + b_4 JUMP_{t-k} + b_5 VIX_{t-k} + b_6 EPU_{t-k} + b_7 MPU_{t-k} + b_8 BAA_{t-k} + b_9 FFR_{t-k} + b_{10} IPI_{t-k} + b_{11} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.002*	-0.009**	-0.022***
	t-stat	(-1.955)	(-2.301)	(-3.894)
FU(k)	Coef.	0.006***	0.012**	0.011*
	t-stat	(2.785)	(2.391)	(1.852)
RV	Coef.	0.493***	0.125***	-0.017
	t-stat	(8.507)	(2.634)	(-0.403)
JUMP	Coef.	-0.296	-0.577	-0.365
	t-stat	(-1.076)	(-0.999)	(-1.092)
EPU	Coef.	0.0001	-0.0001*	-0.0001*
	t-stat	(0.709)	(-1.706)	(1.791)
MPU	Coef.	0.0004	0.0002*	0.0001**
	t-stat	(1.076)	(1.886)	(2.356)
BAA	Coef.	0.013	0.012	0.010
	t-stat	(0.613)	(0.744)	(0.648)
FFR	Coef.	-0.002	-0.001	-0.001
	t-stat	(-0.768)	(-1.221)	(-1.344)
IPI	Coef.	-0.0001	-0.0001	-0.0002
	t-stat	(-1.355)	(-1.376)	(-0.529)
UNEMP	Coef.	-0.002*	-0.009**	-0.022***
	t-stat	(-1.768)	(-2.024)	(-3.014)
% adj. R^2		45.4	23.4	16.1

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

Table A35. Forecasting stock market volatility (RV) in the pre-crisis period (Jan 1990 – Dec 2006) when controlling for fundamentals, including the FU index (instead of MU index)

$$RV_t = b_1 + b_2 FU(k)_{t-k-1} + b_3 RV_{t-k} + b_4 JUMP_{t-k} + b_5 VIX_{t-k} + b_6 EPU_{t-k} + b_7 MPU_{t-k} + b_8 BAA_{t-k} + b_9 FFR_{t-k} + b_{10} IPI_{t-k} + b_{11} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.003	-0.006**	-0.0006
	t-stat	(-1.317)	(-2.164)	(-0.164)
FU(k)	Coef.	0.005***	0.009***	0.013***
	t-stat	(3.769)	(4.085)	(3.178)
RV	Coef.	0.317	-0.539*	0.218
	t-stat	(0.610)	(-1.681)	(0.935)
JUMP	Coef.	0.172	1.183*	-0.421
	t-stat	(0.154)	(1.933)	(-1.022)
EPU	Coef.	-0.0001	-0.0001*	-0.0002***
	t-stat	(-1.507)	(-1.667)	(-2.887)
MPU	Coef.	0.0001	-0.0001	0.0002**
	t-stat	(0.296)	(-1.234)	(2.050)
BAA	Coef.	-0.016	0.022	0.004
	t-stat	(-0.280)	(0.355)	(0.0674)
FFR	Coef.	-0.005	-0.004	-0.020
	t-stat	(-0.660)	(-0.443)	(-1.288)
IPI	Coef.	0.0001	0.0001	-0.0002**
	t-stat	(0.566)	(0.677)	(-2.019)
UNEMP	Coef.	0.013	0.009	-0.084**
	t-stat	(0.683)	(0.355)	(-2.366)
% adj. R^2		54.1	41.9	34.6

In this table we present the regression results of our baseline multivariate regression model on stock-market volatility in which we include the latent (Jurado et al. (2015)) Financial Uncertainty (FU) instead of Macroeconomic Uncertainty (MU). *, ** 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 A36. Forecasting stock market volatility (RV) in the post-crisis (Jan 2007 – Dec 2017) period when controlling for fundamentals, including the FU index (instead of the MU index)

$$RV_t = b_1 + b_2 FU(k)_{t-k-1} + b_3 RV_{t-k} + b_4 JUMP_{t-k} + b_5 VIX_{t-k} + b_6 EPU_{t-k} + b_7 MPU_{t-k} + b_8 BAA_{t-k} + b_9 FFR_{t-k} + b_{10} IPI_{t-k} + b_{11} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.007	-0.082*	-0.061
	t-stat	(-0.477)	(-1.668)	(-1.501)
FU(k)	Coef.	0.015**	0.038*	0.038
	t-stat	(2.120)	(1.832)	(1.374)
RV	Coef.	0.358***	-0.076	-0.181
	t-stat	(5.429)	(-0.549)	(-1.643)
JUMP	Coef.	3.382	-2.587	-0.909
	t-stat	(0.751)	(-1.522)	(-0.800)
EPU	Coef.	0.0001	0.0001	-0.0002**
	t-stat	(0.926)	(0.369)	(-2.130)
MPU	Coef.	0.0001	0.0002	0.0003***
	t-stat	(0.669)	(0.0500)	(2.716)
BAA	Coef.	-0.224	-0.201	-0.052
	t-stat	(-1.199)	(-1.209)	(-0.680)
FFR	Coef.	-0.007	0.031	0.149**
	t-stat	(-0.243)	(1.138)	(2.127)
IPI	Coef.	0.0003	0.0005	0.0002
	t-stat	(0.236)	(1.564)	(1.400)
UNEMP	Coef.	-0.071	-0.005	0.035
	t-stat	(-1.072)	(-0.189)	(1.335)
% adj. R^2		51.6	34.7	33.7

In this table we present the regression results of our baseline multivariate regression model on stock-market jump tail risk in which we include the latent (Jurado et al. (2015)) Financial Uncertainty (FU) instead of Macroeconomic Uncertainty (MU). *, ** 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 A37. Forecasting stock market price jumps (JUMP) when controlling for fundamentals including the FU index (instead of the MU index) (Jan 1990 – Dec 2017 sample)

$$JUMP_t = b_1 + b_2 FU(k)_{t-k-1} + b_3 RV_{t-k} + b_4 JUMP_{t-k} + b_5 VIX_{t-k} + b_6 EPU_{t-k} + b_7 MPU_{t-k} + b_8 BAA_{t-k} + b_9 FFR_{t-k} + b_{10} IPI_{t-k} + b_{11} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	0.0001	-0.0001	-0.004***
	t-stat	(0.400)	(-0.155)	(-4.075)
FU(k)	Coef.	0.002***	0.002***	0.006***
	t-stat.	(5.007)	(4.454)	(3.849)
RV	Coef.	-0.026***	-0.019	-0.024
	t-stat	(-3.526)	(-1.511)	(-1.478)
JUMP	Coef.	0.475***	0.228	0.091
	t-stat	(4.568)	(1.564)	(1.007)
EPU	Coef.	-0.0001	-0.0001	-0.0001
	t-stat	(-1.067)	(-0.548)	(-1.082)
MPU	Coef.	0.0001	-0.0009	0.0001
	t-stat	(0.876)	(-1.026)	(0.938)
BAA	Coef.	-0.012	-0.017	-0.017
	t-stat	(-1.060)	(-1.358)	(-1.574)
FFR	Coef.	-0.003	-0.004	-0.001
	t-stat	(-1.322)	(-0.959)	(-0.382)
IPI	Coef.	-0.0002**	-0.0002**	-0.0001
	t-stat	(-2.358)	(-2.376)	(-0.529)
UNEMP	Coef.	-0.006***	-0.009***	-0.010*
	t-stat	(-2.734)	(-2.749)	(-1.664)
% adj. R^2		45.8	30.2	27.8

In this table we present the regression results of our baseline multivariate regression model on stock-market jump tail risk in which we include the latent (Jurado et al. (2015)) Financial Uncertainty (FU) instead of Macroeconomic Uncertainty (MU). *, ** 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 A38. Forecasting stock market price jumps (JUMP) in the pre-crisis (Jan 1990 – Dec 2006) period when controlling for fundamentals including the FU index (instead of MU index).

$$JUMP_t = b_1 + b_2 FU(k)_{t-k-1} + b_3 RV_{t-k} + b_4 JUMP_{t-k} + b_5 VIX_{t-k} + b_6 EPU_{t-k} + b_7 MPU_{t-k} + b_8 BAA_{t-k} + b_9 FFR_{t-k} + b_{10} IPI_{t-k} + b_{11} UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.001	-0.002	0.001
	t-stat	(-0.735)	(-1.560)	(0.578)
FU(k)	Coef.	0.002***	0.004***	0.006***
	t-stat.	(3.368)	(3.945)	(3.214)
RV	Coef.	0.023	-0.342**	0.046
	t-stat	(0.0996)	(-2.194)	(0.411)
JUMP	Coef.	0.331	0.727**	-0.098
	t-stat	(0.686)	(2.232)	(-0.498)
EPU	Coef.	-0.0001	-0.0001	-0.0001**
	t-stat	(-1.039)	(-1.537)	(-2.431)
MPU	Coef.	0.0002	-0.0001	0.0001**
	t-stat	(0.210)	(-1.196)	(2.229)
BAA	Coef.	0.0002	0.020	0.011
	t-stat	(0.00763)	(0.744)	(0.327)
FFR	Coef.	-0.003	-0.002	-0.013*
	t-stat	(-0.720)	(-0.441)	(-1.914)
IPI	Coef.	-0.0001	-0.0002	-0.0003***
	t-stat	(-0.501)	(-0.339)	(-3.838)
UNEMP	Coef.	0.005	0.006	-0.046***
	t-stat	(0.497)	(0.449)	(-2.605)
% adj. R^2		44.8	34.7	29.8

In this table we present the regression results of our baseline multivariate regression model on stock-market jump tail risk in which we include the latent (Jurado et al. (2015)) Financial Uncertainty (FU) instead of Macroeconomic Uncertainty (MU). *, ** 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 A39. Forecasting stock market price jumps (JUMP) in the post-crisis period (Jan 2007 – Dec 2017) when controlling for fundamentals, including the FU index (instead of the MU index)

$$JUMP_t = b_1 + b_2FU(k)_{t-k-1} + b_3RV_{t-k} + b_4JUMP_{t-k} + b_5VIX_{t-k} + b_6EPU_{t-k} + b_7MPU_{t-k} + b_8BAA_{t-k} + b_9FFR_{t-k} + b_{10}IPI_{t-k} + b_{11}UNEMP_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=12***
Const	Coef.	-0.002**	-0.001	-0.003*
	t-stat	(-2.037)	(-1.215)	(-1.982)
FU(k)	Coef.	0.001***	0.001**	0.002***
	t-stat.	(3.181)	(2.414)	(2.669)
RV	Coef.	-0.015**	0.004	-0.012**
	t-stat	(-2.219)	(0.895)	(-2.026)
JUMP	Coef.	0.011	-0.002	-0.058
	t-stat	(0.126)	(-0.018)	(-0.740)
EPU	Coef.	0.0001	0.0001	-0.0001
	t-stat	(1.208)	(0.595)	(-1.221)
MPU	Coef.	-0.0001	0.0001	0.0001*
	t-stat	(-1.100)	(0.610)	(1.804)
BAA	Coef.	0.002	-0.002	-0.0009
	t-stat	(0.377)	(-0.426)	(-0.179)
FFR	Coef.	0.002	0.001	0.004**
	t-stat	(1.530)	(0.644)	(2.264)
IPI	Coef.	0.0001	0.0002	0.0001
	t-stat	(1.629)	(0.809)	(1.167)
UNEMP	Coef.	0.002	0.0002	0.003
	t-stat	(0.150)	(0.111)	(1.494)
% adj. R^2		30.3	22.1	22.3

In this table we present the regression results of our baseline multivariate regression model on stock-market jump tail risk in which we include the latent (Jurado et al. (2015)) Financial Uncertainty (FU) instead of Macroeconomic Uncertainty (MU). *, ** 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 A40. List of the 501 constituents of the S&P 500 index that was included in our analysis and the list 4 missing companies of the corresponding composition of S&P 500 index.

PANEL A
Companies that comprise our dataset

NAME	NAME	NAME	NAME
AGILENT TECHS.	CVS HEALTH	INTUITIVE SURGICAL	PVH
ALCOA	CHEVRON	GARTNER 'A'	QUANTA SERVICES
AMERICAN AIRLINES GROUP	CONCHO RESOURCES	ILLINOIS TOOL WORKS	PRAXAIR DEAD - DELIST.31/10/18
ADV.AUTO PARTS	DOMINION ENERGY	INVESCO	PIONEER NTRL.RES.
APPLE	DELTA AIR LINES	HUNT JB TRANSPORT SVS.	PAYPAL HOLDINGS
ABBVIE	DEERE	JOHNSON CONTROLS INTL.	QUALCOMM
AMERISOURCEBERGEN	DISCOVER FINANCIAL SVS.	JACOBS ENGR.	QORVO
ABBOTT LABORATORIES	DOLLAR GENERAL	JOHNSON & JOHNSON	ROYAL CARIBBEAN CRUISES
ACCENTURE CLASS A	QUEST DIAGNOSTICS	JUNIPER NETWORKS	EVEREST RE GP.
ADOBE (NAS)	D R HORTON	JP MORGAN CHASE & CO.	REGENCY CENTERS (XSC)
ANALOG DEVICES	DANAHER	NORDSTROM	REGENERON PHARMS.
ARCHER DANIELS MIDLAND	WALT DISNEY	KELLOGG	REGIONS FINL.NEW
AUTOMATIC DATA PROC.	DISCOVERY SERIES A	KEYCORP	ROBERT HALF INTL.
ALLIANCE DATA SYSTEMS	DISCOVERY SERIES C	KRAFT HEINZ	RED HAT
AUTODESK	DISH NETWORK 'A'	KIMCO REALTY	RAYMOND JAMES FINL.
AMEREN	DIGITAL REALTY TST.	KLA TENCOR	RALPH LAUREN CL.A
AMER.ELEC.PWR.	DOLLAR TREE	KIMBERLY-CLARK	RESMED
AES	DOVER	KINDER MORGAN	ROCKWELL AUTOMATION
AETNA	DAWSON PRODUCTION DEAD - MERGER 993174	CARMAX	ROPER TECHNOLOGIES
AFLAC	DUKE REALTY	COCA COLA	ROSS STORES
ALLERGAN	DARDEN RESTAURANTS	MICHAEL KORS HOLDINGS	RANGE RES.
AMERICAN INTL.GP.	DTE ENERGY	KROGER	REPUBLIC SVS.'A'
APARTMENT INV.& MAN.'A'	DUKE ENERGY	KOHL'S	RAYTHEON 'B'
ASSURANT	DAVITA	KANSAS CITY SOUTHERN	SNAP-ON
ARTHUR J GALLAGHER	DEVON ENERGY	LOEWS	SBA COMMS.
AKAMAI TECHS.	DOWDUPONT	L BRANDS	STARBUCKS
ALBEMARLE	DXC TECHNOLOGY	LEGGETT&PLATT	SCANA
ALIGN TECHNOLOGY	ELECTRONIC ARTS	LENNAR 'A'	CHARLES SCHWAB
ALASKA AIR GROUP	EBAY	LABORATORY CORP.OF AM. HDG.	SEALED AIR
ALLSTATE	ECOLAB	LKQ	SHERWIN-WILLIAMS
ALLEGION	CONSOLIDATED EDISON	L3 TECHNOLOGIES	SIGNET JEWELERS
ALEXION PHARMS.	EQUIFAX	ELI LILLY	J M SMUCKER
APPLIED MATS.	EDISON INTL.	LOCKHEED MARTIN	SCHLUMBERGER
ADVANCED MICRO DEVICES	ESTEE LAUDER COS.'A'	LINCOLN NATIONAL	SL GREEN REALTY
AMETEK	EASTMAN CHEMICAL	ALLIANT ENERGY CORP.	SCRIPPS NETWORKS INTERACTIVE A
AFFILIATED MANAGERS	EMERSON ELECTRIC	LOWE'S COMPANIES	SYNOPSYS

AMGEN	EOG RES.	LAM RESEARCH	SOUTHERN
AMERIPRISE FINL.	EQUINIX REIT	JEFFERIES FINANCIAL GROUP	SIMON PROPERTY GROUP
AMERICAN TOWER	EQUITY RESD.TST.PROPS. SHBI	SOUTHWEST AIRLINES	S&P GLOBAL
AMAZON.COM	EQT	LYONDELLBASELL INDS.CL.A	STERICYCLE
ANSYS	EVERSOURCE ENERGY	MASTERCARD	SEMPRA EN.
ANTHEM	EXPRESS SCRIPTS HOLDING	MID-AMER.APT COMMUNITIES	SUNTRUST BANKS
AON CLASS A	ESSEX PROPERTY TST.	MACERICH	STATE STREET
SMITH (AO)	E*TRADE FINANCIAL	MARRIOTT INTL.'A'	SEAGATE TECH.
APACHE	EATON	MASCO	CONSTELLATION BRANDS 'A'
ANADARKO PETROLEUM	ENTERGY	MATTEL	STANLEY BLACK & DECKER
AIR PRDS.& CHEMS.	ENVISION HEALTHCARE DEAD - DELIST.11/10/18	MCDONALDS	SKYWORKS SOLUTIONS
AMPHENOL 'A'	EDWARDS LIFESCIENCES	MICROCHIP TECH.	SYNCHRONY FINANCIAL
APTIV	EXELON	MCKESSON	STRYKER
ALEXANDRIA RLST.EQTIES.	EXPEDITOR INTL.OF WASH.	MOODY'S	SYMANTEC
ACTIVISION BLIZZARD	EXPEDIA GROUP	MONDELEZ INTERNATIONAL CL.A	SYSCO
AVALONBAY COMMNS.	EXTRA SPACE STRG.	MEDTRONIC	AT&T
BROADCOM	FORD MOTOR	METLIFE	MOLSON COORS BREWING 'B'
AVERY DENNISON	FASTENAL	MGM RESORTS INTL.	TRANSDIGM GROUP
AMERICAN WATER WORKS	FACEBOOK CLASS A	MOHAWK INDUSTRIES	TE CONNECTIVITY
AMERICAN EXPRESS	FORTUNE BNS.HM.& SCTY.	MCCORMICK & COMPANY NV.	TARGET
ACUITY BRANDS	FREEPORT-MCMORAN	MARTIN MRTA.MATS.	TIFFANY & CO
AUTOZONE	FEDEX	MARSH & MCLENNAN	TJX
BOEING	FIRSTENERGY	3M	TORCHMARK
BANK OF AMERICA	F5 NETWORKS	MONSTER BEVERAGE	THERMO FISHER SCIENTIFIC
BAXTER INTL.	FIDELITY NAT.INFO.SVS.	ALTRIA GROUP	TAPESTRY
BB&T	FISERV	MONSANTO DEAD - DELIST.07/06/18	TRIPADVISOR 'A'
BEST BUY	FIFTH THIRD BANCORP	MOSAIC	T ROWE PRICE GROUP
BECTON DICKINSON	FOOT LOCKER	MARATHON PETROLEUM	TRAVELERS COS.
FRANKLIN RESOURCES	FLIR SYSTEMS	MERCK & COMPANY	TRACTOR SUPPLY
BROWN-FORMAN 'B'	FLUOR	MARATHON OIL	TYSON FOODS 'A'
BRIGHTHOUSE FINANCIAL	FLOWSERVE	MORGAN STANLEY	TESORO ENTERPRISES
BAKER HUGHES A	FMC	MICROSOFT	TOTAL SYSTEM SERVICES
BIOGEN	TWENTY-FIRST CENTURY FOX CL.A	MOTOROLA SOLUTIONS	TIME WARNER DEAD - DELIST.16/06/18
BANK OF NEW YORK MELLON	FEDERAL REALTY INV.TST.	M&T BANK	TEXAS INSTRUMENTS
BOOKING HOLDINGS	TECHNIPFMC	METTLER TOLEDO INTL.	TEXTRON
BLACKROCK	FORTIVE	MICRON TECHNOLOGY	UNDER ARMOUR A
BALL	GENERAL DYNAMICS	MYLAN	UNITED CONTINENTAL HOLDINGS
BRISTOL MYERS SQUIBB	GENERAL ELECTRIC	NAVIENT	UDR
BERKSHIRE HATHAWAY 'B'	IPG PHOTONICS	NOBLE ENERGY	UNIVERSAL HEALTH SVS.'B'
BOSTON SCIENTIFIC	GILEAD SCIENCES	NORWEGIAN CRUISE LINE HDG.	ULTA BEAUTY

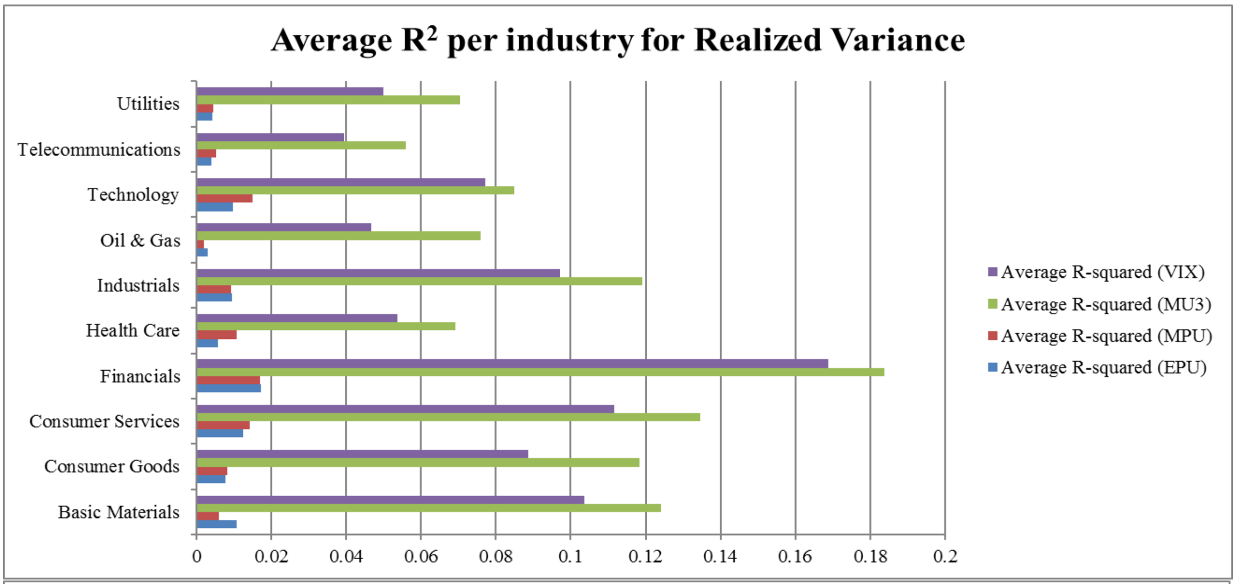
BORGWARNER	GENERAL MILLS	NASDAQ	UNITEDHEALTH GROUP
BOSTON PROPERTIES	CORNING	NEXTERA ENERGY	UNUM GROUP
CITIGROUP	GENERAL MOTORS	NEWMONT MINING	UNION PACIFIC
CA DEAD - DELIST.06/11/18	ALPHABET 'C'	NETFLIX	UNITED PARCEL SER.'B'
CONAGRA BRANDS	ALPHABET A	NEWFIELD EXPLORATION	UNITED RENTALS
CARDINAL HEALTH	GENUINE PARTS	NISOURCE	US BANCORP
CATERPILLAR	GLOBAL PAYMENTS	NIKE 'B'	UNITED TECHNOLOGIES
CHUBB	GAP	NIELSEN	VISA 'A'
CBRE GROUP CLASS A	GARMIN	NORTHROP GRUMMAN	VARIAN MEDICAL SYSTEMS
CBOE GLOBAL MARKETS	GOLDMAN SACHS GP.	NATIONAL OILWELL VARCO	V F
CBS 'B'	GOODYEAR TIRE & RUB.	NRG ENERGY	VIACOM 'B'
CROWN CASTLE INTL.	WW GRAINGER	NORFOLK SOUTHERN	VALERO ENERGY
CARNIVAL	HALLIBURTON	NETAPP	VULCAN MATERIALS
CADENCE DESIGN SYS.	HASBRO	NORTHERN TRUST	VORNADO REALTY TRUST
CELGENE	HUNTINGTON BCSH.	NUCOR	VERISK ANALYTICS CL.A
CERNER	HANESBRANDS	NVIDIA	VERISIGN
CF INDUSTRIES HDG.	HCA HEALTHCARE	NEWELL BRANDS	VERTEX PHARMS.
CITIZENS FINANCIAL GROUP	HCP	NEWS 'A'	VENTAS
CHURCH & DWIGHT CO.	HOME DEPOT	REALTY INCOME	VERIZON COMMUNICATIONS
CHESAPEAKE ENERGY	HESS	ONEOK	WATERS
CH ROBINSON WWD.	HARTFORD FINL.SVS.GP.	OMNICOM GROUP	WALGREENS BOOTS ALLIANCE
CHARTER COMMS.CL.A	HNTGTN.INGALLS INDS.	ORACLE	WESTERN DIGITAL
CIGNA	HILTON WORLDWIDE HDG.	O REILLY AUTOMOTIVE	WEC ENERGY GROUP
CINCINNATI FINL.	HARLEY-DAVIDSON	OCCIDENTAL PTL.	WELLTOWER
COLGATE-PALM.	HOLOGIC	PAYCHEX	WELLS FARGO & CO
CLOROX	HONEYWELL INTL.	PEOPLES UNITED FINANCIAL	WHIRLPOOL
COMERICA	HELMERICH & PAYNE	PACCAR	WILLIS TOWERS WATSON
COMCAST A	HEWLETT PACKARD ENTER.	PG&E	WASTE MANAGEMENT
CME GROUP	HP	PATTERSON COMPANIES	WILLIAMS
CHIPOTLE MEXN.GRILL	H&R BLOCK	PUB.SER.ENTER.GP.	WALMART
CUMMINS	HORMEL FOODS	PEPSICO	WESTROCK
CMS ENERGY	HARRIS	PFIZER	WESTERN UNION
CENTENE	HENRY SCHEIN	PRINCIPAL FINL.GP.	WEYERHAEUSER
CENTERPOINT EN.	HOST HOTELS & RESORTS	PROCTER & GAMBLE	WYNDHAM DESTINATIONS
CAPITAL ONE FINL.	HERSHEY	PROGRESSIVE OHIO	WYNN RESORTS
CABOT OIL & GAS 'A'	HUMANA	PARKER-HANNIFIN	CIMAREX EN.
ROCKWELL COLLINS	INTERNATIONAL BUS.MCHS.	PULTEGROUP	XCEL ENERGY
COOPER COS.	INTERCONTINENTAL EX.	PACKAGING CORP.OF AM.	XL GROUP DEAD - DELIST.12/09/18
CONOCOPHILLIPS	IDEXX LABORATORIES	PERKINELMER	XILINX
COSTCO WHOLESALE	INTL.FLAVORS & FRAG.	PROLOGIS	EXXON MOBIL
COTY CL.A	ILLUMINA	PHILIP MORRIS INTL.	DENTSPLY SIRONA
CAMPBELL SOUP	INCYTE	PNC FINL.SVS.GP.	XEROX

SALESFORCE.COM	IHS MARKIT	PENTAIR	XYLEM
CISCO SYSTEMS	INTEL	PINNACLE WEST CAP.	YUM! BRANDS
CSRA DEAD - DELIST.04/04/18	INTUIT	PPG INDUSTRIES	ZIMMER BIOMET HDG.
CSX	INTERNATIONAL PAPER	PPL	ZIONS BANCORP.
CINTAS	INTERPUBLIC GROUP	PERRIGO	ZOETIS
CENTURYLINK	IQVIA HOLDINGS	PRUDENTIAL FINL.	
COGNIZANT TECH.SLTN.'A'	INGERSOLL-RAND	PUBLIC STORAGE	
CITRIX SYS.	IRON MOUNTAIN	PHILLIPS 66	

PANEL B
Missing companies

Missing companies	ICB Sector	Date that was included in S&P 500 index
Fox Corporation Class B	Communication Services	18/9/2015
News Corp. Class B	Communication Services	18/9/2015
Trane Technologies plc	Industrials	17/11/2010
Under Armour Class C	Consumer Discretionary	8/4/2016

Figure A1. Average R^2 values and t-stats -volatility forecasting (3-month forecasting horizon)
This figure shows the average sectoral R^2 values and t-statistics when forecasting the price jumps (JUMP) of the returns of S&P 500 constituents using the MU1, the VIX index, the AR(1) of Realized Variance, 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 JUMP of the stocks which belong to different sectors. The forecasting horizon of the bivariate regressions on the JUMP of S&P500 constituents is always three-months. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.



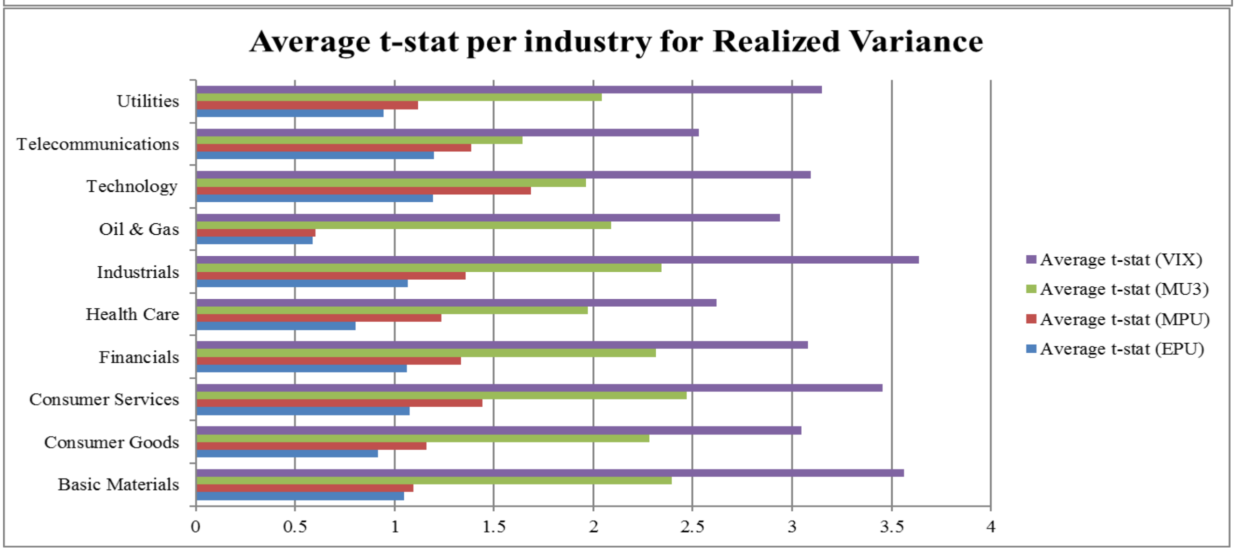
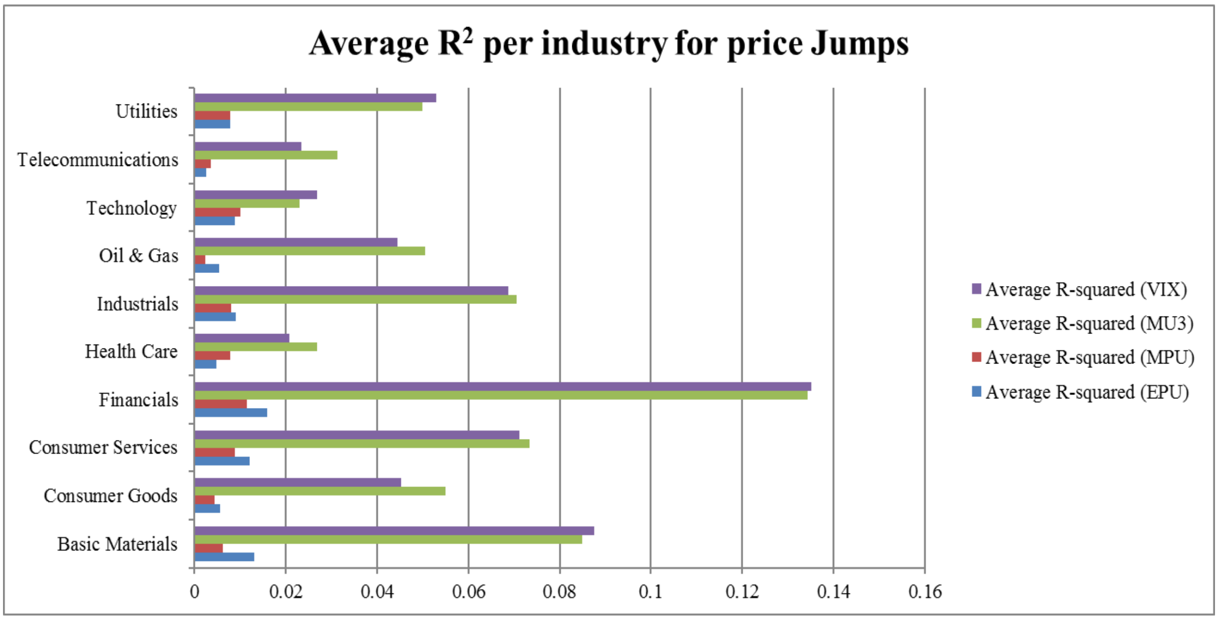


Figure A2. Average R^2 values and t-stats -price jump forecasting (3-month forecasting horizon)
This figure shows the average sectoral R^2 values and t-statistics when forecasting the price jumps (JUMP) of the returns of S&P 500 constituents using the MU1, the VIX index, the AR(1) of Realized Variance, 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 JUMP of the stocks which belong to different sectors. The forecasting horizon of the bivariate regressions on the JUMP of S&P500 constituents is always three-months. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.



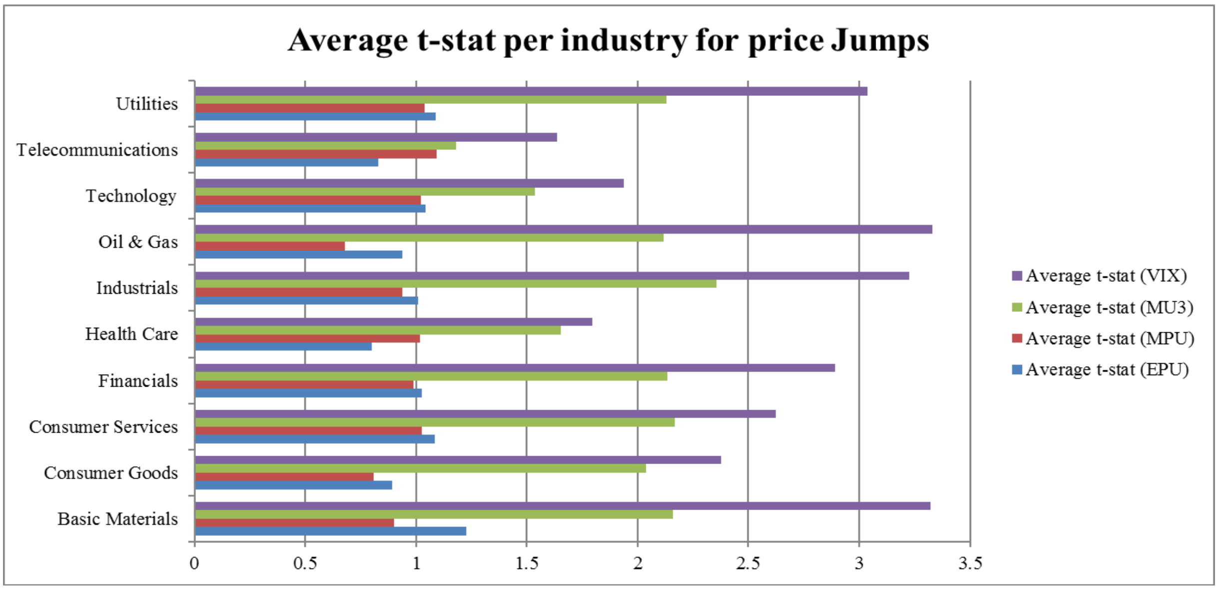


Figure A3. Average R^2 values and t-stats -volatility forecasting (12-month forecasting horizon)
This figure shows the average sectoral R^2 values and t-statistics when forecasting volatility (RV) of the returns of S&P 500 constituents using the MU1, the VIX index, the AR(1) of Realized Variance, EPU 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 three-months. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

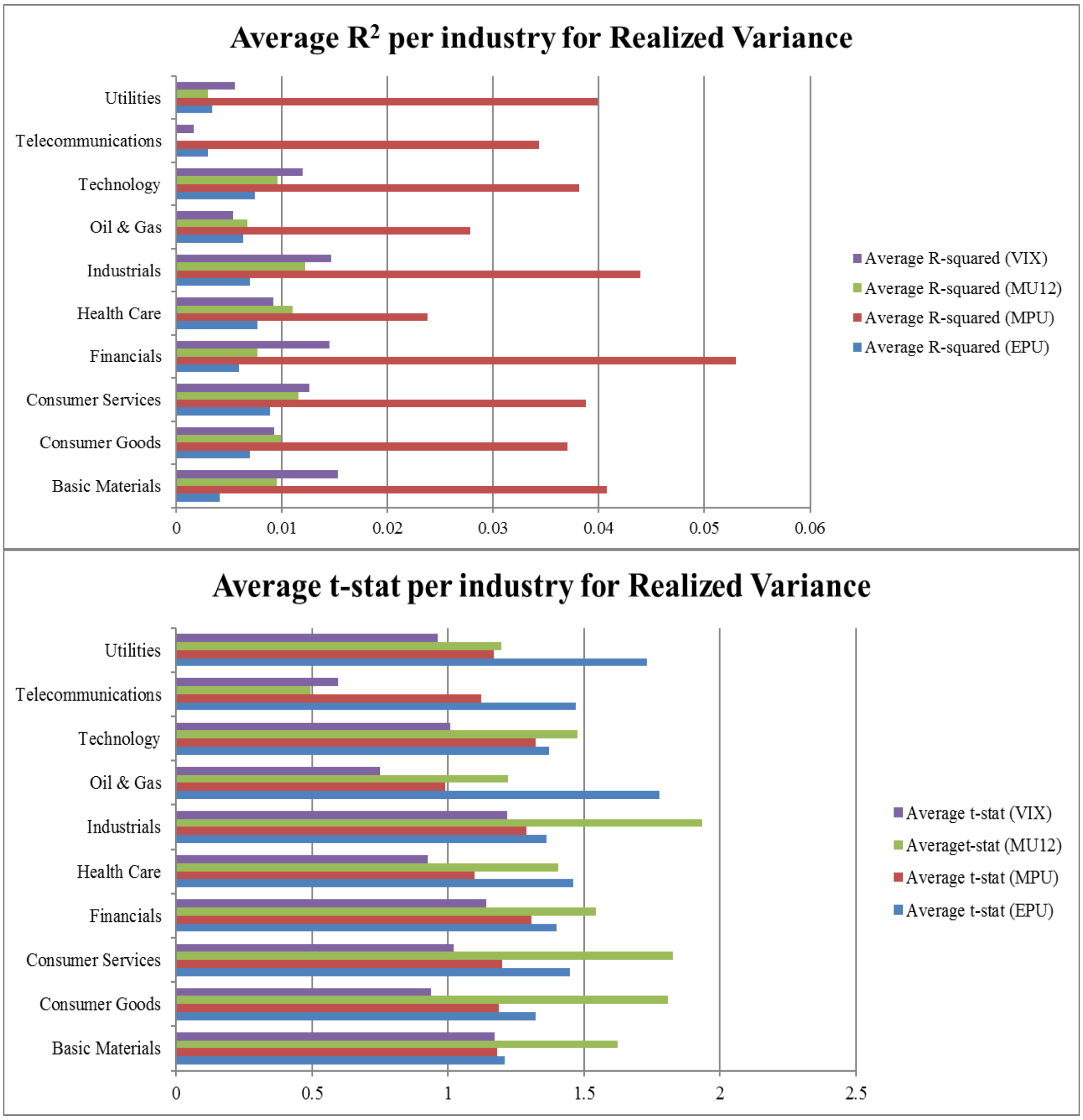
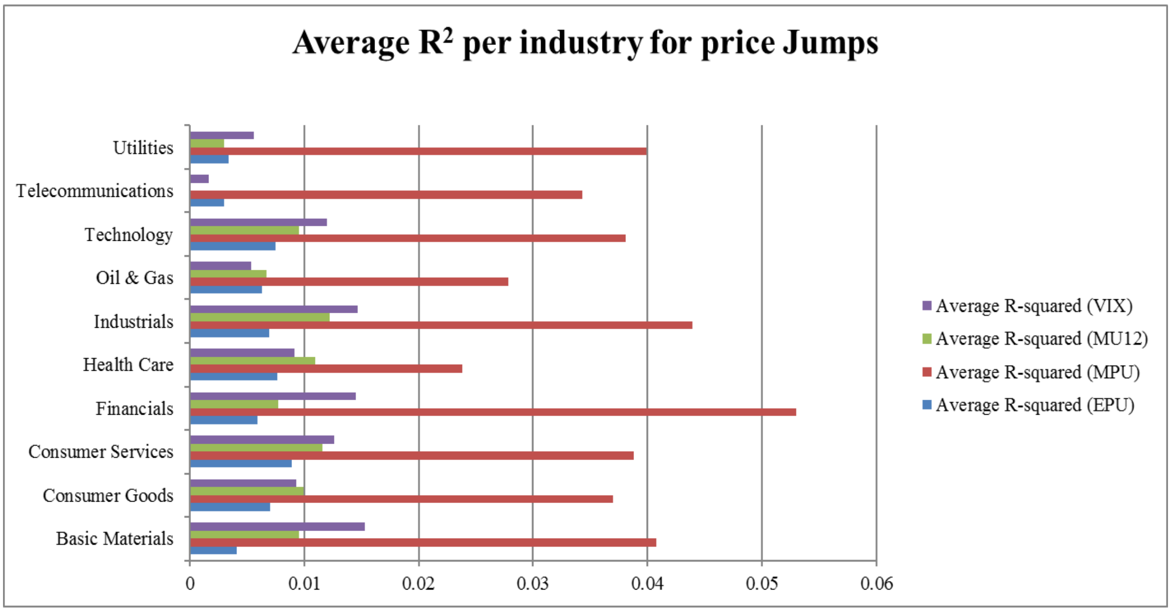


Figure A4. Average R^2 values and t-stats –price jump forecasting (12-month forecasting horizon)
This figure shows the average sectoral R^2 values and t-statistics when forecasting the price jumps (JUMP) of the returns of S&P 500 constituents using the MU1, the VIX index, the AR(1) of Realized Variance, 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 JUMP of the stocks which belong to different sectors. The forecasting horizon of the bivariate regressions on the JUMP of S&P500 constituents is always twelve-months. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.



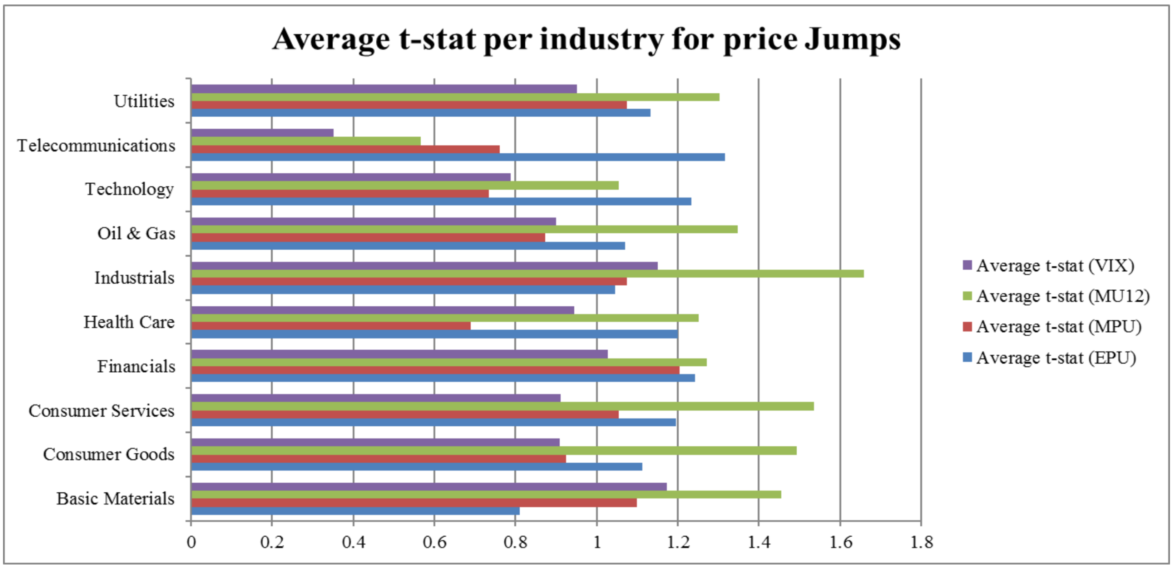
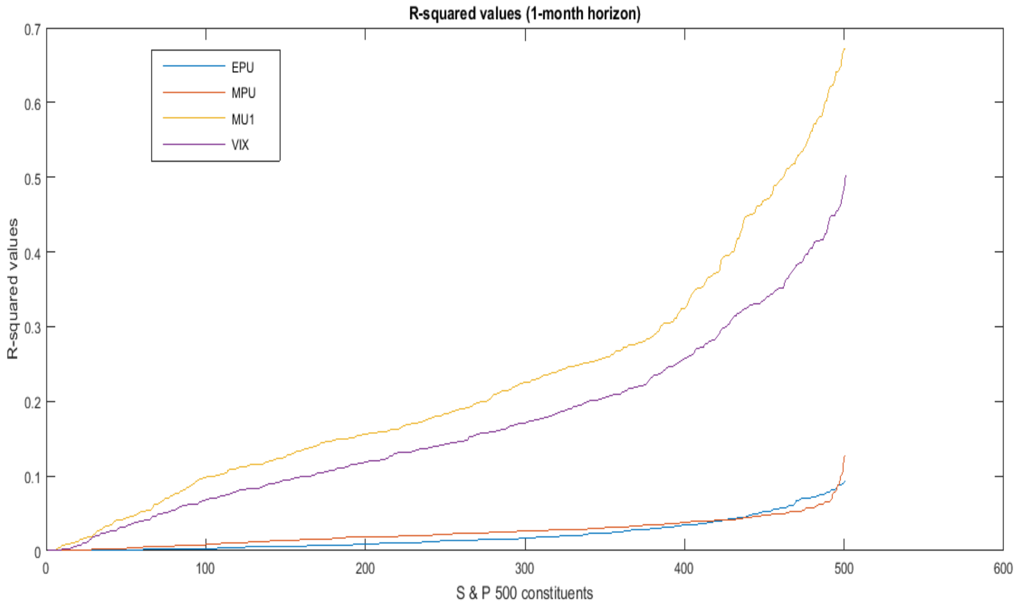


Figure A5. Sorted R^2 values and t-statistics -volatility (RV) (one-month forecasting horizon)

These graphs show the sorted R^2 values and t-statistics of our bivariate forecasting regression models on the monthly Realized Variance (RV) of the intra-day returns of S&P500 constituents using the MU1, lagged RV, EPU, and VIX as predictors of stock-market volatility (RV) having one-month forecasting horizon.



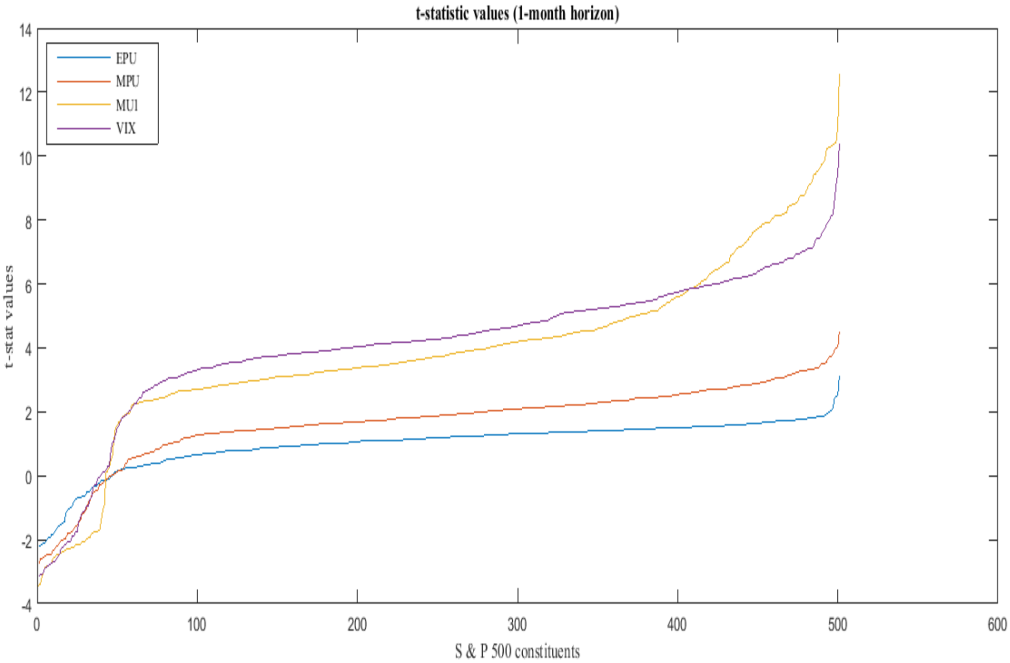
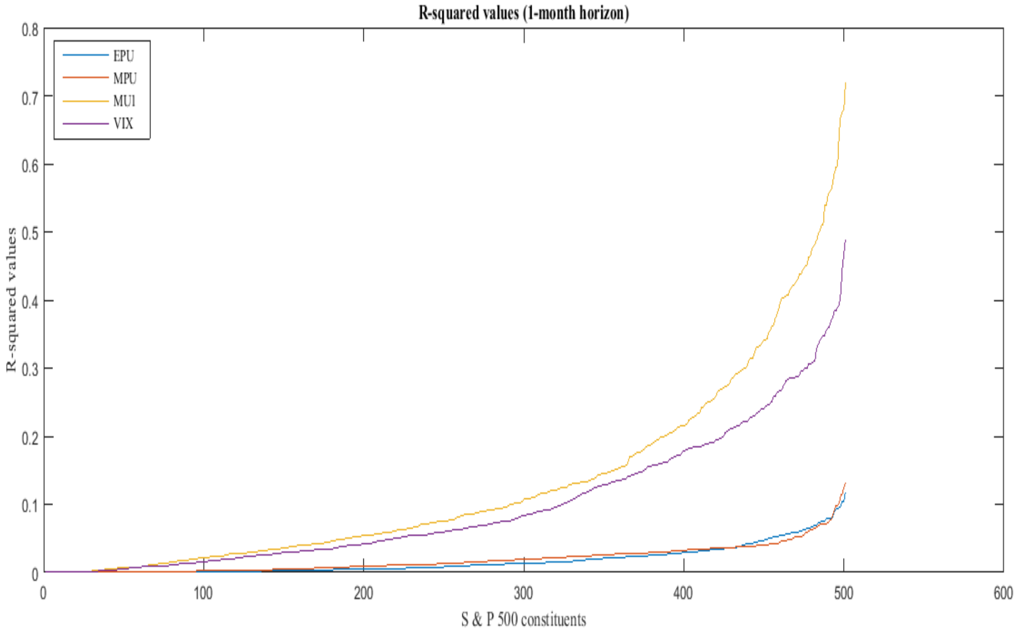


Figure A6. Sorted R^2 values and t-statistics -price Jumps (JUMPS) (one month forecasting horizon)
These graphs show the sorted R^2 values and t-statistics of our bivariate forecasting regression models on the monthly price jumps (JUMP) of the intra-day returns of S&P500 constituents using the MU1, lagged RV, EPU, and VIX as predictors of stock-market volatility (RV) having one-month forecasting horizon.



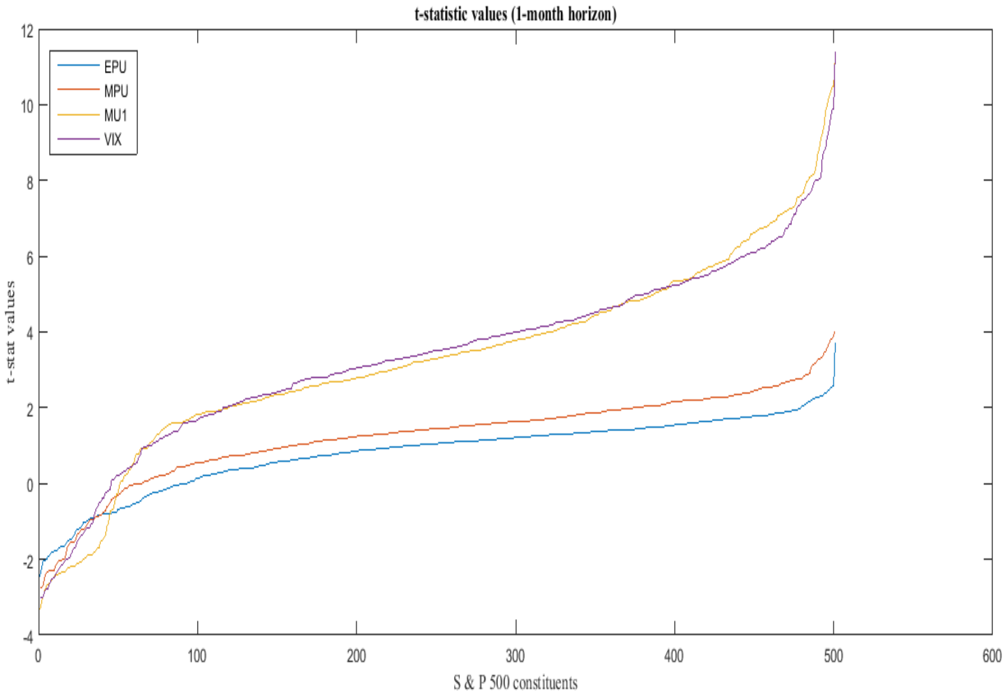
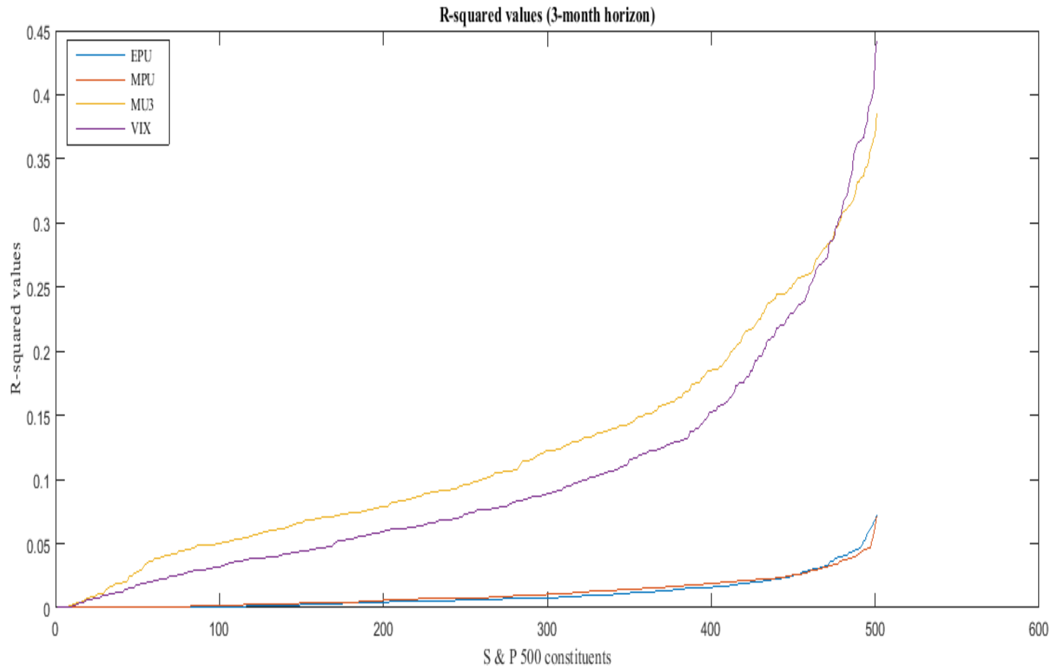


Figure A7. Sorted R^2 values and t-statistics (RV) -volatility (RV) (3-month forecasting horizon)
These graphs show the sorted R^2 values and t-statistics of our bivariate forecasting regression models on the monthly Realized Variance (RV) of the intra-day returns of S&P500 constituents using the MU1, lagged RV, EPU, and VIX as predictors of stock-market volatility (RV) having three-month forecasting horizon.



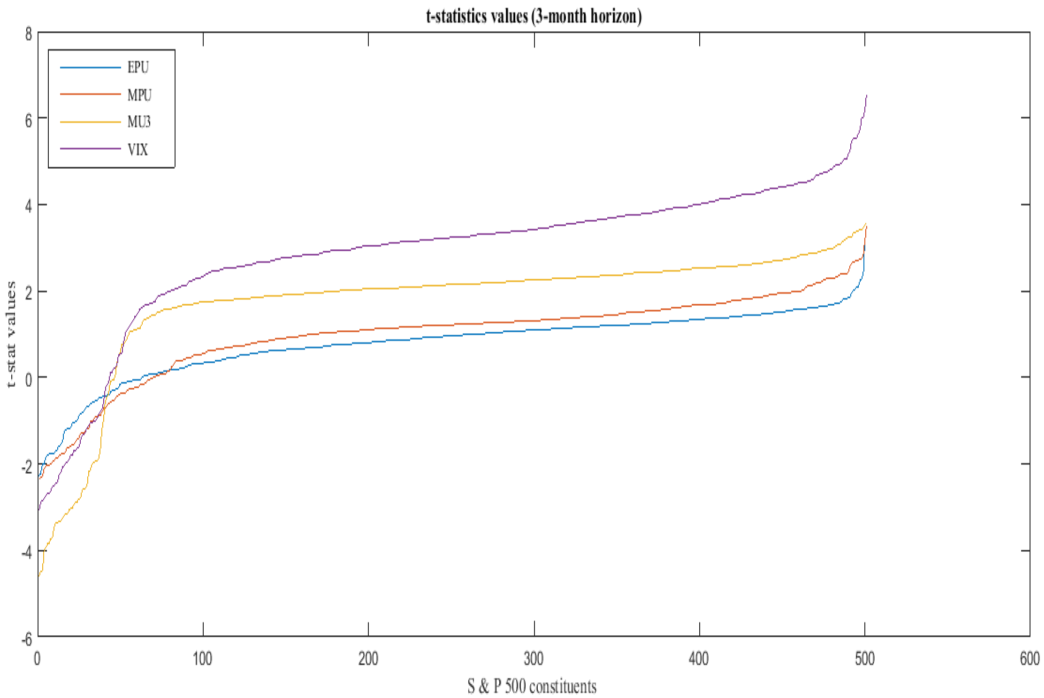
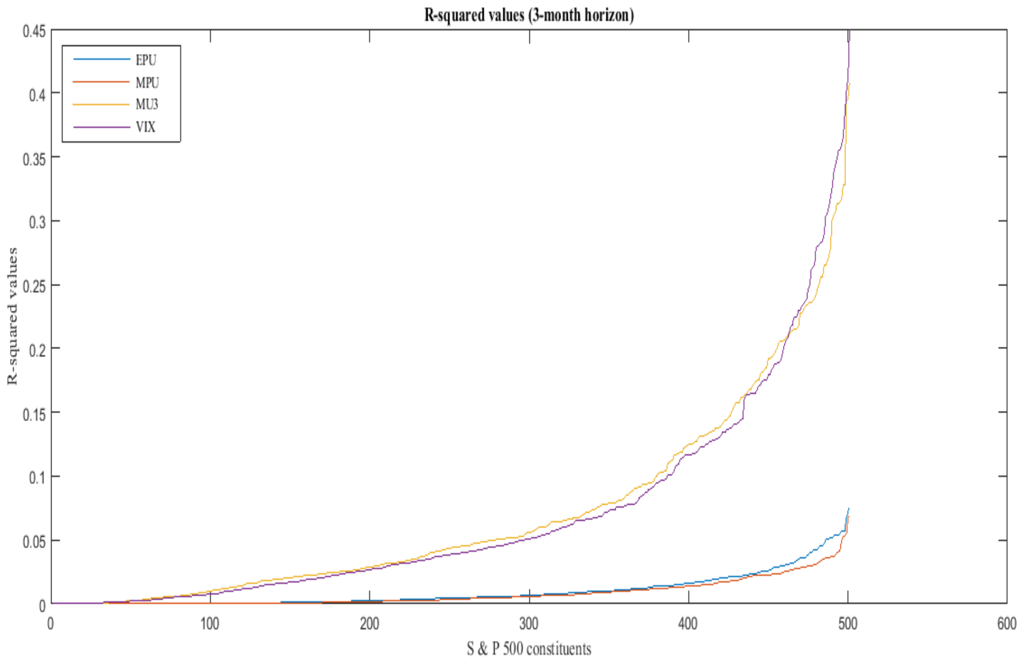


Figure A8. Sorted R^2 values and t-statistics - price jumps (JUMP) (3-months forecasting horizon)
These graphs show the sorted R^2 values and t-statistics of our bivariate forecasting regression models on the monthly price jumps (JUMP) of the intra-day returns of S&P500 constituents using the MU1, lagged RV, EPU, and VIX as predictors of stock-market volatility (RV) having three-month forecasting horizon.



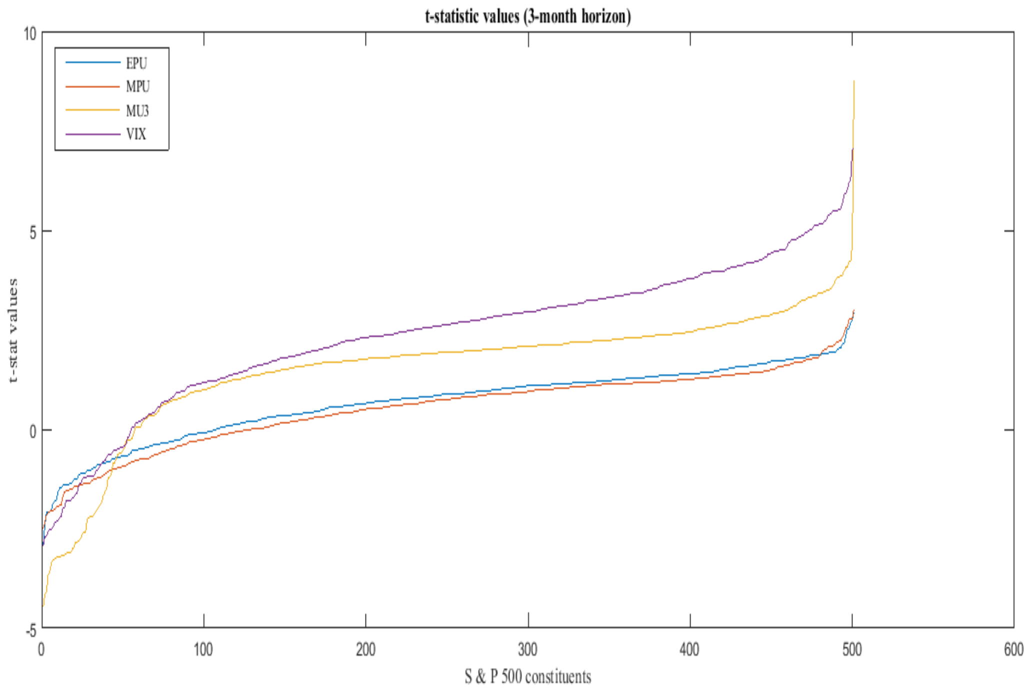
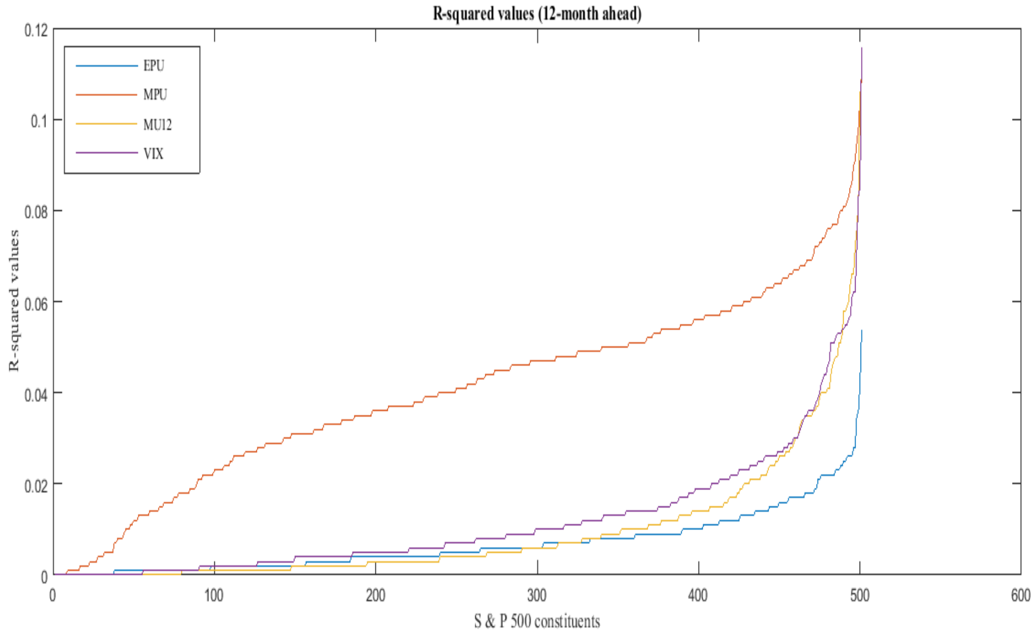


Figure A9. Sorted R^2 values and t-statistics- volatility (RV) (12-months forecasting horizon)
These graphs show the sorted R^2 values and t-statistics of our bivariate forecasting regression models on the monthly Realized Variance (RV) of the intra-day returns of S&P500 constituents using the MU1, lagged RV, EPU, and VIX as predictors of stock-market volatility (RV) having twelve-month forecasting horizon.



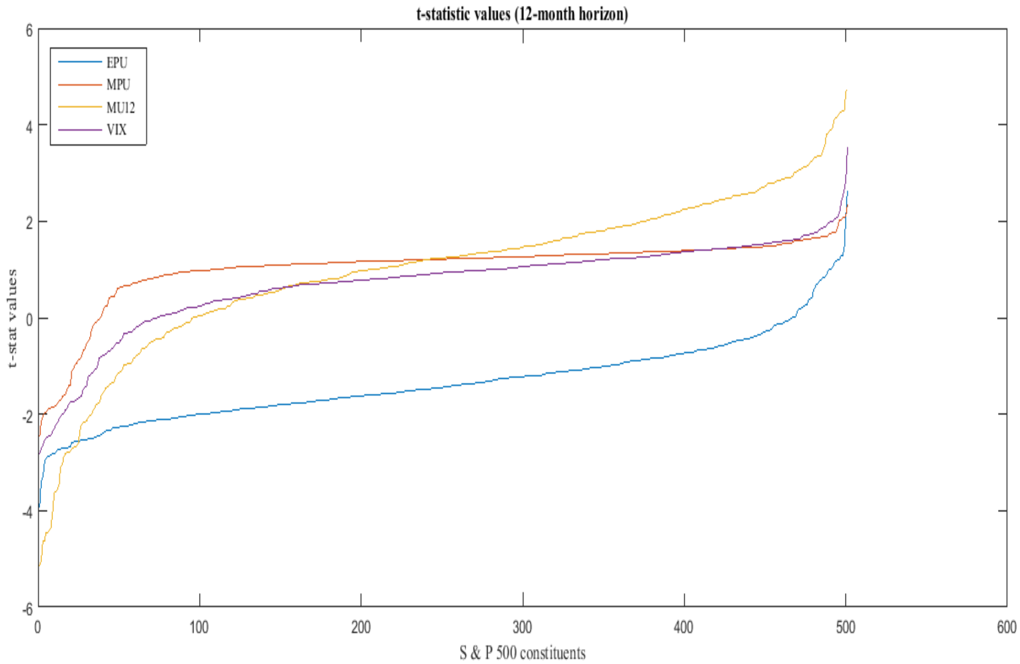
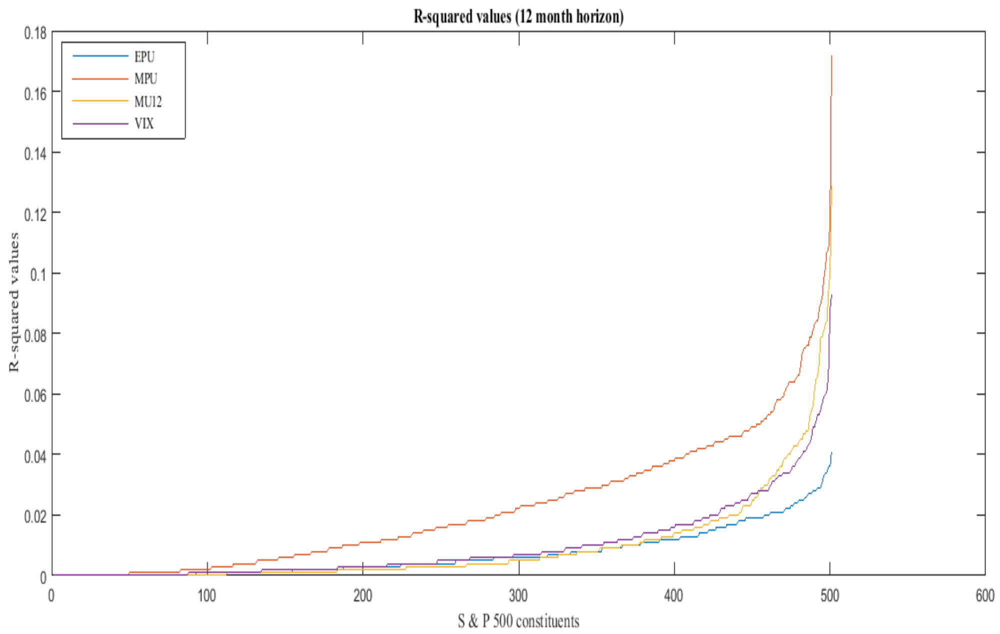


Figure A10. Sorted R^2 values and t-statistics -price jumps (JUMP) (12-month forecasting horizon)
These graphs show the sorted R^2 values and t-statistics of our bivariate forecasting regression models on the monthly price jumps (JUMP) of the intra-day returns of S&P500 constituents using the MU1, lagged RV, EPU, and VIX as predictors of stock-market volatility (RV) having twelve-month forecasting horizon.



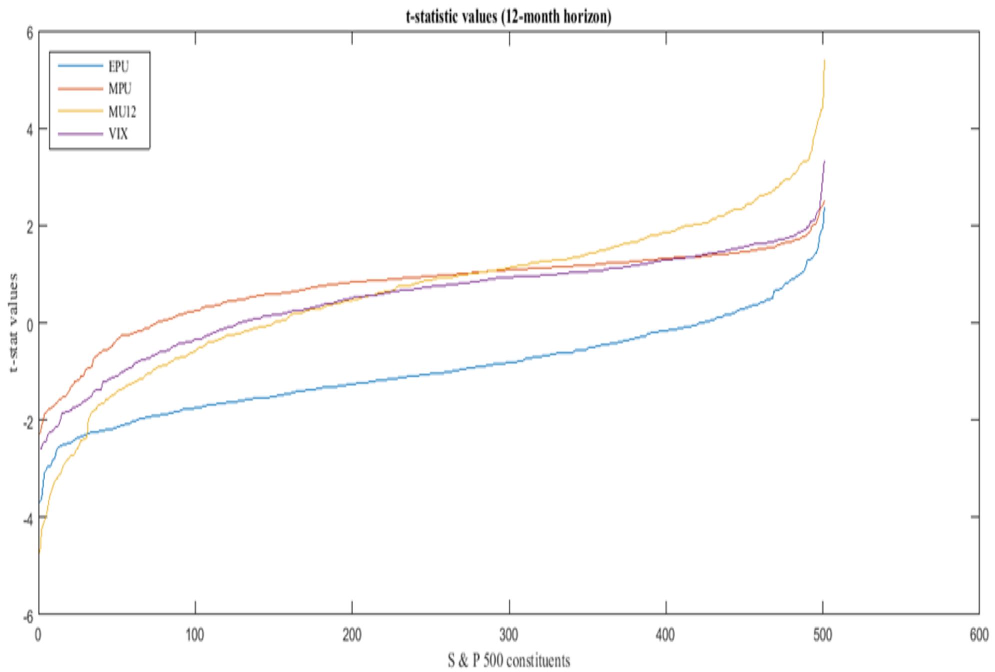


Figure A11. Orthogonalized Impulse Response Functions (OIRFs) of stock-market volatility to uncertainty shocks (using MU3 instead of MU1)

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 3-month forecasting horizon (MU3) 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).

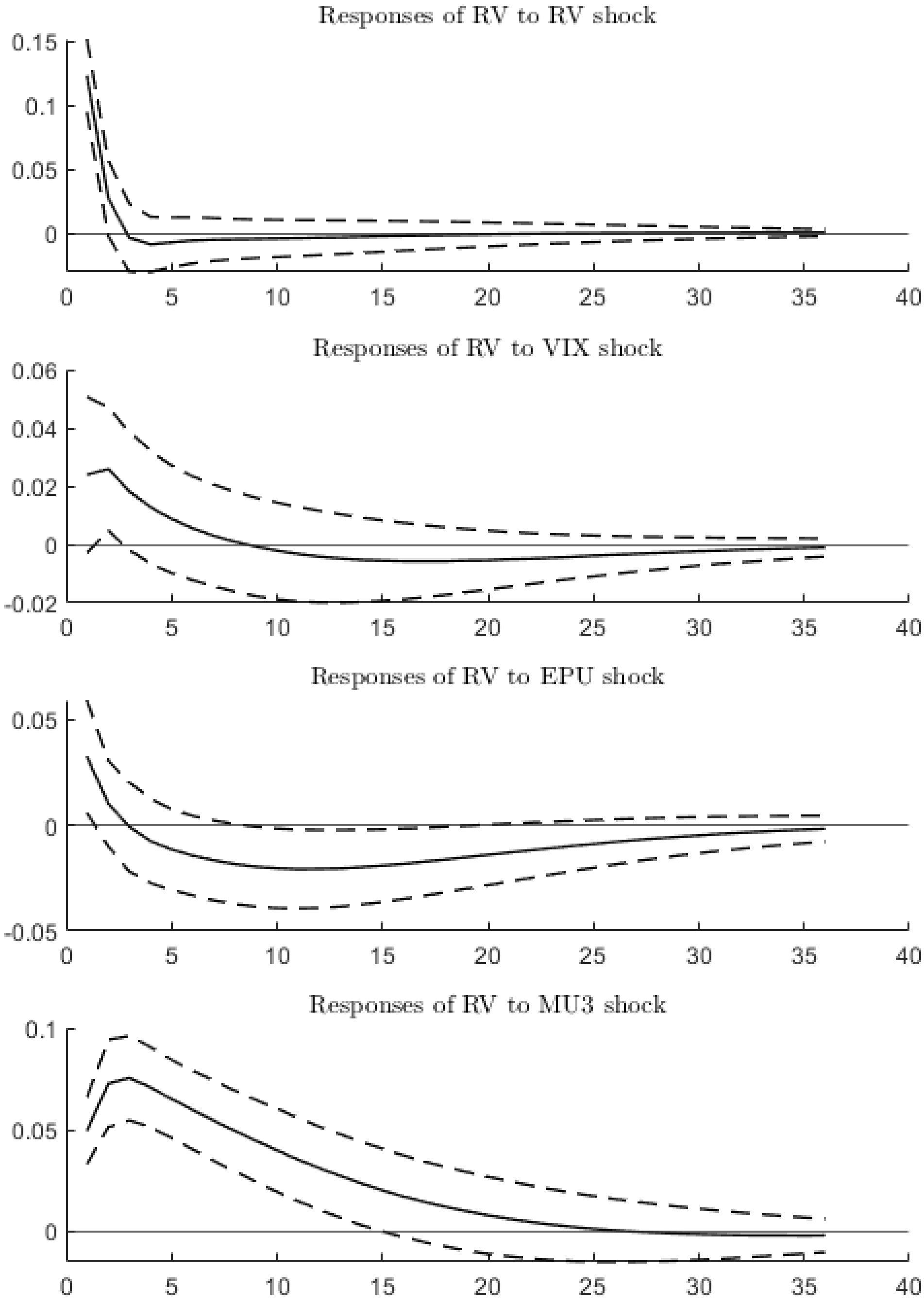


Figure A12. Orthogonalized Impulse Response Functions (OIRFs) of stock-market volatility to uncertainty shocks (using MU12 instead of MU1)

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 twelve-month forecasting horizon (MU12) 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).

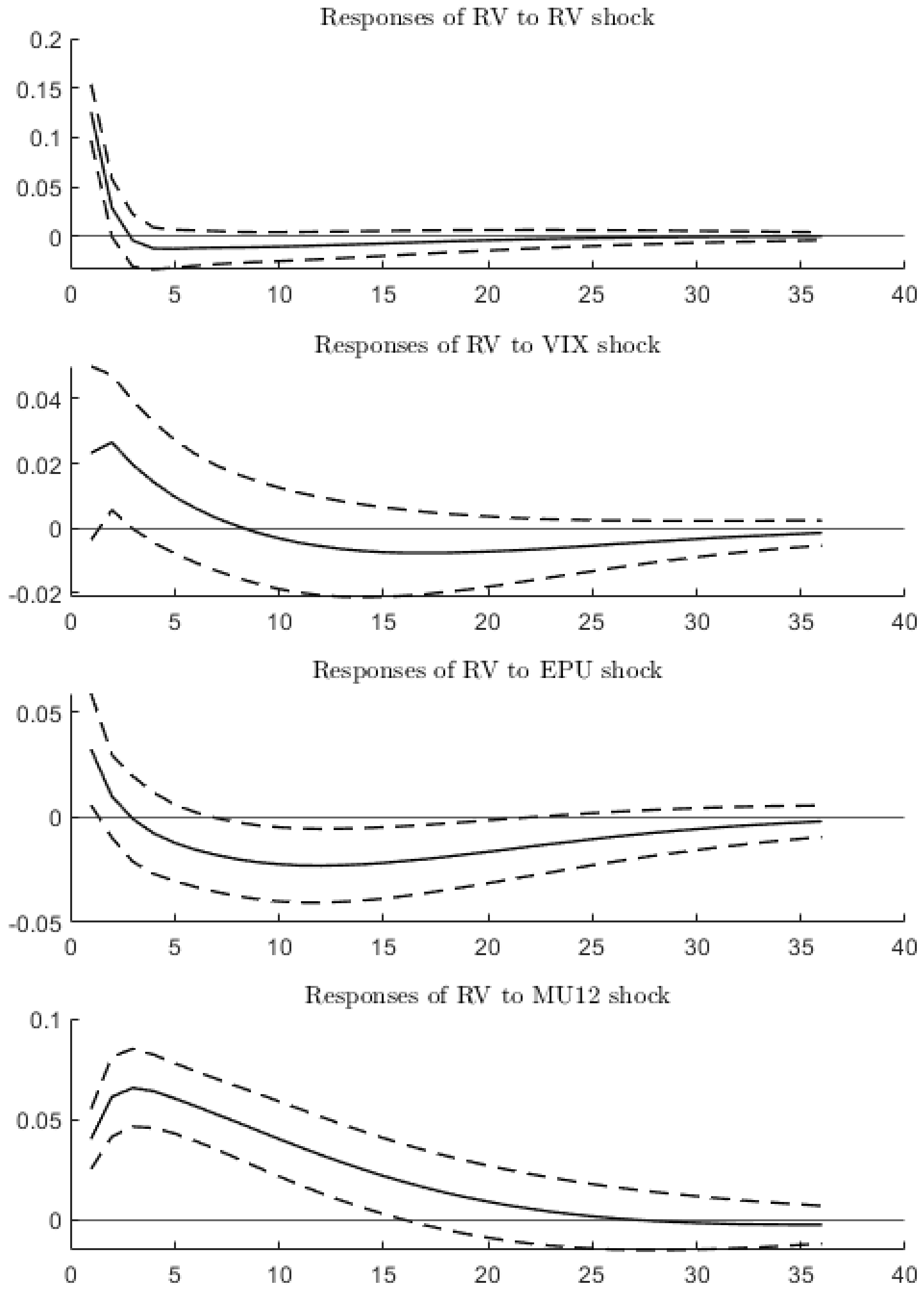


Figure A13. Orthogonalized Impulse Response Functions (OIRFs) of stock-market volatility to uncertainty shocks in the post-crisis period. (using MU3 instead of MU1)

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 three-month forecasting horizon (MU3) 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).

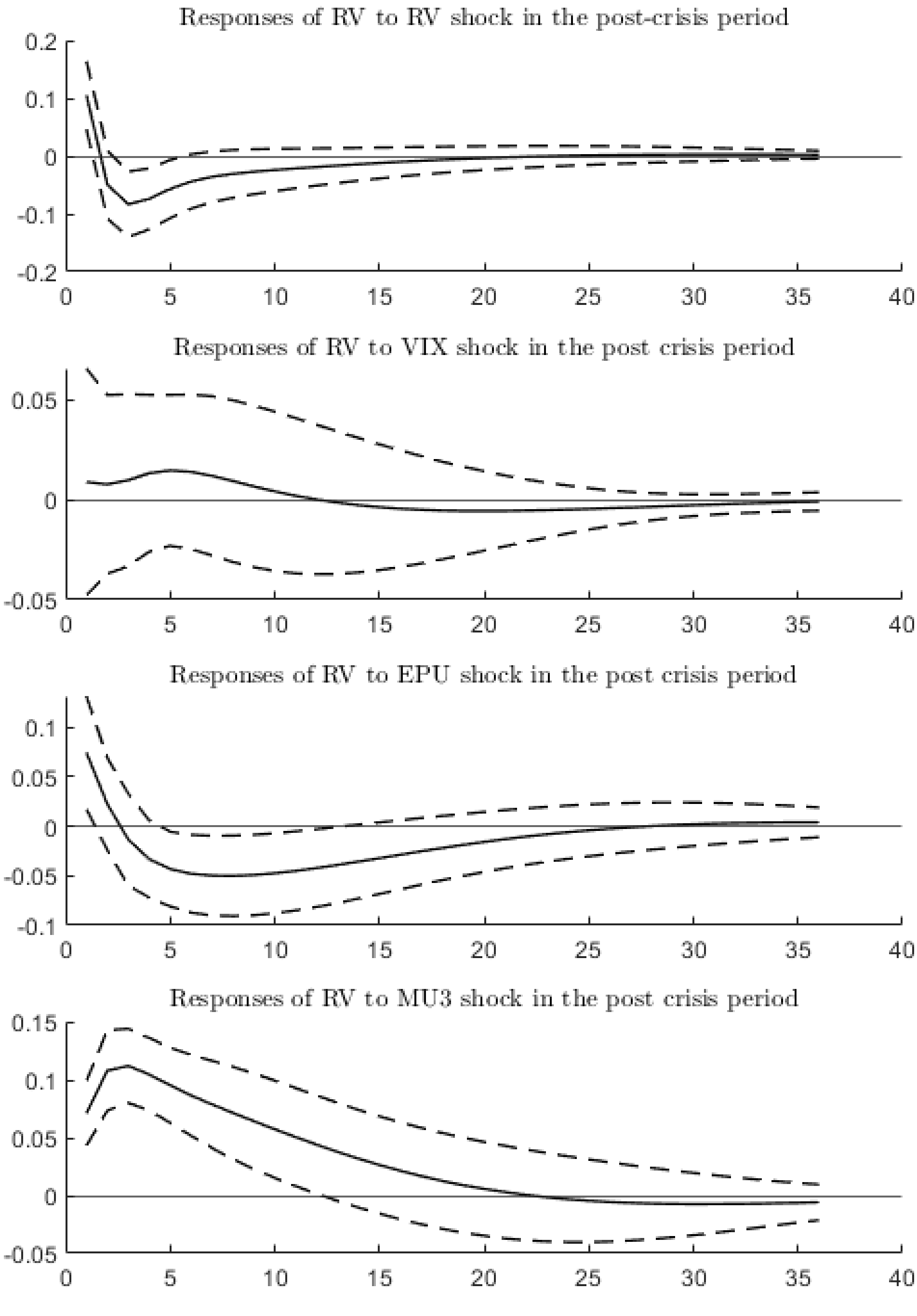


Figure A14. Orthogonalized Impulse Response Functions (OIRFs) of stock-market volatility to uncertainty shocks in the post-crisis period. (using MU12 instead of MU1)

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 twelve-month forecasting horizon (MU12) 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).

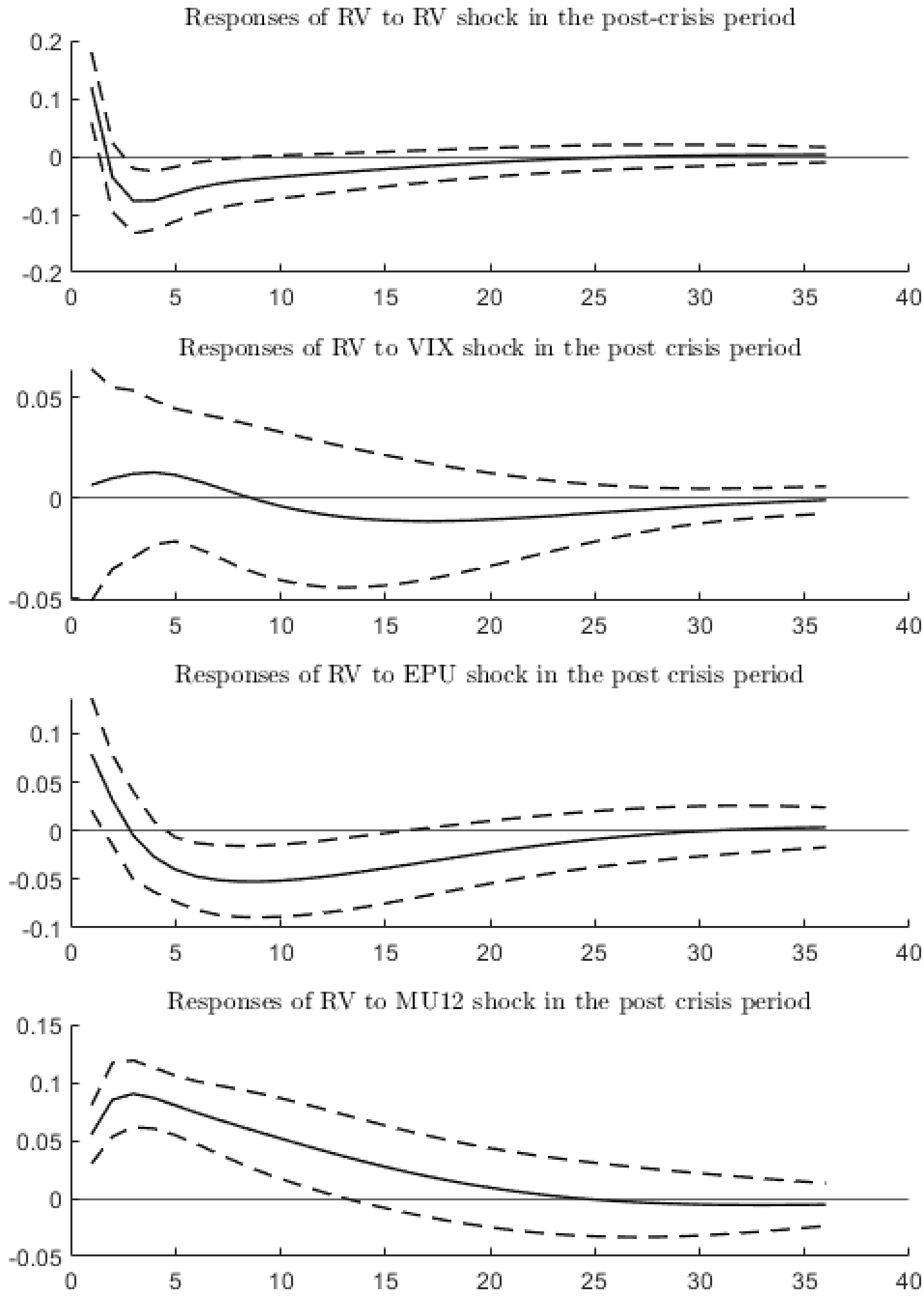


Figure A15. Orthogonalized Impulse Response Functions (OIRFs) of stock-market price jumps (JUMP) to uncertainty shocks. (using MU3 innstead of MU1)

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 three-month forecasting horizon (MU3) 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).

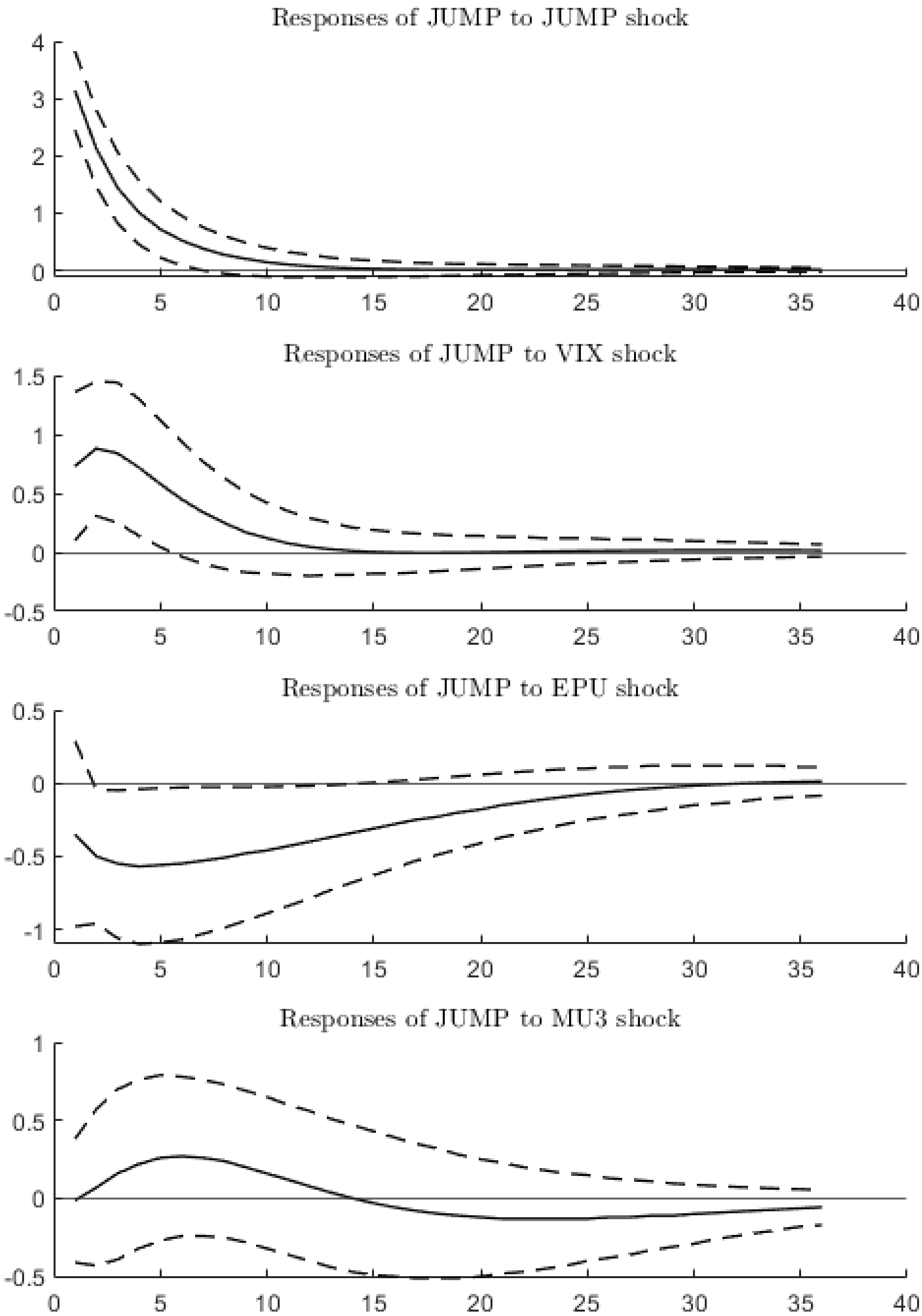


Figure A16. Orthogonalized Impulse Response Functions (OIRFs) of stock-market price jumps (JUMP) to uncertainty shocks. (using MU12 innstead of MU1)

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 12-month forecasting horizon (MU12) 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).

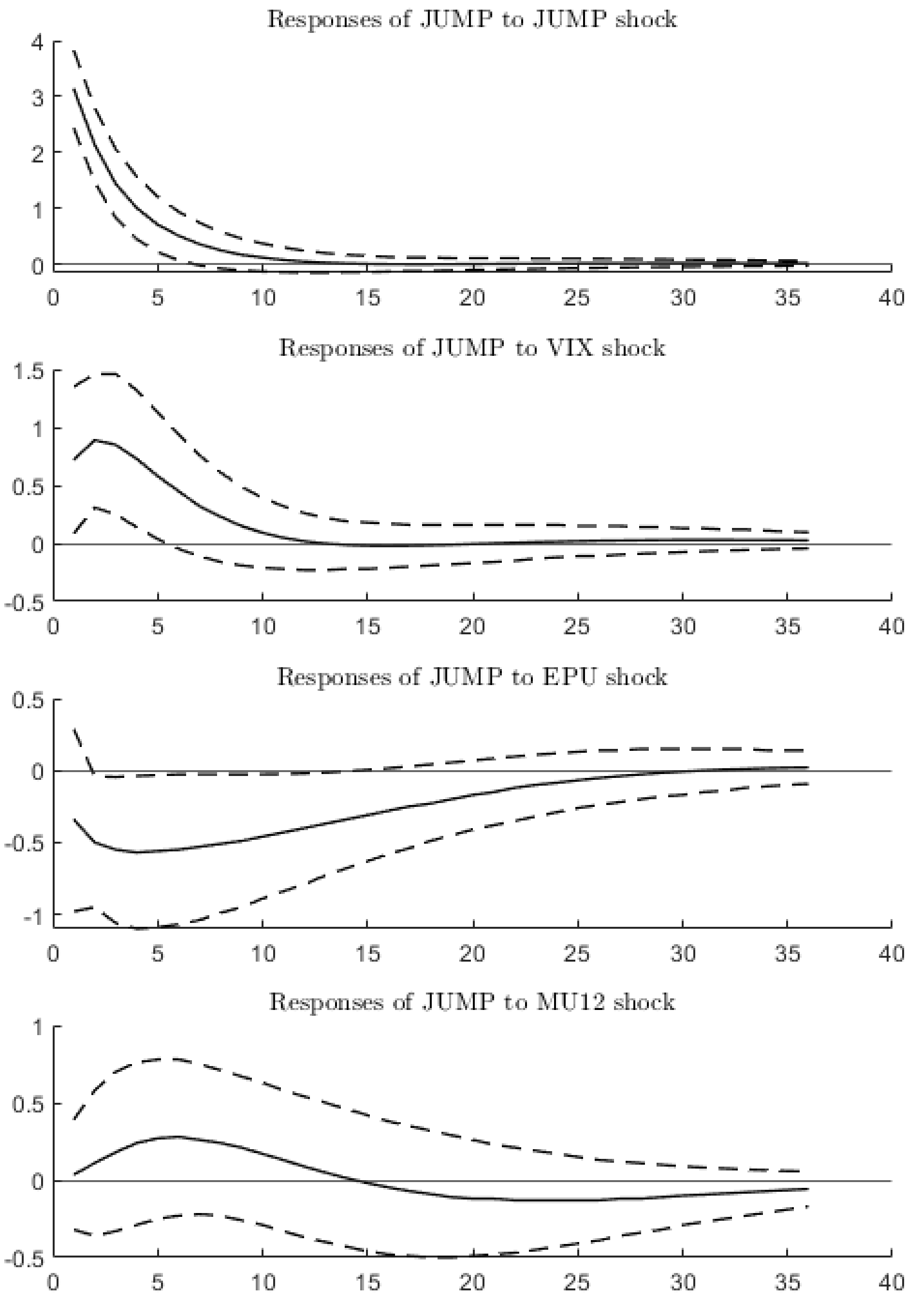


Figure A17. Orthogonalized Impulse Response Functions (OIRFs) of stock-market price jumps (JUMP) to uncertainty shocks in the post-crisis period (using MU3 instead of MU1)

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 three-month forecasting horizon (MU3) 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).

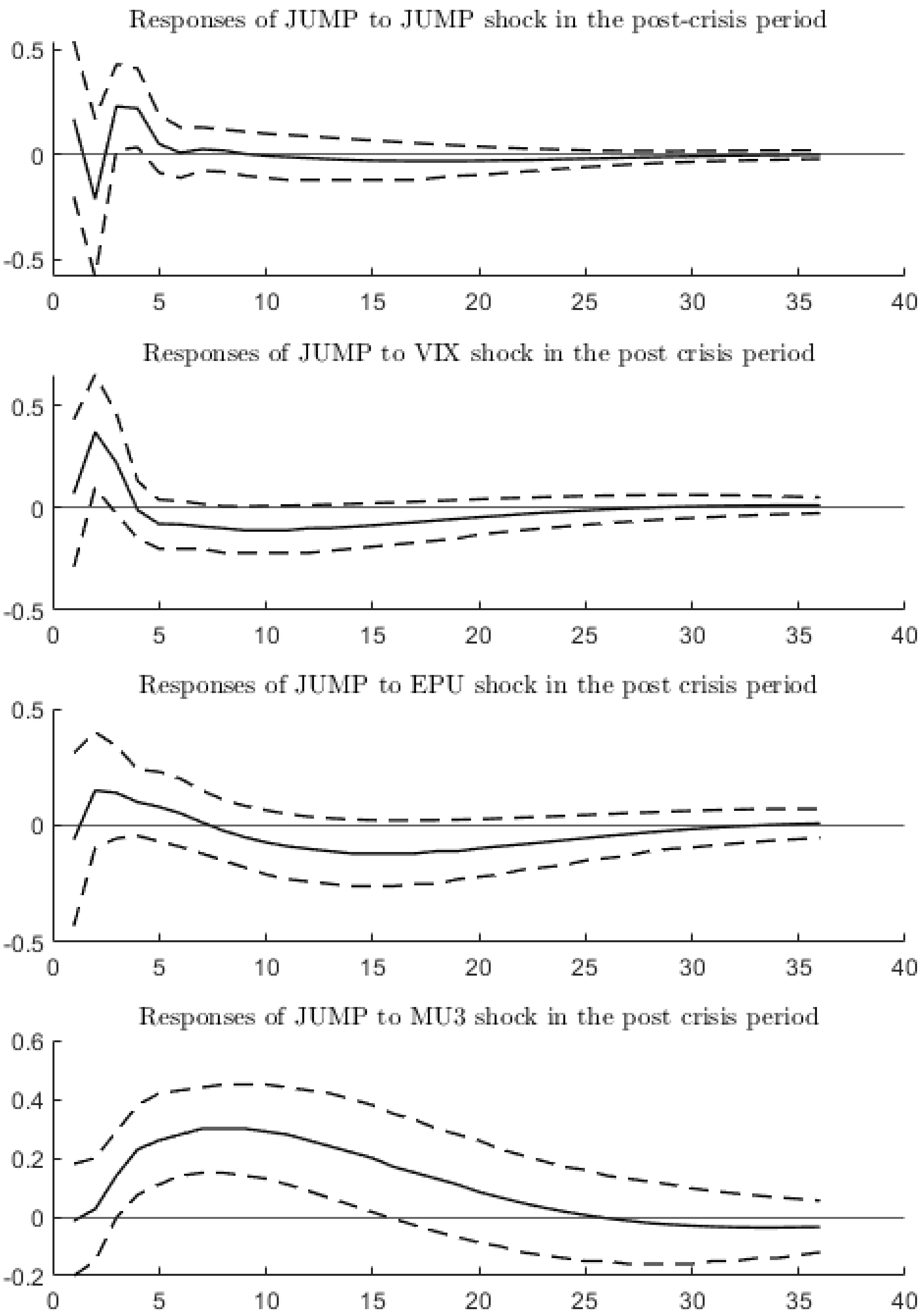


Figure A18. Orthogonalized Impulse Response Functions (OIRFs) of stock-market price jumps (JUMP) to uncertainty shocks in the post-crisis period (using MU12 instead of MU1)

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 twelve-month forecasting horizon (MU12) 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).

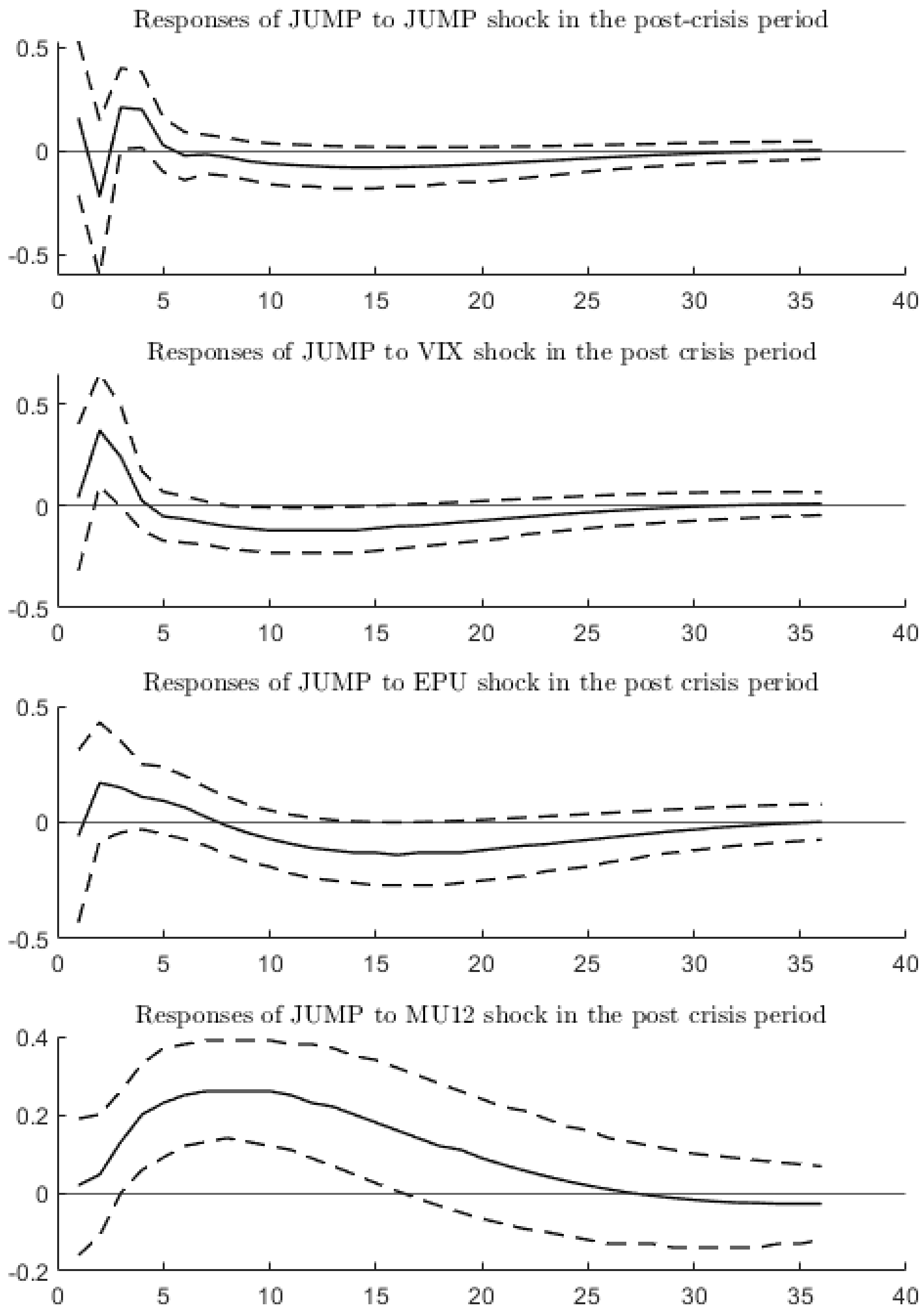


Figure A19. Forecasting the incidence of a financial crisis using macroeconomic uncertainty

This Figure shows the estimated probit probabilities (estimated from a probit model) on the incidence of US stock-market crisis using the MU1, MU3 or MU12 as the crisis predictor. The stock-crisis has been identified as the historical (local) peak of the S&P500 Realized Variance (RV) series. The rolling window for indentifying the stock-market volatitility peaks which indicate the crisis is 1 year (12-months).