Financial Market Risk and the Macroeconomy

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Abbreviations list

CPI→ Consumers price index of U.S.

Defspr → Moody's Baa default spread

EPU → Economic policy uncertainty index of U.S

FFR → Federal fund target rate.

IK → Option-implied Kurtosis

INF → Inflation rate based on CPI of U.S.

IPG → The industrial production growth of U.S.

IPL → The industrial production level of U.S.

IS → Option-implied Skewness

IV → Option-implied Variance

JV → The Jump variation component of the Realized Variance of stock market returns

LEVELRV → The realized variance of the level of the term structure of interest rates

M1growth → The growth rate of monetary aggregate M1 of Federal Reserve.

MPU → Monetary policy uncertainty index U.S.

MUk → The latent macroeconomic uncertainty index of U.S., for k-months ahead

OILRV → The realized variance of the Crude Oil component of the S&P commodities index (GSCI) returns.

PPI→ Producers price index of U.S.

RBV → The Bi-power variation component of the Realized Variance of stock market returns

RIR → Real interest rate.

RV → The realized variance of returns of an underlying asset or index. In the main text, if the abbreviation is not accompanied by any other term, then it refers to the realized variance of stock market returns.

SLOPE → The slope (term spread) of the term structure of interest rates of U.S.

SLOPERV → The realized variance of the slope of the term structure of interest rates

SP500 → The S&P 500 index prices

SP500RET → The S&P 500 index returns

SP500RV → The realized variance of the S&P 500 index returns (it has the same meaning with RV since it is used as a proxy of realized variance of the stock market returns)

TRD → The Taylor rule rate.

VIX → VIX index

Abstract

The first chapter of this thesis is about the predictive power of latent macroeconomic uncertainty on U.S. stock market volatility and price jumps. I find that increasing macroeconomic uncertainty predicts a subsequent rise in volatility and price jumps in the U.S. stock market. Specifically, the latent macroeconomic uncertainty measures of Jurado et al. (2015) have the most significant impact on U.S. stock market volatility and jumps in the equity market when compared to the respective impact of popular observable uncertainty proxies.

In the second chapter, I empirically verify the predictive information content of U.S. Treasury yield curve volatility on stock market volatility. Given the fact that, the yield curve reflects expectations about future interest rates and economic activity, then the rising volatility in the shape of the yield curve will probably result to rising stock market volatility. I document that the volatility of the slope of the yield curve is a statistically significant predictor of stock market volatility in both in-sample and out-of-sample settings.

Lastly, I examine the dynamic impact of monetary policy on option-implied expectations. I use option contracts of S&P 500 index in order to estimate the higher order moments of the risk neutral option-implied distribution of the U.S. stock market. I find that an expansionary monetary policy shock revises upwardly the investors' expectations about the future path of the U.S. equities prices, that is in line with the empirical results of a vast relevant literature (Rigobon and Sack, 2003; Kurov et al., 2019; amongst others). Furthermore, I find that option-implied expectations with long-term horizon are more responsive to lax monetary policy compared to those with short-term horizon. My findings are in line and provide further insights to a recently growing literature on the field (Hanson and Stein, 2015; Kontonikas and Zekaite, 2018; Nakamura and Steinsson, 2018).

Chapter 1

Introduction

We are currently leaving in a period of economic instability. The dot-com bubble (2000-2002), the European sovereign debt crisis (2009-2019), the 2007-2009 financial crisis, are some of the major economic events during the past 20 years, with the latter one, being the worst recession the humanity has faced since the beginning of the 20th century. A recent and growing body in the macro-finance literature has shown that the interdependence between real (macroeconomic) and financial fluctuations has exponentially increased after the Great Recession of 2007-2009 (Abbate et al., 2016, Caldara et al., 2016; among others). The equities return volatility is related to market-specific factors like changes in leverage (Black, 1976; Christie, 1982), expected stock returns (Merton, 1980; Pindyck, 1984; among others) and to macroeconomic factors related with business cycles (Schwert, 1989; Hamilton and Lin, 1996; Barro 2006; Beber and Brandt, 2008; Paye, 2012; Corradi et al., 2013; Engle et al., 2013; Wachter, 2013; Connolly et al., 2017; Bloom et al., 2018; among others) and monetary policy (Bekaert et al., 2013; Kaminska and Roberts-Sklar, 2018; amongst others). Equity 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. Stock market volatility fluctuates over time, with the economic explanation being still a debatable issue. Schwert (1989) is the first who gives a pure macroeconomic answer to the question "Why volatility changes over time" by showing that macroeconomic uncertainty measured as the volatility of the U.S. industrial production and interest rates, forecasts aggregate stock market volatility. Schwert

(1989) is the first to point out that “if macroeconomic aggregates provide information about the volatility of either future expected cash flows, or future discount rates, they can explain why stock return volatility changes over time”. In further support of this argument, Hamilton and Lin (1996) empirically show that stock-return volatility is primarily driven by economic recessions, identifying a key role of macroeconomic variables to act as early warning signals of high volatility episodes in the stock market. Corradi et al. (2013) find that time variation of stock market volatility is largely explained by business cycle variables. Barro (2006) and Wachter (2013) empirically show that the time-varying probability of rare-disaster risk in the economy lies behind the time-variation in aggregate stock market volatility. Cochrane (2007) and Cochrane (2011) finds that the variability of interest rates reveals a significant information content about the equity risk premia. Schwert (1989) finds that macroeconomic uncertainty and interest rate volatility are correlated with the stock market volatility, since the volatility of the stock-price is directly linked with the volatility of the expected cash-flows (volatility of the discount rate). In complete accordance and by using similar methodologies like those of Schwert (1989), Engle et al. (2013) find that industrial production and inflation are significant predictors of stock market volatility both at long and short-term forecast horizons, while Asgharian and Hou (2013) find that macroeconomic variables help in predicting the long-run variance component of U.S. equity returns. Beltratti and Morana (2006) find that macroeconomic volatility, measured by deviations in the Fed funds rate and in M1 growth, causes stock market volatility, while Choudhry et al. (1996) find a bidirectional causal relationship between the business cycle and the stock market volatility in major economies like U.S., Canada, UK and Japan. Kaminska and Roberts-Sklar (2018) and Creal and Wu (2017) show that the monetary policy uncertainty (proxied by the option-implied volatility extracted from U.S. interest rate options) has a significant predictive power on the stock-return volatility and economic activity for both short-term and long-term forecast horizons. Bekaert et al. (2013) and David and Veronesi (2014) show that the lax monetary policy results in lowering stock market volatility and risk aversion.

Motivated by the findings in the relevant macro-finance literature, my main aim in this thesis is the examination of bi-directional linkages between financial market risk and the state of the macroeconomy. Motivated by the recently growing stream of research in the macro-finance literature, I empirically examine whether the financial market risk and market expectations and fears about the future state of the economy, are related to macroeconomic uncertainty shocks and monetary policy. In details my thesis has two main goals. On the one hand, I empirically examine the predictive information content of macroeconomic and monetary policy uncertainty shocks (proxied by the volatility in the U.S. Treasury yield curve) on stock market volatility and jumps and find that both macroeconomic and volatility of the term structure of interest rates has significant in sample and out-of-sample forecasting power on U.S. stock market volatility and jumps. In my thesis, motivated by the above relevant studies, I find that the unpredictability of the subsequent state of the macroeconomy as well as the second moments of the term structure of interest rates are strong predictors of the stock market volatility. My claim is based on Shiller’s pricing formula (similatly to Schwert, 1989) that assumes that the price of an underlying asset is the summary of the expected cashflows discounted by the short-term discount factor. The expected future cashflows, is composed of the actual future cashflows plus a forecast error. My hypothesis is that a measure which captures the unforecastable (by economic agents) variations in key macroeconomic indicators is proxy for the variability of the forecast error. In my thesis, I propose that the measure of latent macroeconomic uncertainty proposed by Jurado et al. (2015) is a sound proxy for uncertainty regarding the level of expected dividend yields, and therefore, it is a major driver of fluctuations in stock market volatility. Following Schwert (1989), I postulate that increased uncertainty about future macroeconomic conditions causes increased volatility of stock prices.

Additionally, I find that the second moments of the term structure of interest rates affect the variance of the expected discounted cash-flows, by affecting both the expected future cashflows and the expected level of the discount rate. Cieslak and Povala (2016) emphasize that since short-rates reveal expectations about monetary policy stance, it is reasonable to assume that their volatility will reveal the uncertainty around this path. Similarly, I argue that since the yield curve reveal investors' expectations about the future state of the economy and discount factor, then the yield curve volatility reflects the risk being present through the increased dispersion of the expectations about the future path of the economy and the variation of the discount factor of the future cashflows. So, it is reasonable to assume that the risk that is reflected from yield curve volatility, is correlated with the volatility of the expected discounted cashflows.

As I mention above, except the factors (check) that affect financial market risk and are related to monetary policy and the macroeconomy, I investigate whether monetary policy can change investors' expectations about the future state of the economy. In the last chapter of my thesis, my purpose is to shed light on these questions by empirically verifying the dynamic impact of monetary policy to option-implied expectations. The consensus in literature is that expansionary monetary policy is related to increased subsequent stock returns. One strand of the literature, starting with Thorbecke (1997), finds a negative relationship between monetary policy changes and subsequent stock returns (Thorbecke, 1997; Patelis,1997; Kuttner, 2001; Goto and Valkanov, 2002; Rigobon and Sack, 2004; Bernanke and Kuttner, 2005; D'Amico and Farka, 2011; Lucca and Moench, 2015; Gorodnichenko and Weber, 2016). Moreover, another line of research examines the impact of monetary policy decisions on stock market uncertainty (Clements, 2007; D'Amico and Farka, 2011; Rosa, 2011; Vähämaa and Äijö, 2011; Gospodinov and Jamali, 2012; Jiang et al., 2012; Bekaert et al., 2013; Fernandez-Perez et al., 2017; Du et al., 2018), on risk aversion (Adrian and Shin, 2008; Bekaert et al., 2013; Ioannidou et al., 2015) and on jump tail risk (Hattori et al., 2016; Beckmeyer et al., 2019). Moreover, another strand of the macro-finance literature investigates the links between the monetary policy stance and the risk-taking behaviour of the financial institutions and investors (risk-taking channel of monetary policy) (Adrian and Shin, 2008; Borio and Zhu, 2012; Bekaert et al., 2013; Angeloni et al., 2015). For instance, Bekaert et al. (2013) that empirically examine the impact of monetary policy on stock market uncertainty (proxied by the VIX index) and risk-aversion (proxied by the Variance Risk Premium). In this thesis, my scope is different, since I examine the impact of monetary policy to option-implied expectations. My proxy for equity investors' expectations is the model-free version of option-implied moments (a model-free version of risk-neutral distribution). Many researchers use option-implied moments in their analysis, since option-implied information is inherently forward-looking and reflects investors' beliefs under the risk-neutral measure about the upcoming evolution of the underlying equities prices (Bates, 1991; Jackwerth and Rubinstein, 1996; Bakshi et al., 1997). Whilst the effects of the monetary policy on option-implied volatility of the stocks returns (implied volatility is used as a proxy of uncertainty) have been examined extensively in the prior literature, considerably less attention has been given to the impact of monetary policy on higher moments of the distribution of option prices[1]. In my analysis, I examine the effect of monetary policy stance to option-implied skewness and kurtosis, due to the rich

[1] There are only a few studies that investigate the impact of monetary policy shocks on higher moments of the returns distribution. For example, Hattori et al. (2016) and Beckmeyer et al. (2019) that identify the impact of monetary policy on option-implied kurtosis as a measure of jump tail risk are two examples of the relevant literature.

information set that the higher moments of RND contain about the investors' expectations and risk aversion (Rubinstein, 1973; and Kraus and Litzenberger, 1976, 1983; Bakshi et al., 2003), as well as their predictive information content about the subsequent path of stock returns (Bali et al., 2013; Conrad et al., 2013; Bali et al., 2019). I find that expansionary U.S. monetary policy shocks have a persistently positive effect on higher order option-implied moments of U.S. equity prices.

In more detail, I examine the responsiveness of the long-term and short-term investors' option-implied expectations to monetary policy shocks. Interestingly, I find that long-term expectations are more severely affected by monetary policy shocks when compared with the short-term ones, implicitly rejecting the "long-run money neutrality" for the U.S. equity options market[2]. Notwithstanding the seminal paper of Lucas (1972) and the theoretical framework that he set up; many relevant studies find empirical results that are not in line with the "long-run money neutrality" (Hanson and Stein, 2015; Kontonikas and Zekaite, 2018; Nakamura and Steinsson, 2018). For example, Kontonikas and Zekaite (2018) use a VAR specification and they find that monetary policy influences inflation expectations in the long-term horizon. Additionally, Hanson and Stein (2015) identify a stronger impact of monetary policy shocks on long-term real interest rates that is at odds with standard Keynesian theory. They attribute this phenomenon to "yield-oriented" investors, namely, they assume that increased trading volume on long-term yield bonds taking place when Fed's chair announces changes on short-term interest rates because investors need to readjust the portfolios positions.

[2] Lucas (1972) in his Nobel-awarded work entitled "Expectations and Neutrality of money", uses a simple example of an open economy to explain how the response of the real output of an economy is neutral to monetary policy decisions in the long-end. He assumes that economic agents receive information about real and monetary disturbances only via changes in the prices, and therefore their subsequent "hedging behavior" to the price shifts during the following period, results in the well-known "long-run money neutrality". Since then, New Keynesian macro-models presume that monetary policy can influence real variables only in the short-term horizon in which goods prices cannot readjust to policy shocks, and therefore inflation expectations are neutral to monetary policy shocks in the long-term horizon.

Despite the significant results of the relevant studies, Hanson and Stein (2015) emphasize that "none of our evidence directly refutes the long-run non-neutrality hypothesis that policy is somehow able to move expected real rates far out into future". Similarly, I am not arguing directly against the long-run non-neutrality hypothesis, but I find empirical evidence that challenge the empirical implication of the hypothesis on investors' ex-ante expectations regarding the long-term horizon.

Chapter 2

Methodology

2.1 Macroeconomic and stock market data

For the estimation of realized variance and jump tail risk, I use high-frequency (5-minute) observations for the S&P 500 index for the period between January 1990 and December 2017. I additionally use 5-minute price observations of the 500 stocks that comprise the S&P500 stock market index for the period from November 2002 to December 2017.[3] In the 3rd chapter of my thesis, I consider the latent macroeconomic uncertainty measure of Jurado et al. (2015), as predictor of stock market volatility and price jumps. More specifically, I include the Macroeconomic Uncertainty variables which quantify the time-varying unpredictability of future macroeconomic outcomes for the next 1-month (MU1), the next 3-month (MU3) and the next 12-month period respectively. The MU1, MU3 and MU12 variables have all monthly frequency and they have been estimated as the squared forecast error of a large-scale Factor Augmented VAR (FAVAR) model on future economic activity (for more details, see equation 1.4)[4]. The aggregation of individual uncertainty of various U.S. economic indicators is the Jurado et al. (2015) measure of latent Macroeconomic Uncertainty (MU).

Furthermore, I obtain daily data for the U.S.-Treasury Bill rates, U.S.-government bonds from the FRED database, in order to estimate the realized variance of the slope and the level of the term structure of interest rates that are going to be used as predictors of stock market volatility, in the 4th chapter of my thesis.

[3] The intraday stock market prices for the S&P500 index and its constituents are obtained from Pi Trading.

[4] The Jurado et al. (2015) uncertainty measures for 1-month, 3-month and 12-month horizon ahead, are downloaded from their website: https://www.sydneyludvigson.com/data-and-appendixes

Additionally, for the estimation of the option-implied moments, I obtain my time series data of the S&P 500 index option prices from the IVY OptionMetrics database. The available daily time series data for the option prices covers the period from 4/1/1996 till 30/6/2019. In my analysis I include a wide spectrum of maturities of the option contracts. Specifically, I use option contracts with 1,2,3,4,5,6,9 and 12 months maturity.

The dataset of the measures of monetary policy stance that are used in my analysis, specifically the fed fund target rate (FFR), the real interest rate (RIR) that is the Fed funds rate target minus the CPI annual inflation rate, the growth rate of the monetary aggregate M1 (M1growth) and the Taylor rule rate (TRD), are obtained from the FRED database. The frequency of the measures of monetary policy stance are monthly except the TRD which is a quarterly time series.

Finally, in my analysis I include many macroeconomic and commodity price series in order to evaluate the robustness of my empirical results. In my analysis, I include the U.S. Economic Policy Uncertainty (EPU) measure of Baker et al. (2016) and its component which measures uncertainty about U.S. monetary policy (Monetary Policy Uncertainty (MPU) index).[5] I also use monthly time series for the Baa default spread (the monthly spread between Moody's Baa corporate bond and the 10-year constant maturity U.S. Treasury Bond yield) which also covers the January 1990 till December 2017 period. The Baa default spread (Defspr) time series is downloaded from FRED database. The monthly VIX index data cover the period from January 1990 till December 2017 and are downloaded from Datastream. Also, the monthly time series data regarding the Consumers price index (CPI), Producers price index (PPI) and

[5] the Economic Policy Uncertainty measures can be found on the EPU and MPU website at: http://www.policyuncertainty.com. Both of uncertainty measures are constructed using articles that meet some pre-specified criteria. The criteria as terms that are related with factors which drive economic uncertainty (flags). For example, one flag is the term "economic". The difference between EPU and MPU is that last-mentioned estimates based on some extra flags that are related to monetary policy. More details are available in the mentioned website and their paper, Baker et al. (2016).

Unemployment rate of U.S (UNEMP) from FRED database. Finally, the data for the daily prices for crude oil nearby futures contracts and the monthly data for the Industrial Production Index (IPI) have been also downloaded from Datastream. Finally, the high frequency data for crude oil futures were obtained from Tick Data.

2.2 Realized Variance and jump tail risk estimation

The time series of realized volatilities[6] is estimated as in Andersen et al. (2001) by calculating the sum of squared 5-minute logarithmic returns filtered through an MA(1) process[7] as shown in **below :**

$$RV_t = \sum_{i=1}^{n} r_i^2 \tag{2.2}$$

where $r_i = \log\,(p_i/p_{i-1})$, with p denoting the price series and i the number of intraday observations in each period[8].

To construct the time series that captures stock price variation due to jumps (JV_t), I 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:

[6] I used this method in order to estimate both the realized volatilities of equities prices and the realized volatilities of crude oil futures prices.
[7] Following Ebens (1999) and Andersen et al. (2001) methodology, I used a moving average filtering in order to reduce the microstructure noise that is observed because of high-frequency data.
[8] The prices are obtained at the end on each time interval i.

$$JV_t = RV_t - RBV_t \tag{2.3}$$

with

$$RBV_t = \mu_1^{-2} \sum_{i=2}^{n} |r_i||r_{i-1}| \tag{2.4}$$

where $\mu_1 = \sqrt{2/\pi}$ and p, i are defined as previously. I 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)[9].

2.3 Volatility of the term structure of interest rates

Following the empirical approach of Estrella and Hardouvelis (1991), I estimate the daily slope (term spread) of the term structure of interest rates as the difference between the daily 10-year U.S.-government bond yield and the 3-month U.S.-Treasury Bill rate. The volatility of the slope of the term structure (SLOPE_RV) is then estimated as the variance of the daily term spread for each monthly period. The average yield is estimated as the daily mean of the 3-month, 6-month, 1 year, 2 year, 3 year, 5 year and 10 year U.S. government bond yield. I compute the variance of the level of the term structure (LEVELRV) as the Realized Variance of the average daily government bond yield across maturities. All the term structure variance series are multiplied by 252 in order to be annualized.

[9] Andersen et al. (2007) show that skip versions of various estimators possess statistical properties superior to those computed using adjacent returns. The ‘‘skip-q” bi-power variation estimator is defined as $\mathrm{RBV}_{q,t} = \mu_1^{-2} \sum_{i=q+2}^{n} |r_i| \left|r_{i-1-q}\right|$ with μ_1, r and n defined as previously. The usual RBV estimator is obtained when q = 0. As noted by Patton and Sheppard (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).”

2.4 The option-implied risk neutral density of the U.S. equity market

Equity prices contain investors' probability assessments about the future price distribution of the underlying stock price. For example, the price of a call option with a strike price K reveals the assessment by equity investors of the probability that the underlying stock price will be larger than K. Consequently, the prices of options contracts which are written on the same stock and have the same maturity date but different strike prices, can reveal an assessment (by option writers) of the probability distribution of the underlying equity price. Hence the prices of observable equity futures options contracts can be used to infer the unobservable option-implied distribution of the underlying equity (or equity index). In this paper I estimate the option-implied distribution of S&P500 index option prices by applying the tool of risk neutral valuation which goes back to contingent claim valuation and Arrow-Debreu securities. (See Debreu, 1959; Arrow, 1964)[10].

Risk neutral valuation is used extensively in mathematical finance as an easier way to price securities. The idea of risk neutral valuation is that any security can be reconstructed (replicated) as a weighted average of a set of primary (or Arrow- Debreu) securities, whose prices can be inferred from prices of securities observed in the market. The price of the security can then be derived as the same weighted average of the prices of the primary securities. The risk neutral measure consists of the rescaled prices of the primary securities, which then look like probabilities.

The underlying economics behind risk neutrality, is that, unlike the real world, an artificial risk neutral world discounts all future events using the same risk-free rate r as

[10] A contingent claim is a security whose price depends on the future state of nature. In this respect, the option contract is a characteristic example of a contingent claim since the price of the option depends on the price of the 'underlying asset' written on the option at some future point in time.

the uniquely defined discount factor. In an artificial risk neutral world, the expected returns are not affected by the risk preferences of investors, and consequently, no risk premia exist. The risk neutral pricing measure Q is practically useful because of its uniqueness. In the real world (or under the physical pricing measure P), I need many different discount factors to price different risky assets, while in the risk neutral world I use the risk-free rate as the unique discount factor for all the different risky assets. Hull (2009) indicates the practical usefulness of the risk neutral measure Q by stating that "when I move from a risk neutral world to a risk averse (real) world, two things happen: The expected growth rate in the stock price changes and the discount rate that must be used for any payoffs from the derivatives also changes. It happens that these two changes always offset each other exactly." Moreover, Cox and Ross (1976) and Breeden and Litzenberger (1978) show that option contracts can be priced independently of investors' risk preferences, as if, investors are risk neutral.

2.5 Variance, skewness and kurtosis of the option-implied distribution

The shape of the risk neutral distribution reveals significant information regarding the expectations of market participants and it is measured by estimating the moments of the distribution. The option-implied moments are useful because they quantify investors' expectations about future volatility and tail risk. For example, Han (2008) shows that the model-free risk neutral skewness which is backed-out from S&P 500 equity options, is associated with a bullish (bearish) equity market, while Jiang and Tian (2005) show that the model-free risk neutral variance subsumes all the information contained in the Black and Scholes (1973) option-implied volatility and in the past realized volatility of the SP500 stock market index[11]. In this section I present the analytical methodology for the estimation of the higher order moments of the option-implied risk neutral distribution of equity markets. More specifically, I estimate the variance, the skewness and the kurtosis of the risk neutral distribution. I compute the model-free option-implied variance, skewness and kurtosis using the method of Bakshi, Kapadia and Madan (2003). The analytical formulas for option-implied variance *(IV)*, option-implied skewness *(IS)* and option-implied kurtosis *(IK)* are given below:

$$IV = E_t{}^Q(R^2) - [E_t{}^Q(R)]^2 \tag{2.5}$$

$$IS = \frac{E_t{}^Q(R^3) - 3E_t{}^Q(R)E_t{}^Q(R^2) + 2[E_t{}^Q(R)]^3}{IV^{\frac{3}{2}}} \tag{2.6}$$

$$IK = \frac{E_t{}^Q(R^4) - 4E_t{}^Q(R)E_t{}^Q(R^3) + 6E_t{}^Q(R)E_t{}^Q(R^2) - 3[E_t{}^Q(R)]^4}{IV^2} \tag{2.7}$$

In the Equations (2.5), (2.6) and (2.7) above,$E_t{}^Q(R)$ is the conditional risk neutral expected return of the S&P500 equity index. Consequently, $E_t{}^Q(R^2)$,$E_t{}^Q(R^3)$and $E_t{}^Q(R^4)$ represent the conditional risk neutral quadratic, cubic and quartic returns respectively. Bakhsi, Kapadia and Madan (2003) prove that quadratic, cubic and quartic expected risk neutral returns are continuous functions of out of the money call and put option prices. In accordance with Bakshi, Kapadia and Madan (2003), I define the "*Quad*", "*Cubic*" and *"Quart"* contracts as follows[12]:

[11] The term 'model-free' stems from the fact that, while for example in the Black & Scholes model the underlying asset price is assumed to follow a log-normal distribution, I do not assume any specific stochastic process for the underlying stock price dynamics.

[12] If I define with R the logarithmic returns of the underlying asset with price S_t [R =ln((S_{t+1}/ln(S_t))], then a *Quad* (or volatility) contract is a theoretical contract with risk neutral quadratic expected return-payoff $E_t{}^Q(R^2)$, a *Cubic* contract is a contract with risk neutral cubic expected return-payoff $E_t{}^Q(R^3)$ and a Quart contract is a contract with quartic expected return-payoff $E_t{}^Q(R^4)$.

$$Quad \equiv e^{-r(T-t)} E_t{}^Q (R^2) \qquad (2.8)$$

$$Cubic \equiv e^{-r(T-t)} E_t{}^Q (R^3) \qquad (2.9)$$

$$Quart \equiv e^{-r(T-t)} E_t{}^Q (R^4) \qquad (2.10)$$

In Equations (2.8), (2.9) and (2.10), r is the risk-free interest rate[13]), t is the trading date, $T$is the expiration date and consequently $T - t$ defines time till maturity. If I substitute the "*Quad*", "*Cubic*"and *"Quart"* expressions given in Equations (2.8), (2.9) and (2.10) into Equations (2.5), (2.6) and (2.7), I get the model free version of option-implied variance *(IV)*, option-implied skewness *(IS)* and option-implied kurtosis *(IK)* given below:

$$IV = e^{r(T-t)} Quad - [E_t{}^Q (R)]^2 \qquad (2.11)$$

$$IS = \frac{e^{r(T-t)} Cubic - 3E_t{}^Q (R) e^{r(T-t)} Quad + 2[E_t{}^Q (R)]^3}{IV^{3/2}} \qquad (2.12)$$

$$IK = \frac{e^{r(T-t)} Quart - 4E_t{}^Q (R) e^{r(T-t)} Cubic + 6E_t{}^Q (R) e^{r(T-t)} Quad - 3[E_t{}^Q (R)]^4}{IV^2} \qquad (2.13)$$

Furthermore, Bakhsi, Kapadia and Madan (2003) show that under the risk-neutral pricing measure Q, the *Quad*, *Cubic* and *Quart* contracts can be expressed as continuous functions of out-of-the-money European calls $C(t, T, K)$ and out-of-the-money European puts $P(t, T, K)$:

[13] In the estimation process, the risk-free rate is the interest rate with the same maturity as the estimated option-implied moment. For example, when I estimate the option-implied moments of 90-days maturity, I use the 3-month U.S. Treasury bill rate.

$$Quad = \int_F^\infty \frac{2\left(1-ln\left[\frac{K}{F}\right]\right)}{K^2} C(t,T,K)dK + \int_0^F \frac{2\left(1+ln\left[\frac{F}{K}\right]\right)}{K^2} P(t,T,K)dK \tag{2.14}$$

$$Cubic = \int_F^\infty \frac{6\,ln\left(\frac{K}{F}\right)-3\,ln\left(\frac{K}{F}\right)^2}{K^2} C(t,T,K)dK - \int_0^F \frac{6\,ln\left(\frac{F}{K}\right)+3\,ln\left(\frac{F}{K}\right)^2}{K^2} P(t,T,K)dK \tag{2.15}$$

$$Quart = \int_F^\infty \frac{12\,ln\left(\frac{K}{F}\right)^2-4\,ln\left(\frac{K}{F}\right)^3}{K^2} C(t,T,K)dK - \int_0^F \frac{12\,ln\left(\frac{F}{K}\right)^2+4\,ln\left(\frac{F}{K}\right)^3}{K^2} P(t,T,K)dK \tag{2.16}$$

K is the strike price of the option contract, $F$is the price of the underlying futures contract, t is the trading date and $T$is the expiration date of the option contract. In addition, Bakhsi, Kapadia and Madan (2003) prove that the expected (conditional on information at time t, risk-neutral returns $E_t^Q(R)$ can be approximated by the following expression:

$$E_t{}^Q(R) = e^{r(T-t)} - 1 - \frac{e^{r(T-t)}}{2} Quad - \frac{e^{r(T-t)}}{6} Cubic \tag{2.17}$$

Knowing the analytical forms of *Quad*, *Cubic* and *Quart* contracts from Equations (2.14), (2.15) and (2.16), and the approximating quantity of conditional risk neutral expected returns $E_t^Q(R)$ from Equation (2.17), I compute by using numerical integration the model free option-implied moments given in Equations (2.11), (2.12) and (2.13).

To compute the option-implied risk neutral moments and the tail risk measure I first match for each day and each maturity, the maturity of the option with the maturity of the corresponding futures to construct the correct mapping between options and underlying futures contracts. To avoid measurement errors, I eliminate deep out-of-the-money and deep in-the money call options. Similarly, with Figlewski (2008) and Neumann and Skiadopoulos (2013), the interpolation is done on an option-implied-volatility – delta space. I construct a fine grid of 1000 delta points with a band ranging between 10% and 90%, for each day and maturity considered. The interpolation is done by fitting a cubic smoothing spline on the grid of deltas and I require a minimum of 4 observations per day and maturity in order to perform the interpolation. The interpolation is performed over the domain of put deltas (Δput) and once the interpolation is fitted, I calculate the corresponding call delta (Δcall) counterpart as Δcall = 1 + Δput. Once this is done, I translate the deltas into their corresponding moneyness. Therefore, when I translate the deltas in moneyness I get a grid of 1000 option-implied volatilities as a function of moneyness. Using the Black (1976) formula for equities option prices, I convert these 1000 option-implied volatilities into option prices. I choose out-of-the-money put options with moneyness level smaller than 100% (K/F <1), and out-of-the-money call options with moneyness level larger than 100% (K/F >1). I use numerical trapezoidal integration to compute the *Quad*, *Cubic* and *Quart* contracts in (2.14), (2.15) and (2.16). I then use the prices of *Quad*, *Cubic and* Quart contracts to compute IS and IV and IK in (2.11), (2.12) and (2.13) for each trading day and each maturity. I construct risk neutral variance (IV), risk neutral skewness (IS) and risk neutral kurtosis (IK) by using linear interpolation, for all the available maturities.

2.6 Term structure of risk-neutral moments

In my analysis, I calculate the risk-neutral moments (option-implied moments) for a wide spectrum of maturities as I mention in the previous subsection. My purpose is to use this wide spectrum of the estimated option-implied moments in order to construct the term structure of option-implied moments, similatly to the term structure of interest rates. I follow this approach, because the term structure of option-implied moments will provide a rich information set about the varying response of the risk neutral density of contracts with different maturities to monetary policy shocks. In details, I calculate 4 components of the term structure of option-implied moments, the term spread, the level, the short-end and the long-end component. The term spread (of each option-implied moment) is calculated, as the difference of the 365 days maturity and the 30 days maturity of the corresponding option-implied moment (for example, the term spread of option-implied skewness is the difference between the 365-days maturity option-implied skewness and the 30-days maturity option-implied skewness). Additionally, I calculate the level, the short term and long-term components as the average of all the estimated option-implied moments for each maturity, as the average of the 1,2- and 3-months option-implied moments and the average of 6,9- and 12-months option-implied moments, respectively. In the following sections of my thesis, for brevity I will use the terms option-implied skewness or option-implied kurtosis to correspond to the level of option-implied skewness or kurtosis. Similarly, I am going to use the terms short-end and long-end option-implied skewness(kurtosis), to correspond to the short-end and long-end components of the term structure of option-implied skewness(kurtosis). Finally, I use the abbreviations IV, IS and IK to refer to option-implied variance, option-implied skewness and option-implied kurtosis respectively.

Chapter 3

Financial market risk and macroeconomic uncertainty

3.1 Introduction

In this chapter I contribute to the literature by empirically examining the incremental predictive power of latent macroeconomic and financial 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 option-implied volatility (Canina and Figlewski, 1993; Engle and Susmel, 1993; Fleming et al., 1995 Christensen and Prabhala, 1998; Andersen et al., 2007; Corsi, 2009; Bekaert and Hoerova, 2014). 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). Schmeling (2009) shows 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. Schwert (1989) uses the Shiller's pricing formula, in an effort to explain the channels that variation in macroeconomic variables (and specifically the interest rates) affect stock market volatility. Motivated by the recent empirical findings that show the significant impact of macroeconomic news releases and monetary policy uncertainty on stock market volatility (Pastor and Veronesi, 2012; Asgharian and Hou, 2013; Corradi et al., 2013; Engle et al., 2013; Conrad and Loch, 2015; Liu and Zhang, 2015;Amengual and Xiu, 2018; Kaminska and Roberts-Sklar, 2018), I investigate the role of unobservable (latent) macroeconomic uncertainty which captures the unforecastable (by economic agents) variations in key macroeconomic and financial indicators[14]. I follow the theoretical approach of Schwert (1989) in order to show the way that macroeconomic uncertainty affects stock market volatility.

Without loss of generality, I assume that the sum of expected discounted cash flows is equal to the actual sum of discounted cash flows to investors plus the forecast error ε_t about future cash flows being made by stock market participants. In general, different assumptions can be made about the distributional properties of the forecast error ε_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 independent and identically 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 (Shiller,

[14] The unobservable measure of uncertainty captures the time variation in the degree of unpredictability of the U.S. macroeconomy and financial markets. Thus, the macroeconomic and financial uncertainty is defined as the squared forecast error when forecasting the time variation in macroeconomic and financial indicators. For more details see Jurado et al. (2015).

1981; Baker and Wurgler , 2006; Baker and Wurgler, 2007; Schmeling, 2009; Baker et al., 2012[15]). Without a loss of generality, I assume that the variance of the stock prices is the summary of the variance of the actual sum of discounted cash flows to investors plus the variance of the forecast error ε_t. My hypothesis is that the latent macroeconomic uncertainty measure proposed by Jurado et al. (2015), which captures the unforecastable (by economic agents) variations in key macroeconomic indicators, is a sound proxy of the variance of the forecast error ε_t.

My empirical findings show that the latent macroeconomic measure of Jurado et al. (2015) (JLN henceforth) are statistically significant predictors of the realized variance and of intraday returns of the SP500 and its constituents. When I decompose the realized variance of equity returns into its continuous and discontinuous parts, I find that a large part of the time variation in equity price discontinuities (or jumps) is explained by the latent macroeconomic uncertainty. A rise in the MU is associated with an increase in both stock market volatility, as well as its jump component. More specifically, my forecasting regressions show that the JNL macroeconomic uncertainty is a strong predicting factor of the volatility and jump tail risk of equities (they enter significantly in forecasting regressions on volatility and jumps of the SP500 and its constituents).

My results indicate that the latent uncertainty measures outperform popular observable uncertainty proxies like Monetary Policy Uncertainty (MPU) and Economic Policy Uncertainty (EPU). More importantly, the JLN uncertainty measures outperform both the VIX and lagged RV for volatility and jump tail risk predictions of the aggregate U.S. equity market, as well as individual securities.

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[15] 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).

When I examine the sectoral decomposition of the SP500, I find that latent macroeconomic uncertainty (MU henceforth) has a high impact on most sectors of the U.S. economy (with the exception of the Technology and Healthcare sectors), with the highest impact detected on the volatility and price jumps of financial firms. It appears that MU also captures the idiosyncratic (or firm level) volatility risk. Splitting my sample to before and after the 2007 financial crisis periods reveals that the high performance of the MU may be driven by the tighter linkages between macroeconomic uncertainty and financial market risk in the post-crisis era: at the stock level MU does not perform well for most sectors in the pre-crisis period[16]. The only notable exception is the Oil&Gas industry, where MU also performed well at the pre-crisis sample. This is an interesting result, as it further exemplifies the tight link between the oil market and the U.S. macroeconomy detected in the relevant literature (see, for example, Guo and Kliesen, 2005; Elder and Serletis, 2010; Elder, 2018).

The results presented in the chapter suggest that the MU contain significant predictive information on U.S. stock market volatility (RV) and jumps (JV) and absorb the information content of uncertainty proxies based on macroeconomic news. 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), I show instead that the key driver of stock market price 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[17]. My findings are broadly in line with those of Rangel (2011)

[16] The predictive power of MU significantly increases during the post-2007 crisis period at the aggregate market level as well.

[17] 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 U.S. 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 significantly affected by the changes in the macroeconomic environment and market expectations in response to macroeconomic news releases.

who finds that the surprise component of macroeconomic announcements (and not the scheduled announcements of macroeconomic news) has significant impact on stock market jumps and jump intensities.

3.2 Descriptive statistics

In this section I present some descriptive statistics of my time series variables. **Table 3.1** below shows the descriptive statistics and **Table 3.2** shows the correlation matrix of the used explanatory variables.

Table 3.1. Descriptive statistics

	MU1	MU3	MU12	RV	JV	VIX	EPU	MPU	Defspr
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

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

Table 3.2. Correlation matrix

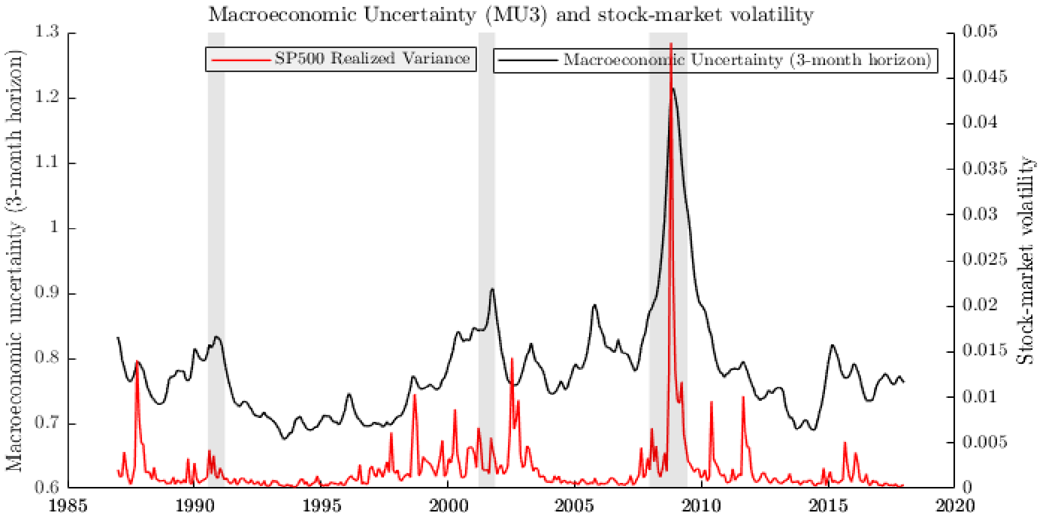
	MU1	MU3	MU12	RV	JV	VIX	EPU	MPU	Defspr
MU1	1.000								
MU3	0.980	1.000							
MU12	0.980	0.990	1.000						
RV	0.570	0.580	0.570	1.000					
JV	0.070	0.070	0.090	0.420	1.000				
VIX	0.620	0.630	0.640	0.790	0.540	1.000			
EPU	0.330	0.320	0.290	0.320	0.090	0.430	1.000		
MPU	0.190	0.180	0.200	0.300	0.410	0.430	0.510	1.000	
Defspr	0.660	0.660	0.640	0.550	0.170	0.660	0.620	0.230	1.000

From **Table 3.1** I observe that the standard deviation of MU series is much smaller compared to observable uncertainty proxies like EPU and MPU. Additionally, the MU series are positively skewed and platykurtic. Moreover, the correlation matrix shown in **Table 3.2** reports low values for the correlations between the explanatory variables used in the empirical analysis. **Figures 3.1** and **3.2** below show the synchronous time series variation of the MU, the VIX index and the RV and JV respectively.

Figure 3.1. Latent macroeconomic uncertainty, the VIX index, stock market volatility and stock market price jumps variation

The panel A include the plots the time series of MU3 and RV while the panel B show the time series of VIX and RV.

Panel A



Panel B

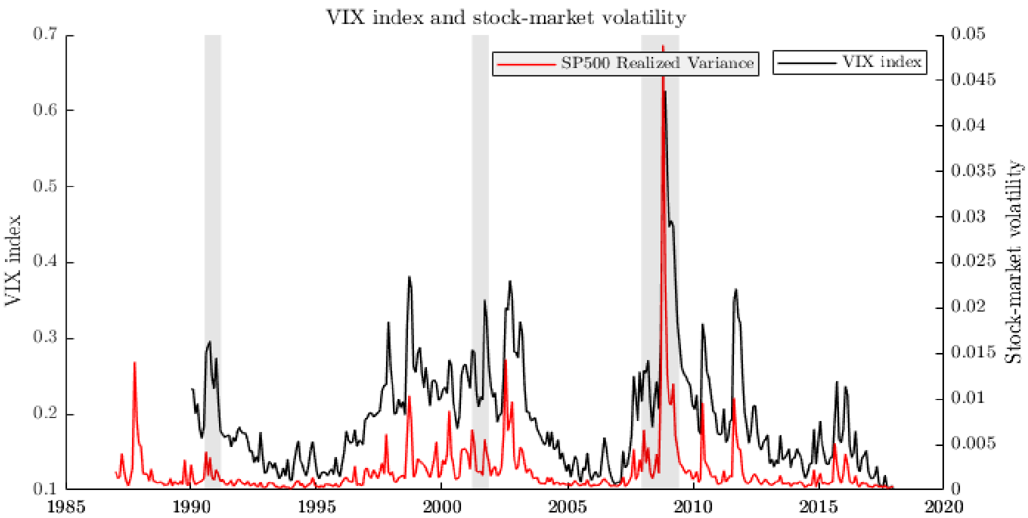
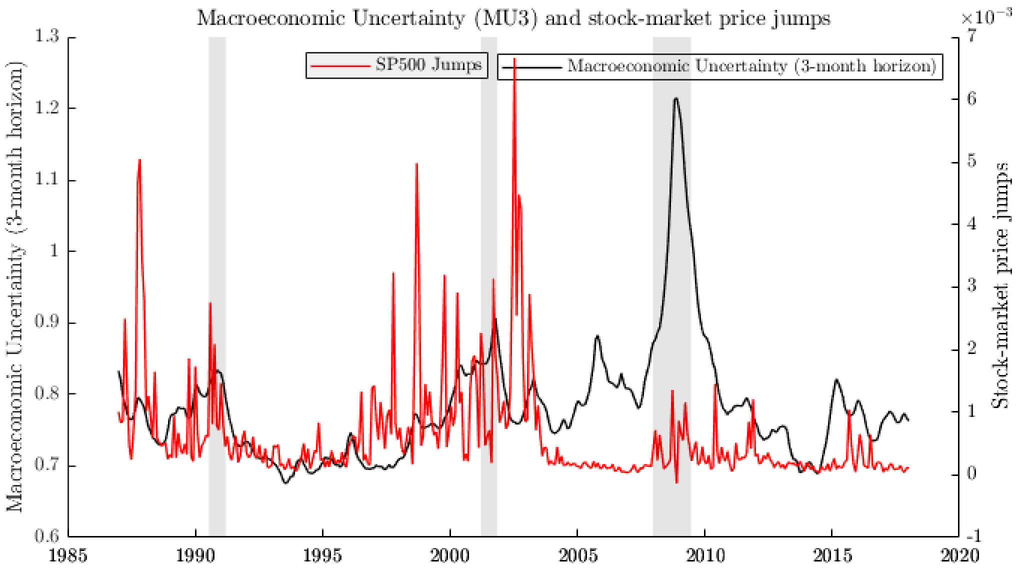


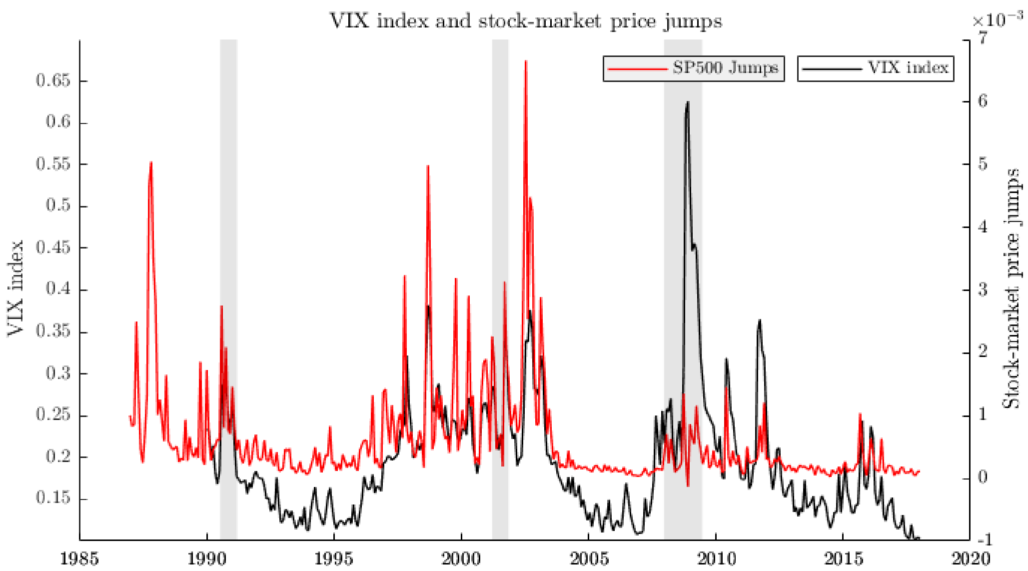
Figure 3.2. Latent macroeconomic uncertainty, VIX index and stock market price jumps

The panel A include the plots the time series of MU3 and JV while the panel B show the time series of VIX and JV.

Panel A



Panel B



I observe from **Figure 3.1** that RV significantly rises after large macroeconomic uncertainty episodes. Moreover, the large volatility spike in the crisis of 2008 was not captured by VIX since VIX increased only as an overreaction of investors in response to the 2008 credit crisis[18]. On the other hand, the MU has increased many months prior

[18] The VIX rose in value after the large 2008 volatility spike. A similar argument is made by Bates (1991) for the 1987 financial crisis.

to the large 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. On the other hand, **Figure 3.2** shows that high levels of the MU index are not frequently associated with increased JV.

3.3 Predictive regression models for stock market volatility and jump variation

I estimate a set of bivariate and multiple regression models on the RV and the JV of the intra-day returns of S&P500 equity index. I, therefore, estimate bivariate OLS forecasting regressions in which I use the MU(k) latent uncertainty as the only predictor of SP500RV. The bivariate time-series predicting regression model is given in **Equation (3.4)** below:

$$RV_t = b_0 + b_1 MU(k)_{t-k-1} + \varepsilon_t \tag{3.4}$$

Where MU(k) is the latent macroeconomic uncertainty with k-month ahead forecast horizon. Since the MU(k) is the squared forecast error of a multivariate dynamic factor model on U.S. economic activity having k-month forecast 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 on my forecasting regression models, I include one more lag on the MU(k) variable so that it can be available to the forecaster in real time when predicting the stock market volatility[19]. Motivated by the results on the literature on equity volatility and jump tail risk forecasting which identifies the VIX index (Canina and Figlewski, 1993; Fleming et al., 1995; among others), the lagged RV (Corsi, 2009; Bekaert and Hoerova, 2014; among others), Economic Policy Uncertainty (Antonakakis et al., 2013; Liu and Zhang, 2015; among others) and monetary policy uncertainty (Bernanke and Kuttner, 2005; Bekaert et al., 2013; Kaminska and Roberts-Sklar, 2018; among others) as strong predictor of stock market volatility, I 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. I 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). My baseline regression model is presented in **Equation (3.5)** below:

$$JV_t = b_0 + b_1 MU(k)_{t-k-1} + \varepsilon_t \tag{3.5}$$

I additionally estimate identical bivariate regression models on JV using the VIX, the lagged RV, EPU and MPU instead of the MU(k).

I present the results of my forecasting regression models on the JV and the RV of SP500 returns. The regression results of my bivariate regression models on RV and JV respectively are shown in **Tables 3.3** and **3.4** below.

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

Table 3.3. Predicting RV for the full period (Jan 1990- Dec 2017)

This table show the output of the bivariate predictive regressions on stock market volatility The corresponding forecast horizons are 1-month, 3-months, and 12-months ahead. The panel A to E show the estimation output of the predicting model when MU, VIX, RV, EPU and MPU is used as explanatory variable respectively.

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	0.001	0.71	0.008**	2.31	3.0

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	0.001*	1.73	6.8
3m	0.001**	2.08	0.001	0.98	0.4
12m	0.003***	3.76	-0.001	-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	0.001**	2.34	5.7
3m	0.001***	5.49	0.001	1.40	0.3
12m	0.001***	5.23	0.001	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 3.4. Predicting JV for the full time period (Jan 1990- Dec 2017)

This table show the output of the bivariate predictive regressions on stock market price jump variation. The corresponding forecast horizons are 1-month, 3-months, and 12-months ahead. The panel A to E show the estimation output of the predicting model when MU, VIX, JV, EPU and MPU is used as explanatory variable respectively.

Panel A

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.001	0.88	0.001	0.95	0.2
3m	0.001	0.82	0.001	0.73	0.1
12m	-0.001	-0.11	0.001	0.57	0.2

Panel B

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.001	-1.08	0.004***	2.68	17.9
3m	-0.001	-0.06	0.003***	2.94	7.9
12m	0.001	0.28	0.002*	1.84	5.6

Panel C

$$JV_t = b_0 + b_1 JV_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.001***	6.03	0.640***	10.72	40.9
3m	0.001***	5.57	0.377***	5.07	14.2
12m	0.001***	6.37	0.260**	2.50	8.2

Panel D

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.001***	2.97	0.001	0.44	0.1
3m	0.001***	3.83	-0.001	-1.33	0.6
12m	0.001***	4.08	-0.001	-1.39	1.2

Panel E

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

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.001**	2.12	0.001***	3.54	9.2
3m	0.001***	4.36	0.001**	2.03	0.9
12m	0.001***	2.90	0.001	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.

The results presented in **Table 3.3** shows that the MU(k) produces statistically significant slope estimates in predictive regressions the monthly RV. My analysis shows that rising macroeconomic uncertainty is associated with rising volatility in the U.S. equity market. More specifically, I find that the MU(k) enters significantly into predicting regressions of stock market volatility for both short and long-term forecast horizons ranging from 1 up to 12 months. For example, when running predicting regressions using the MU1, MU3 and MU12 as predictors of RV, I report positive and statistically significant coefficients for the MU series and R^2 values of 23.2%, 14.9% and 3.5% for 1-month, 3-months and 12-months forecast horizon respectively. The results presented in **Table 3.4** show that the MU outperforms the VIX for medium and long-term volatility forecasts. For example, when using the VIX as the only predictor RV, I get an R^2=11% for 3-month forecast horizon and R^2=3% for a twelve-month horizon, while the respective R^2 values for the univariate regression models having the MU(k) as predictor are 14.9% and 3.5%[20]. My bivariate regression analysis also indicates that the latent macroeconomic uncertainty explains a larger part of time variation of stock market volatility than other popular uncertainty proxies like the EPU and monetary policy uncertainty (MPU). The results of **Table 3.4** which report the regression results on JUMPS indicate that the MU fails to provide significant forecasts regarding the discontinuous (jump) component of stock market volatility.

Following the recent literature on the role of the 2007 Great Recession to the time varying macro-finance linkages (Hubrich and Tetlow, 2015; Caldara et al., 2016; Prieto et al., 2016), I estimate the same bivariate forecasting regression models (presented in

[20] The VIX index corresponds to the constant (interpolated) 30-day S&P500 index option-implied volatility. Therefore, it is not totally fair to compare a measure that corresponds to investors' expectations about the following month, with MU3 and MU12 that correspond to uncertainty of 3 and 12 months respectively. So, I also estimate the option-implied volatilities (IV) which are backed-out from 3-month and 12-month maturity S&P500 option contracts, by including the respective IV series with constant (interpolated) 90-day and 360-day maturity. I estimate the same bivariate and multiple regression models using the interpolated IV of 90-day and 360-day maturity and the results are identical. The results are available upon request.

Equations (3.1)-(3.2)) in two subsamples, one before the occurrence of the financial crisis occurred (Jan/1990-Dec/2006), and one after recent financial crisis (Jan/2007-Dec/2017). **Tables 3.5** and **3.6** report the regression results of my bivariate predicting models on RV and JV respectively for the dataset covering the post-2007 crisis period.

Table 3.5. Predicting RV during the post-crisis period (Jan 2007- Dec 2017 period)

This table show the output of the bivariate predictive regressions on stock market volatility, during the post-crisis period. The corresponding forecast horizons are 1-month, 3-months, and 12-months ahead. The panel A to E show the estimation output of the predicting model when MU, VIX, RV, EPU and MPU is used as explanatory variable respectively.

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	0.001	1.65	8.4
3m	0.002	1.25	0.001	0.35	0.1
12m	0.005*	1.86	-0.000	-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	0.001	1.62	16.6
3m	0.002***	4.78	0.001*	1.98	2.9
12m	0.002***	3.35	0.001*	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 3.6. Predicting JV during the post-crisis period (Jan 2007- Dec 2017)

This table show the output of the bivariate predictive regressions on stock market price jumps variation, during the post-crisis period. The corresponding forecast horizons are 1-month, 3-months, and 12-months ahead. The panel A to E show the estimation output of the predicting model when MU, VIX, RV, EPU and MPU is used as explanatory variable respectively.

Panel A

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

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

Panel B

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

Horizon (k)	b_0	t-stat(b_0)	b_1	t-stat(b_1)	% adj. R^2
1m	0.000	0.37	0.001***	3.70	19.0
3m	0.000	0.56	0.001***	7.45	19.3
12m	0.001***	3.47	0.001	1.26	1.2

Panel C

$$JV_t = b_0 + b_1 JV_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	t-stat(b_0)	b_1	t-stat(b_1)	% adj. R^2
1m	0.001***	5.23	0.267***	3.08	7.2
3m	0.001***	5.43	0.249**	2.39	6.2
12m	0.001***	7.51	0.028	0.32	0.1

Panel D

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

Horizon (k)	b_0	t-stat(b_0)	b_1	t-stat(b_1)	% adj. R^2
1m	0.001	0.67	0.001**	2.15	5.3
3m	0.001	0.27	0.001**	2.32	7.3
12m	0.001***	3.32	-0.001	-0.47	0.2

Panel E

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

Horizon (k)	b_0	t-stat(b_0)	b_1	t-stat(b_1)	% adj. R^2
1m	0.001***	4.15	0.001*	1.67	2.5
3m	0.001***	2.63	0.001**	2.37	8.2
12m	0.001***	3.59	0.001	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.

The subsample (post-crisis) regression results shown in **Table 3.5** 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 predictive horizon regressions and from 14.9% to 19.5% for 3-month predictive horizon when I run the regressions using the post-crisis dataset. Additionally, the EPU and MPU also have higher predictive power in the post-crisis especially in a mid-term and long-term predictions[21]. 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, my findings regarding the role of financial crisis on the linkages between macro-uncertainty and stock market volatility is broadly in line and provides further empirical insights on the findings on the macro-finance literature according to which the macro-financial linkages have exponentially increased after the 2007 U.S. credit crash (Hubrich and Tetlow, 2015; Abbate et al., 2016; Caldara et al., 2016; Prieto et al., 2016; Ellington et al., 2017).

[21] I additionally perform the same regression analysis for the pre-crisis period (Jan 1987-Dec 2006). For brevity I do not report the bivariate regression results in this chapter but they can be found in the Appendix.

The post-crisis regression results on JV (reported in **Table 3.6**) show that the predictive power of MU on the price jumps in U.S. stock market increases significantly in the post-crisis period. More specifically, when regressing MU on the JV, I get positive and statistically significant coefficients for MU for forecast horizon ranging from 1 up to 12 months. The estimated R^2 values equal to 18.1% and 18.0% for the bivariate forecasting models with 1 and 3 monthsJV forecast horizon respectively. My regression analysis shows for the first time that the latent macroeconomic uncertainty has similar to the VIX predictive power on JV. Moreover, the predictive power of MPU on JV also increases during the post-crisis period. Overall, my 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; Lahaye et al., 2011; Miao et al., 2014). I contribute to this literature by showing that the predictive power of latent uncertainty (or rising unpredictability) has a significant explanatory power on stock market price jumps and that the predictive power of macro-uncertainty increases exponentially in the post-crisis era.

Additionally, I estimate a multiple regression model in order to ensure that the predictive power of the MU remain statistically significant after the inclusion of other well-known predictors of stock market volatility and price jumps.

The baseline multiple predicting regression model on RV is given in **Equation (3.6)** below:

$$RV_t = b_0 + b_1 MUk_{t-k-1} + b_2 RV_{t-k} + b_3 JV_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 Defspr_{t-k} + \varepsilon_t \qquad (3.6)$$

I run an identical forecasting regression model when predicting JV of SP500 returns.

Hereby, I present the results of my multiple regression models (**Equation 3.3**). **Tables 3.7-3.10** present estimation results of multiple predicting regressions for stock market volatility and jumps for the full sample, the pre-crisis and the post-crisis subsample respectively.

Table 3.7. Predicting RV using multiple regressions

This table show the output of the multiple predictive regressions on stock market volatility. The corresponding forecast horizons are 1-month, 3-months, and 12-months ahead.

$$RV_t = b_0 + b_1 MUk_{t-k-1} + b_2 RV_{t-k} + b_3 JV_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 Defspr_{t-k} + \varepsilon_t$$

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.	0.0117	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)
JV	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.	0.001	-0.001*	-0.001 **
	t-stat	(0.54)	(-1.89)	(-2.31)
MPU	Coef.	0.001	-0.001	0.001
	t-stat	(0.28)	(-0.31)	(1.34)
Defspr	Coef.	-0.028	0.026	-0.04
	t-stat	(-0.59)	(0.67)	(-0.69)
% adj. R^2		44.3	18.6	9.2

*, ** 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 3.8. Predicting JV -using multiple regressions

This table show the output of the multiple predictive regressions on stock market price jump variation. The corresponding forecast horizons are 1-month, 3-months, and 12-months ahead.

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

Horizon (k)		*k=1*	*k=3*	*k=12*
Const	Coef.	0.001*	0.001*	0.001
	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)
JV	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.	-0.001***	-0.001**	-0.001***
	t-stat	(-2.90)	(-2.05)	(-2.90)
MPU	Coef.	0.001	-0.001	0.001
	t-stat	(0.88)	(-0.49)	(1.09)
Defspr	Coef.	0.005	0.004	-0.003
	t-stat	(0.43)	(0.28)	(-0.25)
% adj. R2		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 3.9. Predicting RV using multiple regressions – stability of coefficients before and after the financial crisis

This table show the output of the multiple predictive regressions on stock market volatility. The corresponding forecast horizons are 1-month, 3-months, and 12-months ahead. The panel A and B show the multiple regression results during the pre-crisis period and post-crisis period respectively.

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

Panel A: pre-crisis period (Jan/1990-Dec/2006)

Horizon (k)		*k=1*	*k=3*	*k=12*
Const	Coef.	-0.001	-0.001	-0.001
	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)
JV	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.	-0.001	-0.001*	-0.001***
	t-stat	(-1.34)	(-1.79)	(-4.53)
MPU	Coef.	-0.001	-0.001	0.001
	t-stat	(-0.29)	(-1.36)	(1.55)
Defspr	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)

Horizon (k)		*k=1*	*k=3*	*k=12*
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)
JV	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.	0.001	-0.001	-0.001**
	t-stat	(0.45)	(-1.03)	(-2.58)
MPU	Coef.	0.001	0.001	0.001***
	t-stat	(1.27)	(1.44)	(2.96)
Defspr	Coef.	-0.031	-0.062	-0.300*
	t-stat	(-0.55)	(-0.8)	(-1.83)
% adj. R^2		57.2	56.6	27.3

*. ** 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 3.10. Predicting JV using multiple regressions – stability of coefficients before and after the financial crisis

This table show the output of the multiple predictive regressions on stock market price jump variation. The corresponding forecast horizons are 1-month, 3-months, and 12-months ahead. The panel A and B show the multiple regression results during the pre-crisis period and post-crisis period respectively

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

Panel A: pre-crisis period (Jan/1990-Dec/2006)

Horizon (k)		*k=1*	*k=3*	*k=12*
Const	Coef.	0.000	0.000	-0.001
	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)
JV	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.	0.000	-0.001	-0.001***
	t-stat	(-0.5)	(-0.94)	(-3.50)
MPU	Coef.	-0.000	-0.001	-0.001***
	t-stat	(-0.56)	(-1.54)	(1.74)
Defspr	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)

Horizon (k)		*k=1*	*k=3*	*k=12*
Const	Coef.	-0.001	-0.001**	-0.001*
	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)
JV	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.	-0.001	0.001	0.001**
	t-stat	(-0.42)	(1)	(2.33)
Defspr	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.

The results from multiple regressions over the full sample, the post-crisis and pre-crisis period clearly show that the predictive power of MU on stock market volatility and jumps, while is not statistically significant in the pre-crisis period, it becomes statistically significant and provides incremental predictive power during the post-crisis period. Surprisingly, my results are the first to identify that, while the MU does not have any additive predictive information about the subsequent RV when running the regressions using the pre-crisis data (Jan 1987-Dec 2006) in the 3-month and 12-month forecast horizon, exactly the opposite is the case for the post-crisis regression estimation. Overall, my multiple predictive regressions show that Great Recession has turned the occurrence macroeconomic uncertainty shocks as the most significant indicator and early warning signal of rising volatility and tail risk in the U.S. equity market. My analysis is also the first to show that MU outperforms the VIX for short and long-term volatility and jump tail risk predictions during the recent post-2007 period. My 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 on stock market volatility (Schwert, 1989; Becker et al., 1995; Errunza, and Hogan, 1998; Bomfim, 2003; Paye, 2012), as well as the impact of macroeconomic news surprises on stock market price jumps (Corradi et al., 2013; Engle et al., 2013).

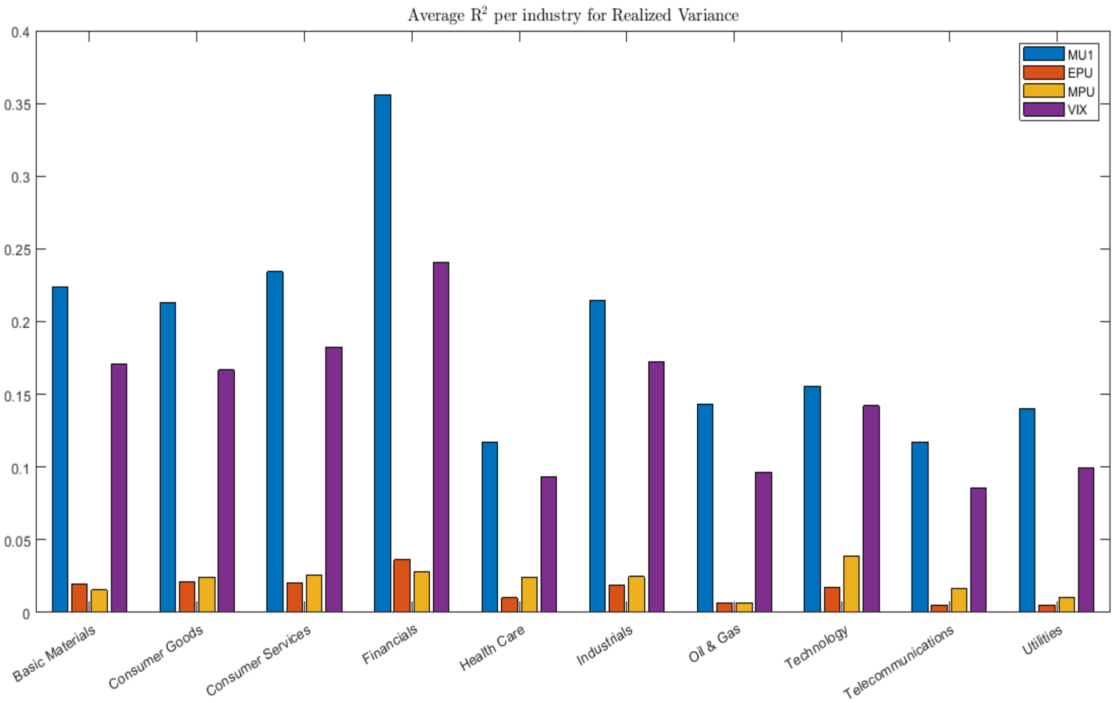
3.4 Predictive regressions for the realized volatility and jump variation of the S&P500 constituents

In this section I present the results from time series regressions on the RV and JV of the constituents of the SP500. This allows us to investigate whether the MU is a common volatility and jump tail risk predictor of the SP500 constituents. In order to better understand my results at the aggregate market level, it may be beneficial to examine the sectoral decomposition of the SP500. To this end, in this section I perform a sectoral (industry-specific) analysis to examine the sectors of the U.S. equity market which are most significantly affected by latent 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 SP500 constituents, I report the average values of adjusted R^2 and t-statistics for the forecasting regressions on the U.S. equities which belong to each sector. I follow ICB industry classification[22], which defines 10 categories: Utilities, Telecommunications, Technology, Oil and Gas, Industrials, Health Care, Financials, Consumer Services, Consumer Goods and Basic Materials. **Figure 3.3** below reports the average adjusted R^2 coefficients and t-statistics when predicting the RV of SP500 constituents having one-month forecast horizon for each of the previously mentioned broad industry categories.

[22] ICB classification data are obtained from Refinitiv DataStream.

Figure 3.3. Average R^2 values and t-statistics per industry for the bivariate regression models on the RV of SP500 constituents. (1-month ahead horizon)

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, 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 forecast 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.



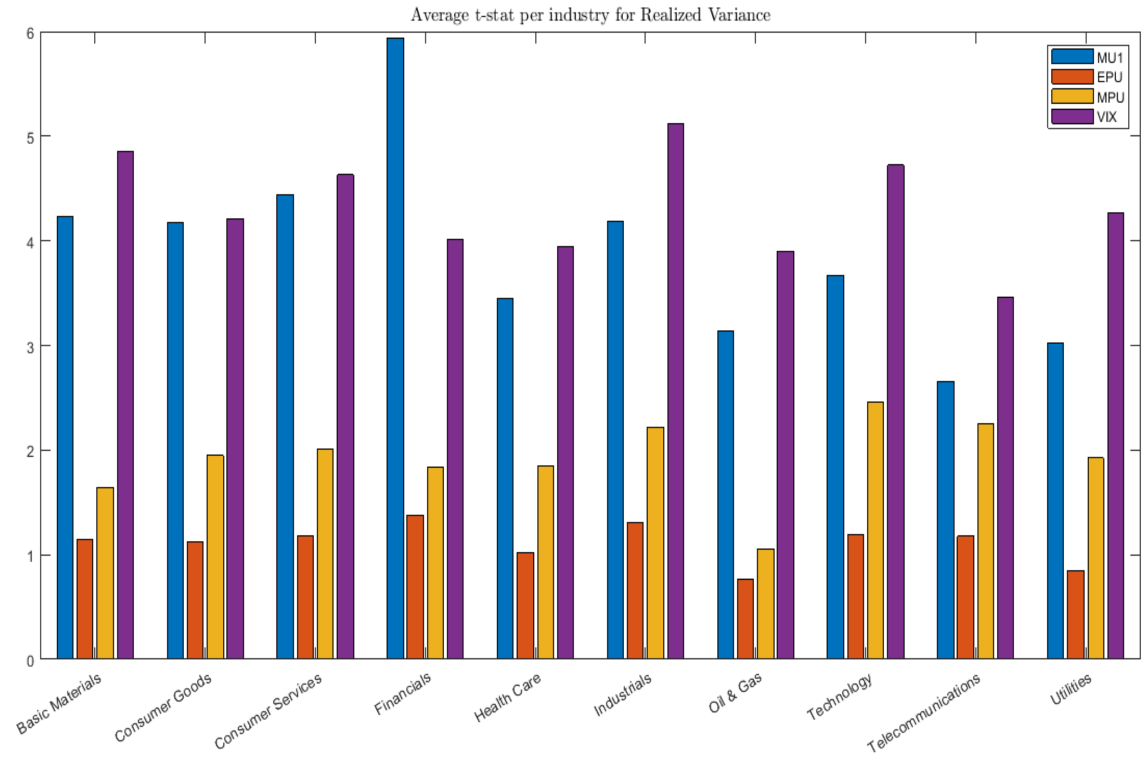
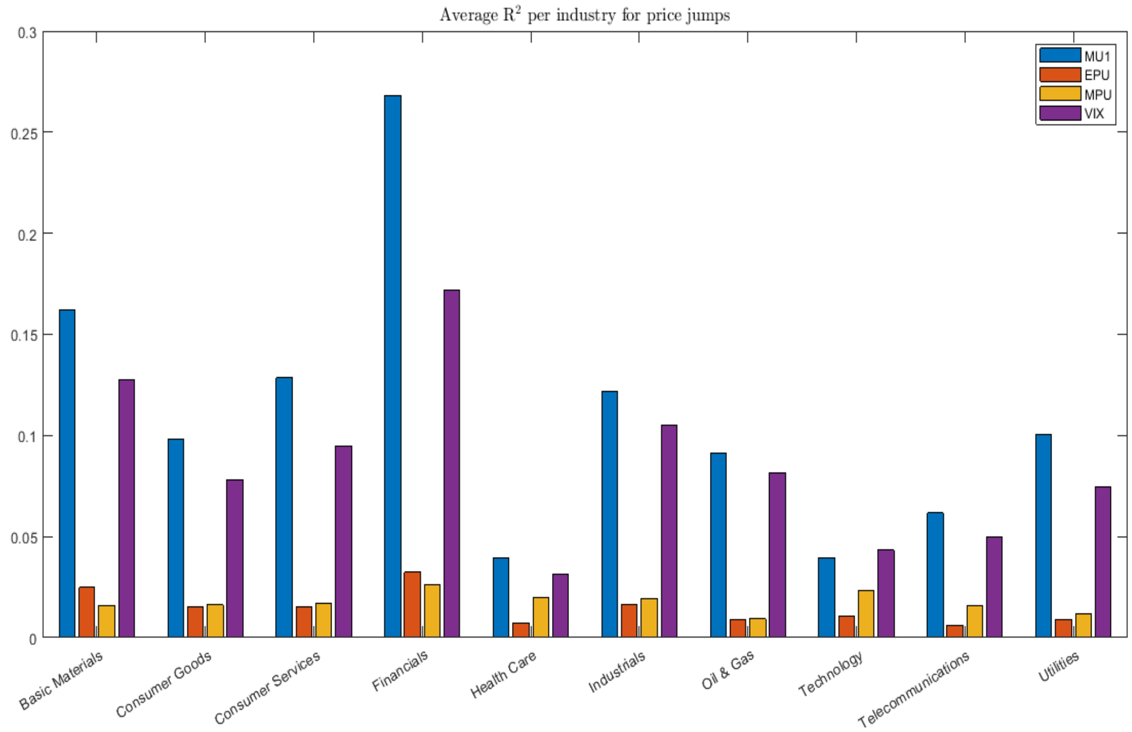


Figure 3.3 clearly shows that the MU measure does not only explain the largest part of time variation in the volatility of S&P500 constituents, but also that this relationship holds for most sectors of the U.S. equity market. More specifically, the average t-statistics show that the estimated coefficients of VIX and MU are statistically significant predictors for the volatility of all sectors of the equity market. On the other hand, the EPU and MPU do not have significant predictive ability stock market for the volatility of the U.S. equity market sectors. Hence, the MU is the only macroeconomic measure which provides robust volatility predictions, not only at the aggregate market level, but also at the sectoral. **Figure 3.3** shows that the average R^2 values for predictive regressions using individual stocks is greater than 20% for half of the sectors in the U.S. stock market and greater than 10% for the rest. This means that the MU alone explains a large part of the time-varying volatility in almost all the sectors in the U.S. stock market. My analysis also shows that the MU outperforms (in terms of explanatory power on the volatility of equity prices) the VIX across all sectors. Hence my analysis reveals that, the MU outperforms the VIX when used for forecasting firm-level (idiosyncratic) equity return volatility risk. One other interesting finding is that the maximum predictive power of the MU occurs for the Financials sector. It appears that the rising volatility in financial stocks is primarily driven by latent macroeconomic and not financial uncertainty shocks (as quantified by the VIX index).

I also perform the same type of bivariate regression models (shown in **Equation (3.2)**) for predicting the JV of the SP500 constituents. I undertake the same analysis by averaging the R^2 values and t-statistics across the 500 bivariate regressions on JV on SP500 constituents using the MU, EPU, MPU and VIX as predictors of jumps in the S&P500 constituents. **Figure 3.4** below reports the average R^2s and t-statistics of the bivariate regressions on the jump tail risk of SP500 constituents.

Figure 3.4. Average R^2 values and t-statistics per sector for bivariate regression models on the JV of SP500 constituents.

This figure shows the average sectoral R^2 values and t-statistics of the univariate regression models on stock market price jumps variation when using the MU1, the VIX index, EPU and MPU as predictors. In more detail, the bar chart shows the average R^2s and t-statistics for the univariate regressions on the price jumps of the stocks which belong to different sectors. The forecast 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.



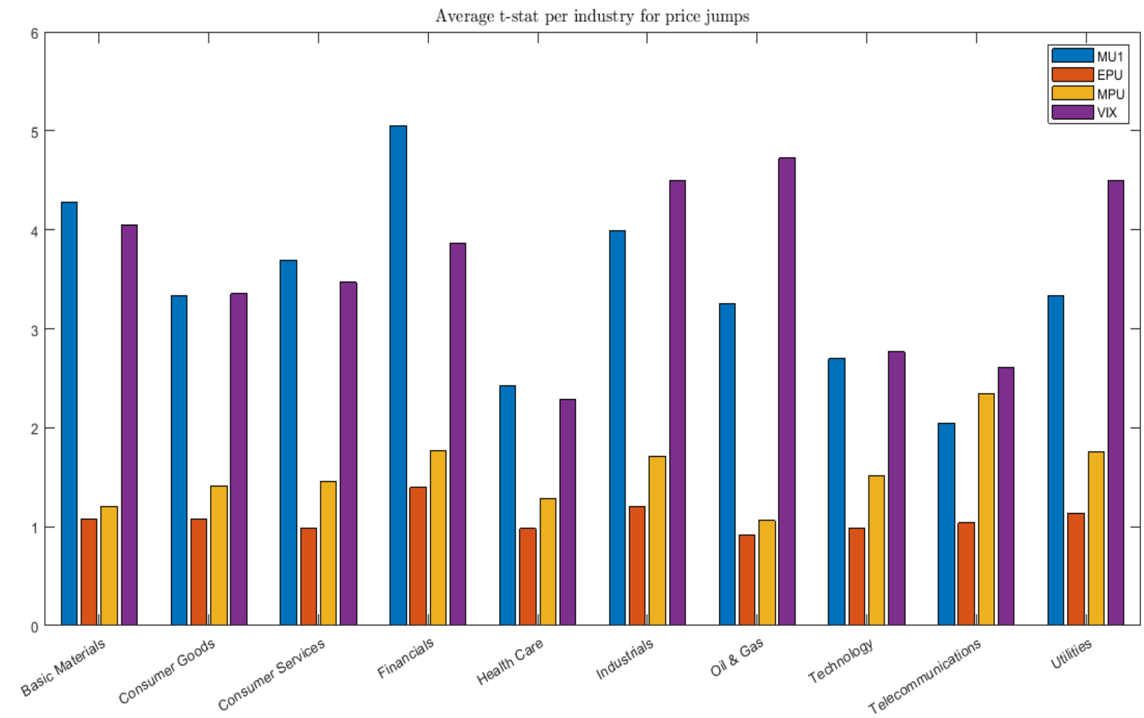


Figure 3.4 shows that the MU explains the largest part of the JV of different stock market sectors when compared to EPU, MPU and the VIX. Interestingly, the MU performs best on stock market price jumps of the financial sector with average adjusted R^2 values of approximately 15.5%. Thus, except forecasting return volatility of the equities which belong to the financial sector, the MU variable has the highest explanatory power when used as a predictor of price jumps of financial and banking stocks. My analysis is the first to show that the instability and turbulence in the U.S. financial services industry (measured as rising market volatility and price jumps in the U.S. 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 U.S. macroeconomy[23]. 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 estimated coefficients shows that on average, the MU coefficient is significant at the 1% level for most sectors except Telecommunications and Health Care sector that is significant at the 5% level.

[23] Since the MU measures the rising degree of unpredictability in the future state of U.S. macroeconomic indicators, then the rising unpredictability in the U.S. macroeconomy predicts, according to our findings, rising market turbulence in the financial services industry.

[24] Our predictive regressions do not necessarily imply causality, but they are initial empirical evidence showing that the MU 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.

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

Following Bekaert et al. (2013), I estimate a multivariate VAR model for stock market volatility (RV) in which I control for latent macroeconomic uncertainty (MU), the VIX index and U.S. Economic Policy Uncertainty (EPU). In this way, I estimate a 4-variable VAR model in which I include as endogenous variables the observable economic uncertainty shocks (VIX, lagged RV and EPU, see Bloom, 2009; Baker et al., 2016) and unobservable (latent) economic uncertainty shocks which are defined as the surprise component (forecast error) of macroeconomic fluctuations (see Jurado et al., 2015; Henzel and Rengel, 2017). In this way, I control for the interaction between various types of observable and unobservable uncertainty and stock market volatility. My reduced-form VAR model is specified as follows:

$$Y_t = A_0 + A_1 Y_{t-1} + \ldots + A_k Y_{t-k} + \varepsilon_t \tag{3.7}$$

The choice of the length of lags of the specified VAR model is based on the optimal-length AIC criterion which suggests the inclusion of two lags in the VAR model ($k=2$)[25]. The ordering of my baseline 4-variable VAR model is shown in **Equation (3.8)** below[26].

$$Y_t = [RV_t \; VIX_t \; EPU_t \; MU1_t] \tag{3.8}$$

---

[25] 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 can be available upon request.

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

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 Scwartz (*SBIC*) optimal-lag length information. The *RV* is the monthly realized variance of the intra-day (5-minute) returns of the S&P 500 stock market index, VIX is the monthly level of the VIX uncertainty index, EPU is logarithm of the monthly economic policy uncertainty index, MU1 is the latent macroeconomic uncertainty having one-month horizon[27]. I base my analysis on the estimated Orthogonalized Impulse Response Functions (OIRFs) using the Cholesky identification method for the orthogonalization of shocks in the VAR model.

Hereby, I present the impact of the dynamic effect of economic uncertainty shocks on stock market volatility and price jumps. I base my analysis on the estimated Orthogonalized Impulse Response Functions (OIRFs) derived by the baseline 4-variable VAR model analytically described in Subsection 2.4. **Figures 3.5**-**3.6** below show the estimated OIRFs of stock market volatility (RV) and jumps (JUMP) to their own innovations and to different types of financial and macroeconomic uncertainty shocks.

[27] In our paper I choose to present the VAR model in which I 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-variable VAR model. These results which provide robustness to our findings, can be found in my Appendix.

Figure 3.5. Orthogonalized Impulse Responses (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 forecast horizon (MU1) shock.The estimated responses are obtained from the baseline 4-variable 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).

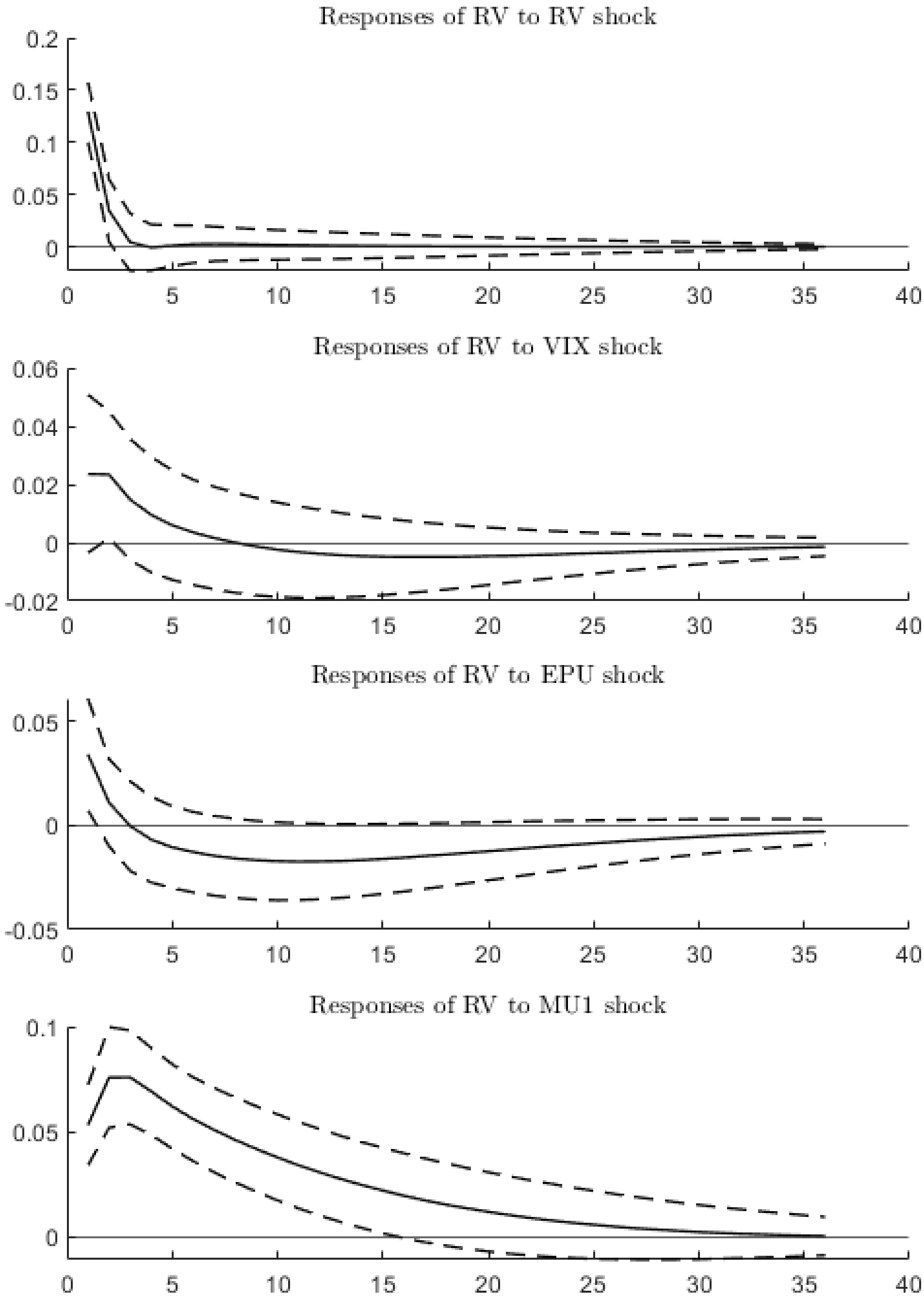
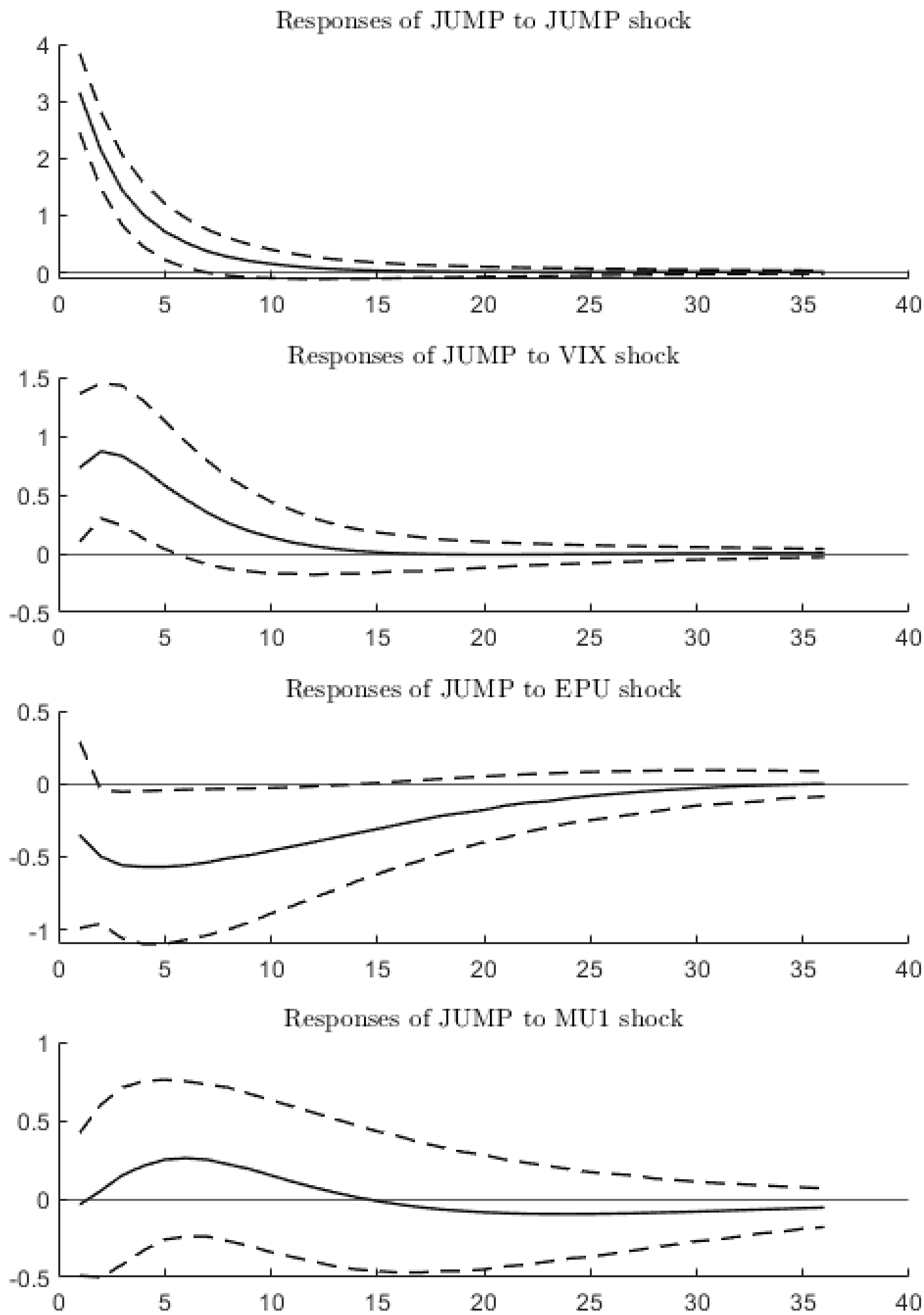


Figure 3.6. Orthogonalized Impulse Responses (OIRFs) of stock market price jumps (JUMP) to uncertainty shocks.

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 forecast horizon (MU1) shock.The estimated responses are obtained from the baseline 4-variable 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).



Several interesting conclusions emerge from observing the results regarding the empirical behavior of OIRFs. **Figure 3.5** 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 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 forecast 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, my 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 with the dynamic effect of VIX and EPU shocks. Interestingly, the MU shocks have a more long-lasting impact even when compared with the response of RV to its own innovations. This is a tremendous finding given the fact that stock market volatility is a highly persistent series (see for example findings on the persistence of equity volatility and volatility clustering, e.g. Chou, 1988; Choudhry, 1996). The estimated OIRFs of **Figure 3.6** 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 U.S. equity market. In order to empirically examine the dynamic effect of economic uncertainty shocks on price jumps in the recent post-recession period, I estimate my 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 3.7** and **3.8.**

Figure 3.7. 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 forecast horizon (MU1) shock.The estimated responses are obtained from the baseline 4-variable 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).

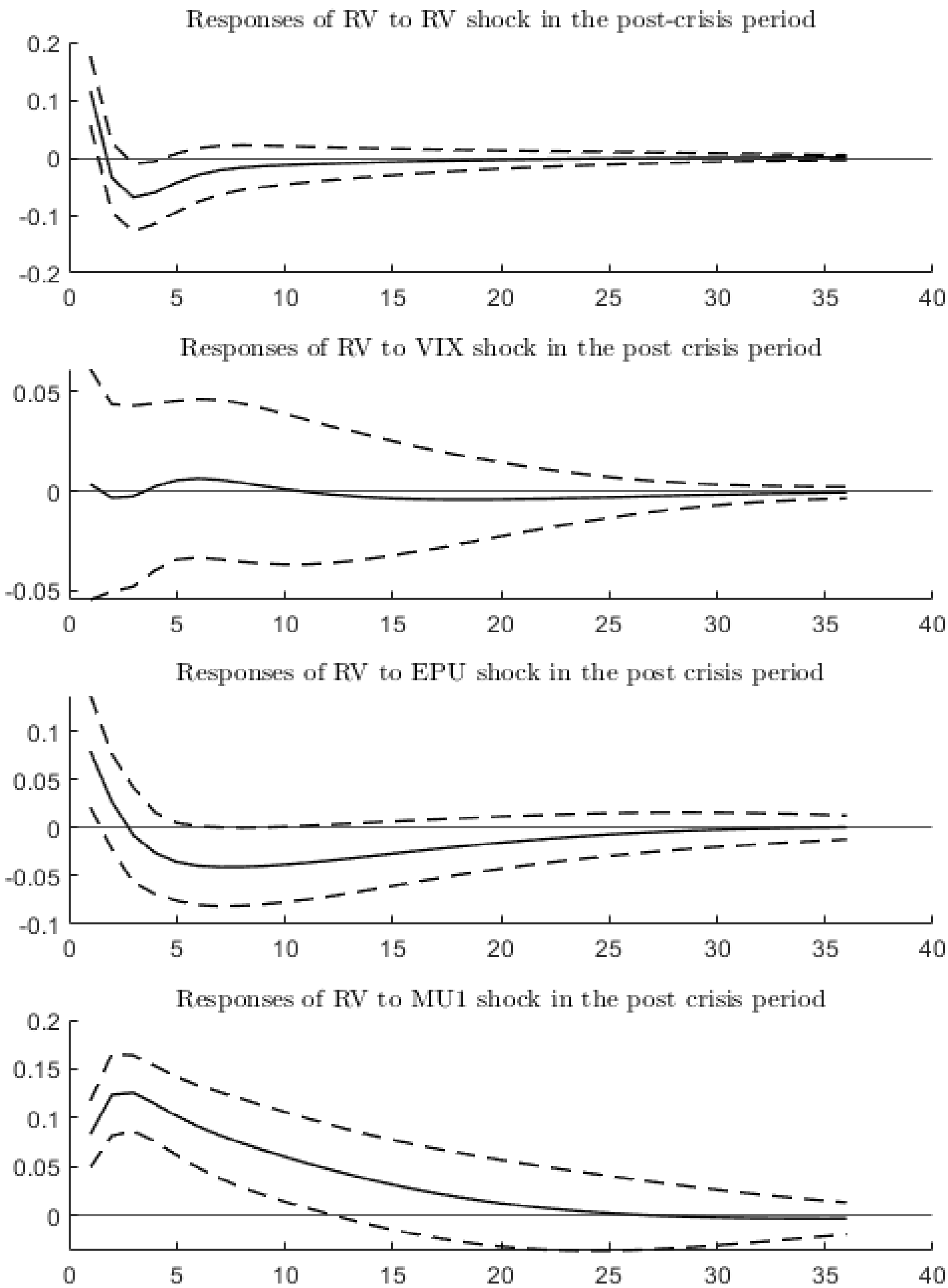
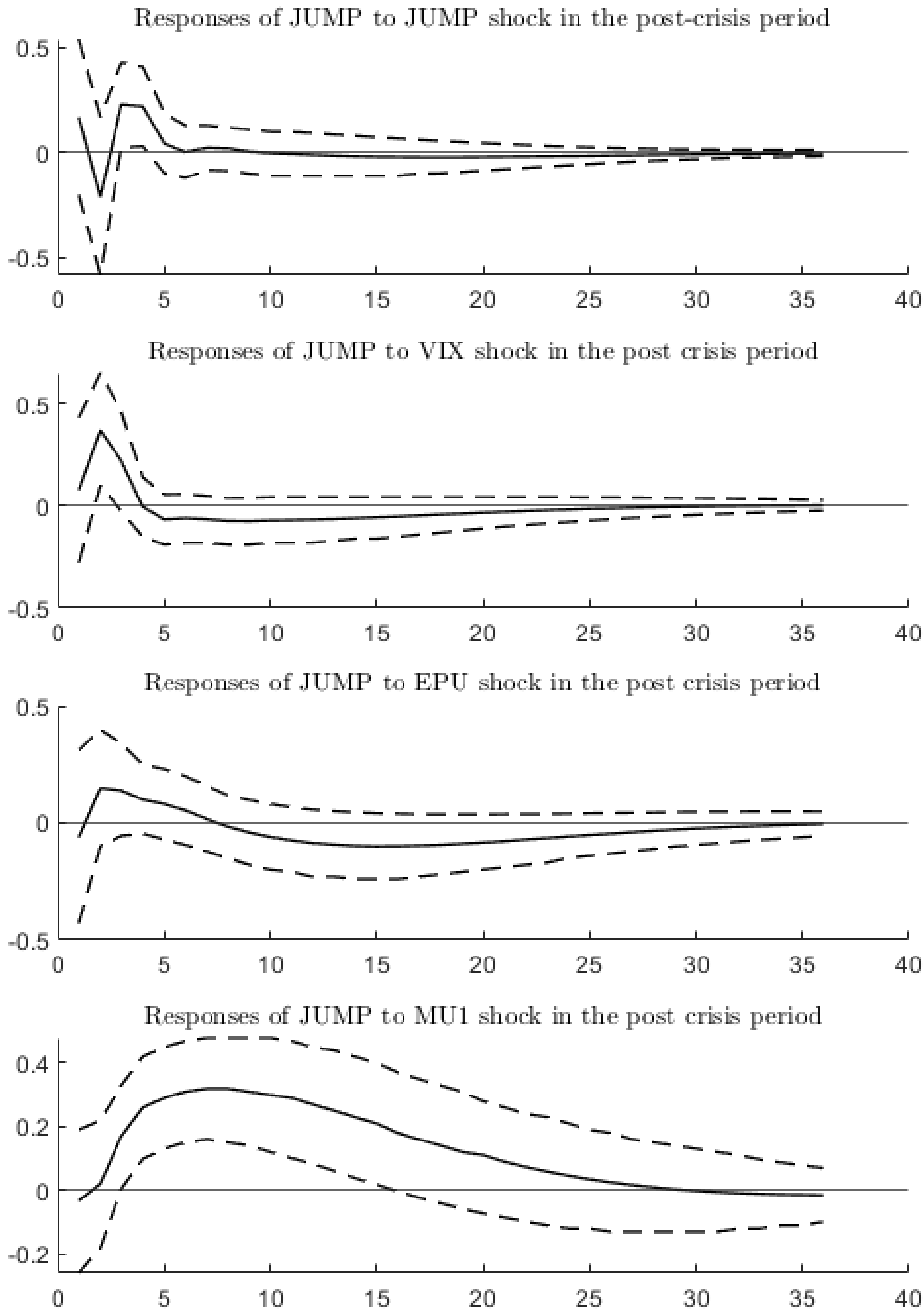


Figure 3.8. Orthogonalized Impulse Response Functions (OIRFs) of stock market price jumps (JUMP) to uncertainty shocks in the post-crisis period.

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-variable 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).



The estimated responses of the price jumps to uncertainty shocks after the U.S. 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 3.7** I observe that the dynamic response of RV to MU shocks has increased in magnitude during the post-crisis period. Moreover, from **Figure 3.8** I 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, my post-crisis VAR estimates show that during the recent post-crisis era, the latent macroeconomic shocks are the most significant types of uncertainty shocks affecting the time varying volatility and jump tail risk in U.S. equity market.

3.6 Conclusions

I find that the latent macroeconomic uncertainty measure of Jurado et al. (2015) is robust predictor of equity market volatility and jumps. My analysis is the first to show that the latent macroeconomic uncertainty outperforms the VIX when forecasting volatility and jump tail risk in U.S. equity market. Moreover, my 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 with the respective effect of VIX shocks and shocks in other popular observable economic uncertainty proxies. Overall, I show that U.S. stock market is heavily impacted by changes in unpredictability of the U.S. macroeconomy, while it is relatively immune to observable (but more predictable) changes in macroeconomic fluctuations. While Jurado et al. (2015) show that latent macroeconomic uncertainty, which captures the time varying unpredictability of U.S. macroeconomy, is mostly correlated with U.S. economic activity, I additionally show that it is the most significant determinant of stock market volatility and price jumps for forecast horizons ranging from one up to twelve months. My findings are in line with those of the relevant literature which show that the surprise component (unexpected macro-shocks) of macroeconomic news announcements is important driver of equity market volatility and price jumps (Bomfim, 2003; Andersen et al., 2007; Rangel, 2011; among others). When forecasting volatility of individual stock market prices, I find that the latent macroeconomic uncertainty is a common volatility and jump tail risk forecasting factor across different sectors of the U.S. stock market. More specifically, the latent uncertainty measure 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 U.S. stocks. Interestingly, the predictive power of the MU measure is significantly higher when forecasting the return volatility of stocks belonging in the financial industry. Lastly, my analysis shows that the predictive power of MU on stock market volatility and price jumps is significantly increased in the post-2007 crisis period. My 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 (Hubrich and Tetlow, 2015; Abbate et al., 2016; Caldara et al., 2016; Prieto et al., 2016; Ellington et al., 2017)

Chapter 4

U.S. Treasury yield curve and stock market volatility

4.1 Introduction

The information content of the term structure of interest rates have been extensively studied by many researchers (Christie, 1982; Hardouvelis, 1987; Schwert, 1989; Fama and French, 1989; Estrella and Hardouvelis, 1991; Hamilton and Lin, 1996; Ang and Piazessi, 2003; Diebold et al., 2005; Diebold et al., 2006; Gürkaynak et al., 2005; Coroneo et al., 2016 amongst others). Concretely, the literature on the term structure of interest rates has shown that the slope of the term structure reveals information about future economic activity (Estrella and Hardouvelis, 1991; Doshi et al., 2018; Cremers et al., 2021) and about the future price path of stock market returns[28] (Campbell, 1986; Chen et al., 1986). For example, the recent findings of Cremers et al. (2021) show that the treasury yield volatility predicts both the growth rate and the volatility of U.S. GDP growth and of other macroeconomic variables like Industrial Production, consumption expenditure and unemployment. Even though these works have shown the structural linkages between the slope of the term-structure of interest rates, economic activity and financial market returns[29], the evidence of the predictive information content of yield curve volatility on stock market volatility remains limited. Motivated by the findings in the literature showing the significant effect of monetary policy and business cycle fluctuations on stock

[28]According to Chen et al. (1986) the "systematic forces that influence returns are those that change discount factors and expected cash flows". Following this kind of empirical approach, Chen et al. (1986) find that the slope of the term structure, the industrial production growth, the default spread and both the expected and unexpected component of inflation are the systematic macroeconomic variables priced in the stock-market.

[29] Recent empirical research shows that stock-market prices are mainly driven by revisions in expected cash flows (Chen et al.,2013). In further support of the results of Chen et al. (2013) and Maio (2013) find that the negative relationship between monetary policy and stock-market "comes from a corresponding negative effect on future expected cash flows". In addition, Patelis (1997) finds that shifts in monetary policy are significant predictors of equity market returns since they affect both the time-variation in expected cash flows and in discount rates.

market volatility, I empirically examine the predictive power in the volatility in the term structure of interest rates on stock market volatility. Specifically, I find that realized variance of the slope of the yield curve (SLOPERV) explains a large part of the time variation in the stock market volatility (RV), at both short-term and long-term forecast horizons (from one to twelve months).

In this chapter, I follow the methodology of Schwert (1989) in order to explain the channels that the volatility of the slope of the yield curve affect stock market volatility. Specifically, I argue that the variance of the stock returns will be related to the variance of the investors' expectations about the future discounted cashflows.

Therefore, I argue that the SLOPERV is related to subsequent stock market volatility through two structurally different channels: the first one is the time variation of the volatility of the discount factors used for the discounting of future payoffs (the dividends and capital gains) of stocks, especially during the Zero-lower bound period that Fed fund rates hits the lower bound. The other, is the risk being present through the increased dispersion of the expectations about the future path of the economy (and consequently, the increased volatility risk in the stock market which under the efficient market hypothesis, must reflect macroeconomic fundamentals). I find that the 'volatility in slope' is the most significant forecasting factor. My findings are in line with those of Estrella and Hardouvelis (1991), since I empirically show that the 'volatility in slope' factor conveys information which is related to economic forces which are different and not related to short-term interest rate volatility and monetary policy uncertainty.

My results suggest that the SLOPERV exhibits stronger predictive power for long-term horizon forecasts than other famous uncertainty measures (like EPU, MPU measures of Baker et al. (2016)) that is widely used as a predictors of stock market volatility. The SLOPERV strongly predicts stock market volatility, that significantly concerns economic agents and policy makers.

My analysis includes multiple regression models, as well as on a VAR specification. Additionally, I estimate the regressions using an in-sample and an out-of-sample framework. The estimated results augment my claim about the SLOPERV predictability on RV. I provide evidence that it is not the variance of the level of the term structure of interest rates (LEVELRV) which provide the most significant information content about the future stock market volatility. On the contrary, the SLOPERV contain the most significant information content about the aggregate stock market volatility. In addition to previous research, I empirically show that the slope of the whole term structure of interest rates (short end and long end interest rates) provides further and conceptually different information content from other known measures of economic policy and monetary policy uncertainty measures.

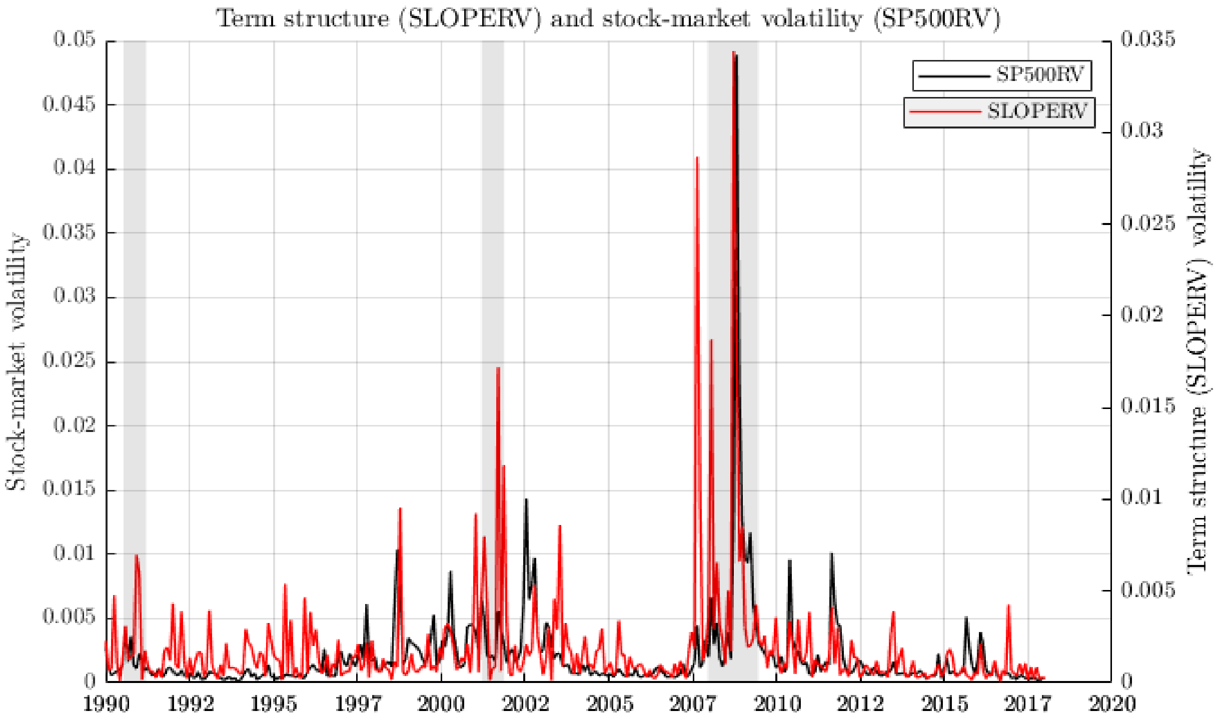
More interestingly, I find that the forecasting power of the SLOPERV and LEVELRV on the stock market volatility, substantially increases during the period after the recent financial crisis of 2007. In details, my empirical results show that during the period after the recent financial crisis, the variation of the term structure of interest rates provide a richer information set about the subsequent stock market volatility. My novel results are partially in line with the output of many relevant studies which identify a time-varying linkage between the term structure of interest rates or monetary policy shocks (measured by changes in short-term interest rates) and the future stock market returns (Kontonikas et al., 2013; Laopodis, 2013; Kiley, 2014; amongst others). Additionally, when I predict the RV of SP500 constituents using the LEVELRV and SLOPERV, I find that both of them explain a larger fraction of the volatility of cyclical and capital-intensive companies, that is in line with a relevant literature which identifies a higher sensitivity of these companies to monetary policy news and interest rates changes (Ehrmann and Fratzscher, 2004; Bernarke and Kuttner, 2005; amongst others).

4.2 Descriptive statistics

Figures 4.1 below, shows the synchronous time series variation of the SLOPERV and the RV of SP500.

Figure 4.1. Term structure volatility (SLOPERV) and stock market volatility (SP500RV).

The shaded areas identify NBER U.S. recessions.



I observe from **Figure 4.1,** that the SLOPERV significantly rises the period before of significant rises in the stock market volatility, or before identified NBER U.S. recessions.

Additionally, I present the descriptive statistics of the explanatory variables. I report some basic descriptive statistics about the variables that are used in my baseline predictive regressions models, as well as in my multiple regression mode. Additionally, I perform a unit root test (using a ADF test) for my explanatory variables, and I present the values of the ADF test alongside with the descriptive statistics. The **Table 4.1** below reports the mentioned descriptive statistics:

Table 4.1. Descriptive statistics

This table shows the descriptive statistics along with the ADF unit root tests for the explanatory variables which I include in the left-hand side of the forecasting regressions. With *, **, and *** I reject the hypothesis of a unit root for 10%, 5% and 1% confidence level respectively. All the time series have monthly frequency and cover the period from January 1990 till December 2017.

	VIX	SLOPE	LN(SLOPERV)	LN(RV)	LN (MPU)	LN (EPU)	IPG	Defspr	LN(OILRV)	LN(LEVELRV)
Mean	0.194	0.018	-8.461	-6.699	4.318	4.627	0.002	0.024	-6.409	-9.325
Median	0.175	0.019	-8.544	-6.819	4.297	4.592	0.002	0.022	-6.571	-9.243
Maximum	0.626	0.037	-4.978	-3.019	6.011	5.502	0.021	0.060	-3.111	-5.856
Minimum	0.101	-0.007	-11.078	-8.693	2.808	4.047	-0.043	0.013	-8.846	-12.855
Std. Dev.	0.076	0.011	0.979	0.922	0.583	0.291	0.006	0.008	1.175	1.187
Skewness	1.971	-0.216	0.477	0.671	0.090	0.408	-1.589	1.609	0.321	-0.122
Kurtosis	9.420	2.080	3.518	3.428	2.666	2.539	11.797	7.536	2.388	2.856

The **Table 4.1** show that most of the variables reject the null hypothesis that they have a unit root. Additionally, I observe that the SLOPERV is positively skewed, exhibiting similar skewness values with the realized variance of S&P 500 index, while the LEVELRV is less positively skewed[30]. Additionally, I report the correlation matrix in the below **Table 4.2:**

[30] I estimate the natural logarithm of all the realized volatility measures (RV, SLOPERV, LEVELRV, OILRV), as well as MPU and EPU measures, following a similar approach with Paye (2012), in order to obtain reliable output of the estimated regressions. Specifically, the OLS regression results are not robust

Table 4.2. Correlation matrix

	Defspr	IPG	LN(LEVELRV)	LN(EPU)	LN(MPU)	LN(OILRV)	LN(RV)	LN(SLOPERV)	SLOPE	VIX
Defspr	1.00									
IPG	-0.43	1.00								
LN(LEVELRV)	-0.05	-0.09	1.00							
LN(EPU)	0.63	-0.23	-0.03	1.00						
LN(MPU)	0.25	-0.22	0.36	0.52	1.00					
LN(OILRV)	0.58	-0.32	-0.29	0.46	-0.04	1.00				
LN(RV)	0.58	-0.22	0.27	0.33	0.38	0.27	1.00			
SLOPERV	0.26	-0.14	0.53	0.21	0.34	0.07	0.48	1.00		
SLOPE	0.34	0.01	0.07	0.45	0.11	0.05	-0.01	0.09	1.00	
VIX	0.66	-0.25	0.25	0.41	0.41	0.24	0.90	0.45	0.06	1.00

Table 4.2 above shows us that the most mostly variables are not strongly correlated. Only the Defspr exhibits correlation values over 55% with a few variables like the EPU and the OILRV. These results are going to be considered in the multivariate analysis in the following sections[31].

4.3 Predicting stock market volatility using the volatility of the yield curve

In this section, I describe the forecasting regression models that I use in my empirical analysis. I estimate a bivariate regression model using only SLOPERV as predictor of RV, as shown in the **equation 4.1** below:

$$LN(RV)_t = b_0 + b_1 LN(SLOPERV)_{t-k} + \varepsilon_t \tag{4.1}$$

when the estimated errors are non-normal and fat-tailed. By estimating the natural logarithm of realized volatility, we obtain a series that is approximately Gaussian, as shown by Andersen et al. (2001).

[31] I additionally test for possibly multicollinearity in my baseline multiple regression models. I estimate a VIF criterion, and the results suggest that there is no multicollinearity problem. The results are available upon request.

In the following **Tables 4.3** and **4.4,** I present the results of my forecasting regression models when using the LEVELRV and SLOPERV as predictors of U.S. stock market volatility. Similarly, with the previous chapter, I split the sample in two subsamples one that covers the period before the recent financial crisis (the pre-crisis period) and one after (the post-crisis period). Specifically, I attempt to find if there is a time-varying relationship amongst the yield curve volatility and stock market volatility motivated by a relevant strand of the literature who identify a time-varying relationship amongst the variation of the interest rates and the stock market returns Kontonikas et al., 2013; Laopodis, 2013; Kiley, 2014; amongst others) and generally a time-varying macro-finance linkages (Hubrich and Tetlow, 2015; Caldara et al., 2016; Prieto et al., 2016) especially during the recent financial crisis of 2007 period, that coincides with the Zero-lower bound period.

Table 4.3. Predicting RV using LEVELRV as predictor

This table shows the results predictive regressions of the U.S. stock market volatility (SP500RV) on the LEVELRV. The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 to December 2017. Panel A reports the regression results for the full dataset (1990-2017), Panel B reports the regression results for the pre-crisis subperiod (Jan 1990 – Dec 2006) and Panel C reports the regression results for the post-crisis sub-period (Jan 2007 – Dec 2017). The estimated bivariate predictive regression model is given below:

$$LN(RV)_t = b_0 + b_1 LN(LEVELRV)_{t-k} + \varepsilon_t$$

Panel A: Full sample (Jan 1990-Dec 2017)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	% R^2
1m	-5.27***	-5.63	0.15*	1.77	3.6
2m	-5.72***	-6.04	0.11	1.23	1.5
3m	-5.60***	-5.57	0.12	1.24	2.0
6m	-5.54***	-5.49	0.13	1.30	2.2
9m	-5.54***	-4.55	0.13	1.07	2.2
12m	-5.52***	-4.52	0.13	1.10	2.3

Panel B: Pre-crisis sample (Jan 1990-Dec 2006)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	% R^2
1m	-6.43***	-8.04	0.04	0.42	-0.3
2m	-7.45***	-8.71	-0.08	-0.89	0.2
3m	-7.44***	-7.72	-0.08	-0.79	0.2
6m	-7.50***	-7.86	-0.08	-0.92	0.3
9m	-7.32***	-6.40	-0.06	-0.53	-0.1
12m	-7.14***	-7.52	-0.04	-0.45	-0.2

Panel C: Post-crisis sample (Jan 2007-Dec 2017)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	% R^2
1m	-3.11***	-2.53	0.36***	3.07	20.2
2m	-3.19***	-2.61	0.35***	3.02	19.3
3m	-2.95***	-2.61	0.37***	3.52	22.2
6m	-2.64***	-2.22	0.40***	3.62	26.0
9m	-2.88***	-1.75	0.38***	2.50	23.1
12m	-3.06***	-2.46	0.36***	3.12	20.9

Table 4.4 . Predicting RV using SLOPERV as predictor

This table shows the results predictive regressions of the U.S. stock market volatility (SP500RV) on the SLOPERV. The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 to December 2017. Panel A reports the regression results for the full dataset (1990-2017), Panel B reports the regression results for the pre-crisis subperiod (Jan 1990 – Dec 2006) and Panel C reports the regression results for the post-crisis sub-period (Jan 2007 – Dec 2017). The estimated bivariate predictive regression model is given below:

$$LN(RV)_t = b_0 + b_1 LN(SLOPERV)_{t-k} + \varepsilon_t$$

Panel A: Full sample (Jan 1990-Dec 2017)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	% R^2
1m	-3.83***	-4.04	0.34***	3.25	12.7
2m	-4.36***	-4.53	0.28***	2.69	8.3
3m	-4.54***	-4.57	0.26**	2.32	6.9
6m	-4.53***	-4.44	0.26**	2.22	6.9
9m	-4.81***	-5.92	0.23**	2.58	5.2
12m	-4.60***	-6.31	0.25***	3.35	6.5

Panel B: Pre-crisis sample (Jan 1990-Dec 2006)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	% R^2
1m	-5.24***	-9.42	0.18***	2.78	2.9
2m	-5.87***	-9.95	0.10	1.59	0.7
3m	-5.98***	-10.98	0.10	1.59	0.4
6m	-6.02***	-10.09	0.09	1.21	0.3
9m	-6.3***	-8.90	0.05	0.72	-0.2
12m	-5.61***	-10.22	0.13***	2.65	1.4

Panel C: Post-crisis sample (Jan 2007-Dec 2017)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	% R^2
1m	-2.21	-1.57	0.52***	3.33	31.8
2m	-2.63**	-2.36	0.47***	3.86	25.8
3m	-2.90	-1.59	0.44***	2.03	22.0
6m	-2.79***	-3.29	0.45***	5.08	23.1
9m	-3.04**	-2.36	0.43***	3.01	20.0
12m	-3.39***	-3.36	0.39***	3.59	16.2

From **Tables 4.3** and **4.4** I observe that the SLOPERV is a statistically significant predictor of stock market volatility for forecast horizon ranging from 1 up to 12 months, while the LEVELRV is not, when I use the full sample. The predicting power of LEVELRV and SLOPERV is significantly increased during the post-crisis (post-2007) period. For example, when I use the post-crisis subsample, the SLOPERV exhibit almost 10-times higher R^2 value when it comes to 1-month ahead RV prediction, compared to the corresponding prediction using the pre-crisis subsample. In addition, the R^2 and t-statistic values of the bivariate regression using the SLOPERV are higher than the corresponding values when LEVELRV is used as explanatory variable of the regression, for almost all the available forecast horizons. Furthermore, I estimate the same bivariate models (equation 4.2), using EPU and MPU indices as independent variables, motivated by a strand of the literature that documented the rich predictive information content about the subsequent stock market volatility of economic policy and monetary policy uncertainty (Antonakakis et al., 2013; Amengual and Xiu, 2018; Kaminska and Roberts-Sklar, 2018; among others). The **Tables 4.5** and **4.6** present the estimated results of the bivariate model (**equation 4.1**), when I use the EPU, MPU indices as predictors of stock market volatility respectively.

Table 4.5. Predicting RV using EPU as predictor

This table shows the results predictive regressions of the U.S. stock market volatility (SP500RV) on the EPU. The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 to December 2017. Panel A reports the regression results for the full dataset (1990-2017), Panel B reports the regression results for the pre-crisis subperiod (Jan 1990 – Dec 2006) and Panel C reports the regression results for the post-crisis sub-period (Jan 2007 – Dec 2017). The estimated bivariate predictive regression model is given below:

$$LN(RV)_t = b_0 + b_1 LN(EPU)_{t-k} + \varepsilon_t$$

Panel A: Full sample (Jan 1990-Dec 2017)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	*%* R^2
1m	-9.96***	-4.84	0.703	1.56	4.66%
2m	-8.902***	-4.74	0.476	1.16	1.97%
3m	-8.156***	-4.85	0.315	0.85	0.69%
6m	-6.709***	-4.25	0.003	0.01	-0.31%
9m	-6.264***	-3.70	-0.094	-0.26	-0.22%
12m	-4.950***	-3.24	-0.379	-1.19	1.14%

Panel B: Pre-crisis sample (Jan 1990-Dec 2006)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	*%* R^2
1m	-9.402***	-4.19	0.588	1.16	1.98%
2m	-7.830***	-3.20	0.240	0.43	-0.09%
3m	-6.835***	-2.82	0.020	0.04	-0.49%
6m	-5.931**	-2.55	-0.181	-0.35	-0.26%
9m	-5.093*	-1.67	-0.366	-0.53	0.46%
12m	-3.036	-1.17	-0.821	-1.40	4.28%

Panel C: Post-crisis sample (Jan 2007-Dec 2017)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	*%* R^2
1m	-11.320***	-4.17	0.977*	1.71	7.73%
2m	-10.152***	-4.69	0.735	1.56	4.01%
3m	-9.289***	-4.60	0.554	1.31	1.94%
6m	-6.219***	-2.90	-0.082	-0.19	-0.75%
9m	-6.019***	-2.85	-0.126	-0.30	-0.69%
12m	-4.891**	-2.26	-0.363	-0.85	0.35%

Table 4.6. . Predicting RV using MPU as predictor This table shows the results predictive regressions of the U.S. stock market volatility (SP500RV) on the MPU. The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 to December 2017. Panel A reports the regression results for the full dataset (1990-2017), Panel B reports the regression results for the pre-crisis subperiod (Jan 1990 – Dec 2006) and Panel C reports the regression results for the post-crisis sub-period (Jan 2007 – Dec 2017). The estimated bivariate predictive regression model is given below:

$$LN(RV)_t = b_0 + b_1 LN(MPU)_{t-k} + \varepsilon_t$$

Panel A: Full sample (Jan 1990-Dec 2017)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	*%* R^2
1m	-8.402***	-13.02	0.394**	2.29	5.87%
2m	-7.888***	-13.99	0.274*	1.76	2.66%
3m	-7.635***	-14.54	0.216*	1.68	1.53%
6m	-7.041***	-16.54	0.080	0.68	-0.06%
9m	-6.892***	-10.07	0.044	0.26	-0.23%
12m	-7.055***	-10.38	0.081	0.47	-0.06%

Panel B: Pre-crisis sample (Jan 1990-Dec 2006)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	*%* R^2
1m	-8.007***	-9.76	0.287	1.53	3.19%
2m	-7.428***	-11.51	0.154	1.03	0.57%
3m	-6.998***	-11.08	0.058	0.40	-0.35%
6m	-6.941***	-12.43	0.044	0.35	-0.41%
9m	-6.616***	-7.68	-0.030	-0.14	-0.46%
12m	-6.509***	-7.81	-0.053	-0.27	-0.37%

Panel C: Post-crisis sample (Jan 2007-Dec 2017)

Horizon (k)	b_0	*t-stat* (b_0)	b_1	*t-stat* (b_1)	*%* R^2
1m	-9.404***	-7.50	0.661**	2.03	12.98%
2m	-8.988***	-7.79	0.562*	1.81	8.87%
3m	-9.003***	-9.65	0.565**	2.33	8.94%
6m	-7.478***	-8.31	0.205	0.90	0.43%
9m	-7.619***	-5.95	0.235	0.70	0.79%
12m	-8.273***	-7.13	0.387	1.25	3.54%

My empirical results suggest that the SLOPERV and LEVELRV are stronger predictors of stock market volatility than both EPU and MPU indices especially during the post-crisis period. In details, when using the SLOPERV as the only predictor of S&P500 index volatility, I get an R^2=12% for 1-month forecast horizon and R^2=6% for a twelve-month horizon, while the respective R^2 values for the univariate regression models having the EPU and MPU as predictors are 4.6%, 1.1% and 5.9% and 0% respectively. Additionally, the estimated coefficients of the regression model that include SLOPERV in the right side, are more statistically significant from the corresponding estimated coefficients when I use EPU and MPU as predictors of stock market volatility. In general, the predictability of all the used variables as predictors of stock market volatility (SLOPERV, LEVELRV, EPU and MPU) is is substantially increased during the period after the recent financial crisis, with a higher rise in the predictability of SLOPERV and LEVELRV compared to the corresponding predictive information content of EPU and MPU.

Furthermore, in order to ensure that the SLOPERV remains a statistically significant predicting factor of stock market volatility when I include other commonly used factors of stock market volatility, I estimate a multiple regression model. More specifically, motivated by the relevant literature that identify the strong predictive information content of lagged realized volatility on subsequent equity market volatility (Andersen et al., 2007; Bekaert and Hoerova, 2014; Corsi, 2009), I include the lagged Realized Variance (RV) as predictors of the realized variance (RV) of the equity index. Notably, there are many empirical papers that investigate the effects of EPU on stock market return or volatility (see, e.g., Antonakakis et al., 2013, Kang and Ratti, 2013, Liu and Zhang, 2015; Amengual and Xiu, 2018; among others), hence, I include the Economic Policy Uncertainty (EPU) in the right-hand side of the predictive regression equation. In addition, following the strand of the literature which shows that monetary policy shocks and FOMC announcements have a significant effect on stock market volatility, and they are also related with subsequent stock-price jumps (Bekaert et al., 2013; Kaminska and Roberts-Sklar, 2018), I use uncertainty about U.S. monetary policy (MPU). Lastly, following the results of the relevant macro-finance literature which show that business cycle variables influence stock-price returns and volatility (Schwert, 1989; Engle and Rangel, 2008; Flannery and Protopapadakis, 2002; Paye, 2012) I include some business cycle variables which are linked with stock market volatility like growth rate of U.S. Industrial Production, the Baa Moody's corporate yield spread[32], the level of the term spread (10-year government bond rate minus the 3-month U.S. Treasury yield) and volatility of the oil price[33]. The baseline multiple regression model on the RV of SP500 is given below:

$$LN(RV_t) = b_0 + b_1 LN(RV_{t-h}) + b_2 TermSpread_{t-h} + b_3 LN(SLOPERV_{t-h}) + b_4 LN(EPU_{t-h}) + b_5 LN(MPU_{t-h}) + b_6 Defspr_{t-h} + b_7 IPG_{t-h} + b_8 LN(OILRV_{t-k}) + \varepsilon_t \quad (4.2)$$

[32] The Baa default spread is the yield spread between the Baa corporate borrowing rate minus the long-term (10-year) U.S. government bond rate. The Baa spread is treated in the literature as a measure of global financial risk (Epstein et al., 2019; Akinci, 2013).

[33] The volatility of the oil price is estimated similatly to the volatility of the S&P 500 index using high frequency data of crude oil price of GSCI index, obtained by tick data. We include the volatility of the oil as a business cycle variable following Antonakakis et al. (2014), and in order to check for volatility spillovers following Arouri et al. (2011) and Degiannakis et al. (2014).

The **Table 4.7** shows the estimated multiple predictive regression model of **equation 3.2**, using the 3 different samples, all the available dataset, the pre-crisis subsample, and the post-crisis subsample respectively.

Table 4.7. Predicting RV using multiple regression model

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (SP500RV). The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 to December 2017. Panel A reports the regression results for the full dataset (1990-2017), Panel B reports the regression results for the pre-crisis subperiod (Jan 1990 – Dec 2006) and Panel C reports the regression results for the post-crisis sub-period (Jan 2007 – Dec 2017). The estimated multiple predictive regression model is given below:

$$LN(RV_t) = b_0 + b_1 LN(RV_{t-h}) + b_2 SLOPE_{t-h} + b_3 LN(SLOPERV_{t-h}) + b_4 LN(EPU_{t-h}) + b_5 LN(MPU_{t-h}) + b_6 Defspr_{t-h} + b_7 IPG_{t-h} + b_8 LN(OILRV_{t-k}) + \varepsilon_t$$

Panel A: full sample period (Jan 1990- Dec 2017)

Sample		1m	2m	3m	6m	9m	12m
Constant	Coef.	-1.216	-1.260	-0.420	-0.0563	-1.534	-0.0475
	t-stat	(-1.38)	(-0.99)	(-0.27)	(-0.03)	(-0.87)	(-0.03)
RV	Coef.	0.742***	0.634***	0.592***	0.550***	0.527***	0.443***
	t-stat	(15.33)	(10.30)	(8.55)	(8.39)	(7.32)	(6.26)
SLOPE	Coef.	-2.839	-3.005	-1.764	-6.424	-16.58***	-21.07***
	t-stat	(-0.83)	(-0.60)	(-0.27)	(-0.85)	(-2.66)	(-3.59)
SLOPE RV	Coef.	-0.000658	-0.0101	-0.00238	0.0600	0.0590	0.117*
	t-stat	(-0.02)	(-0.21)	(-0.05)	(1.02)	(0.90)	(1.91)
EPU	Coef.	-0.185	-0.341	-0.547	-0.462	-0.0694	-0.553
	t-stat	(-0.89)	(-1.17)	(-1.61)	(-1.06)	(-0.16)	(-1.44)
MPU	Coef.	-0.0791	-0.108	-0.0773	-0.199	-0.278*	-0.0717
	t-stat	(-0.92)	(-1.06)	(-0.73)	(-1.42)	(-1.83)	(-0.53)
Defspr	Coef.	18.01**	21.44**	19.69	13.36	3.931	8.297
	t-stat	(2.10)	(1.99)	(1.62)	(0.91)	(0.28)	(0.61)
IPG	Coef.	-8.166	-14.99	-13.54	-10.10	-12.63*	-1.438
	t-stat	(-0.84)	(-1.56)	(-1.51)	(-1.05)	(-1.68)	(-0.20)
Oil RV	Coef.	-0.0487	-0.0519	-0.0165	-0.0553	-0.0928	-0.0531
	t-stat	(-1.45)	(-1.03)	(-0.25)	(-0.74)	(-1.18)	(-0.60)
% adj. R^2		62.3	47.5	40.6	32.8	30	31.2

Panel B: pre-crisis period (Jan 1990- Dec 2006)

Sample		1m	2m	3m	6m	9m	12m
Constant	Coef.	-2.868**	-2.406	-1.978	-2.330	-1.789	1.518
	t-stat	(-2.28)	(-1.41)	(-0.99)	(-1.32)	(-1.08)	(0.91)
RV	Coef.	0.710***	0.586***	0.497***	0.503***	0.537***	0.475***
	t-stat	(11.25)	(6.90)	(5.11)	(6.72)	(7.03)	(5.71)
SLOPE	Coef.	-8.668**	-9.101	-10.80	-16.26**	-19.14***	-21.95***
	t-stat	(-2.20)	(-1.62)	(-1.60)	(-2.26)	(-3.15)	(-3.87)
SLOPE RV	Coef.	-0.068	-0.103*	-0.087*	-0.071	-0.069	0.042
	t-stat	(-1.28)	(-1.86)	(-1.77)	(-1.20)	(-1.37)	(0.82)
EPU	Coef.	0.0278	-0.283	-0.373	-0.562	-0.474	-1.293***
	t-stat	(0.09)	(-0.66)	(-0.76)	(-1.31)	(-1.19)	(-3.72)
MPU	Coef.	-0.101	-0.135	-0.200	-0.0822	-0.195	0.0528
	t-stat	(-0.89)	(-1.01)	(-1.31)	(-0.63)	(-1.45)	(0.49)
Defspr	Coef.	32.44***	45.27***	52.67***	49.39***	31.66	31.04
	t-stat	(3.25)	(3.18)	(3.12)	(2.68)	(1.65)	(1.42)
IPG	Coef.	2.588	-0.541	-0.323	8.361	-16.18**	-4.996
	t-stat	(0.28)	(-0.06)	(-0.03)	(0.89)	(-2.04)	(-0.52)
Oil RV	Coef.	-0.017	0.024	0.068	-0.072	-0.110	-0.09
	t-stat	(-0.33)	(0.35)	(0.89)	(-0.90)	(-1.27)	(-1.23)
% adj. R^2		65.3	52.7	47.6	46.1	45.8	49.5

Panel C: post-crisis period (Jan 2007- Dec 2017)

Sample		1m	2m	3m	6m	9m	12m
Constant	Coef.	-0.317	-1.456	-0.458	1.821	-0.763	-1.560
	t-stat	(-0.29)	(-1.02)	(-0.23)	(0.72)	(-0.29)	(-0.63)
RV	Coef.	0.648***	0.530***	0.540***	0.467***	0.475***	0.512***
	t-stat	(6.34)	(4.57)	(4.17)	(3.13)	(2.63)	(2.92)
SLOPE	Coef.	12.72*	17.18*	26.37**	22.26	-0.364	-3.068
	t-stat	(1.91)	(1.86)	(2.11)	(1.34)	(-0.04)	(-0.29)
SLOPE RV	Coef.	0.108*	0.114	0.085	0.259**	0.251**	0.160
	t-stat	(1.73)	(1.51)	(1.04)	(2.48)	(2.19)	(1.31)
EPU	Coef.	-0.373	-0.435	-0.820*	-0.743	-0.303	-0.799
	t-stat	(-1.42)	(-1.29)	(-1.97)	(-1.10)	(-0.49)	(-1.59)
MPU	Coef.	-0.002	0.052	0.259	-0.059	-0.09	0.335
	t-stat	(-0.01)	(0.29)	(1.46)	(-0.21)	(-0.32)	(1.27)
Defspr	Coef.	6.685	2.725	-8.049	-26.39*	-23.35*	-25.73
	t-stat	(0.48)	(0.20)	(-0.55)	(-1.67)	(-1.66)	(-1.46)
IPG	Coef.	-16.01	-29.59***	-30.60***	-31.89***	-18.42	-18.42
	t-stat	(-1.18)	(-3.04)	(-4.23)	(-3.29)	(-1.48)	(-1.22)
Oil RV	Coef.	-0.045	-0.140	-0.121	-0.177	-0.357**	-0.539***
	t-stat	(-0.50)	(-1.37)	(-0.86)	(-1.11)	(-2.21)	(-2.96)
% adj. R^2		60.3	46.6	42.0	33.6	26.6	35.9

The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. *, ** and *** denote statistical significance at the 10%, 5% and 1% respectively based on the Newey-West standard errors for the coefficients.

The results show that during the period after the recent financial crisis, the SLOPERV contain an additive information content about the subsequent min-term and long-term stock market volatility. In details, I find that SLOPERV remains a statistically significant predictor of stock market volatility, in the inclusion of other well-known drivers of equities market volatility in mid-term and long-term forecast horizon. Specifically, when I predict stock market volatility using the full sample, the estimated coefficient of the SLOPERV is statistically significant in a 10% significance level, only in the 12-month ahead forecast horizon. Interestingly, the results of the multiple predictive models suggest that the predicting power of SLOPERV is increased during the post-crisis period, likewise with the corresponding results of the bivariate regression model. Specifically, the results. SLOPERV has statistically significant coefficients in a 5% significance level when it comes to 6-month and 9-month ahead volatility predictions, which indicate that SLOPERV has an additive predicting information content about mid-term and long-term stock market volatility.

4.4 Predicting the volatility of S&P 500 constituents using the yield curve volatility

In this section, I present the results of my univariate forecasting regression model on the RV of the constituents of SP500. In order to examine the explanatory power of SLOPERV and LEVELRV in different sectors, I consider sectors of the SP500 according to the ICB industry classification[34], which contains 10 industry categories: Basic Materials, Consumer Goods, Consumer Services, Health care, Industrials, Financials, Oil and Gas, Technology, Telecommunications and Utilities, and additionally each industry classified in different sectors[35]. My purpose is to understand in depth, my results on the previous section on the aggregate stock market volatility, and I use the same regression model like in previous section, using the same explanatory variables, in order to predict the RV of the SP500 constituents. The sample of the RV of the SP500 constituents covers from the November of 2002 till November of 2017. So, the period that this sample covers, is very similar with the second subsample (post-crisis subsample) that I use previously. In the next figures, **Figures 4.2**, **4.3** and **4.4**, I show the average R^2 and the average t-statistic values, per industry for the estimated regression models on the RV

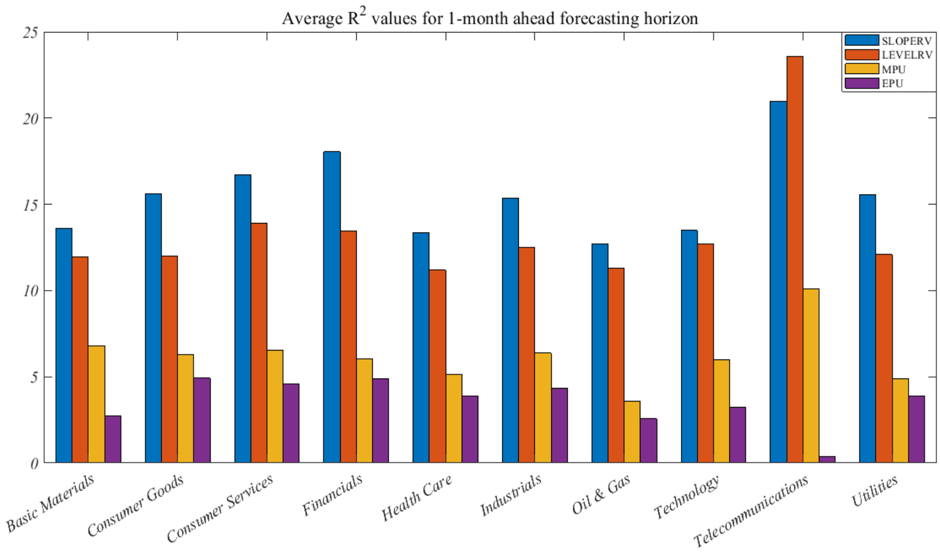
[34] ICB classification data are obtained from Thomson Reuters DataStream.
[35] I report the sectors with details in the appendix section for brevity.

of the constituents of SP500. I present the regression output when I use the SLOPERV, LEVELRV, EPU and MPU, for three different forecast horizons, one six and twelve months respectively. Hereby I present my figures:

Figure 4.2. Predicting the RV of SP500 constituents for 1-month ahead

This figure shows the average R^2 values of the bivariate regressions (shown in Equation (4)) on the RV of the SP500 constituents, when using LEVELRV, SLOPERV, EPU and MPU in the right-hand side of the regression model. More specifically, in this table I report, for each industrial sector in the U.S. stock market, the average of the R^2 values for the SP500 constituents who belong to the same sector. Panel A reports the sectoral averages of the R^2 values, while panel B reports the respective averages of t-statistics. The t-statistics for the predictive regressions on S&P500 constituents are corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The monthly dataset for the predictive regressions on the monthly RV of S&P500 constituents spans the period from November 2002 till December 2017.

Panel A



Panel B

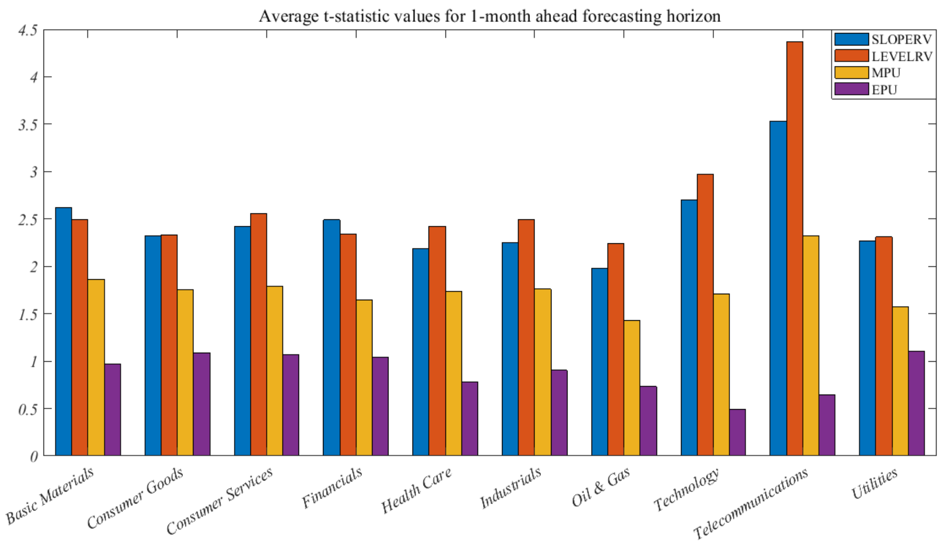
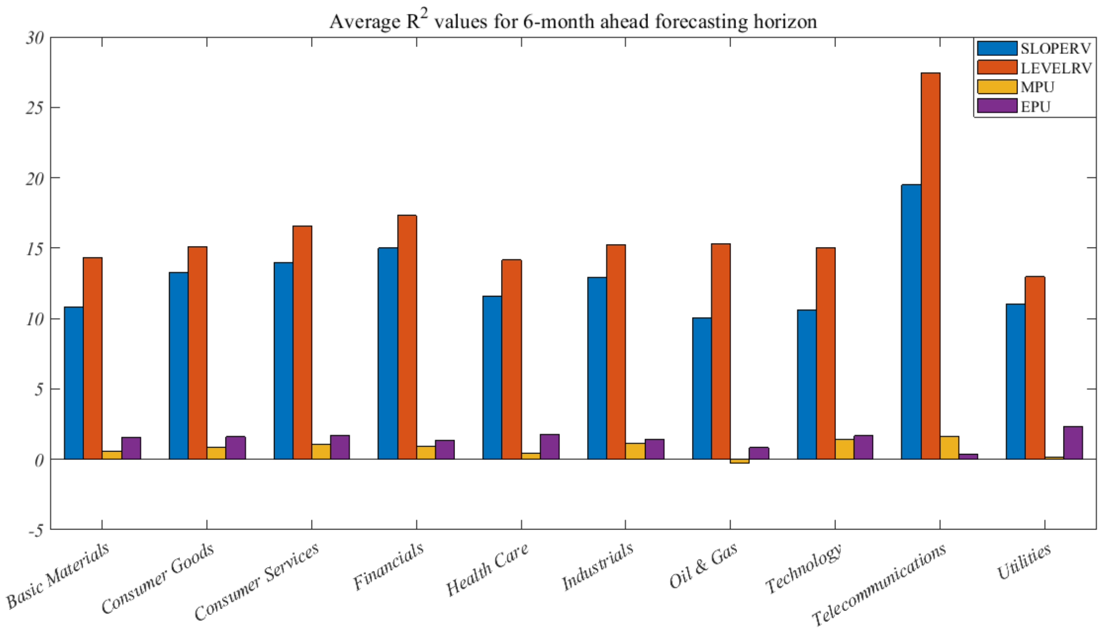


Figure 4.3. Predicting the RV of SP500 constituents for 6-month ahead

This figure shows the average R^2 values of the bivariate regressions (shown in Equation (4)) on the RV of the SP500 constituents, when using LEVELRV, SLOPERV, EPU and MPU in the right-hand side of the regression model. More specifically, in this table I report, for each industrial sector in the U.S. stock market, the average of the R^2 values for the S&P500 constituents who belong to the same sector. Panel A reports the sectoral averages of the R^2 values, while panel B reports the respective averages of t-statistics. The t-statistics for the predictive regressions on SP500 constituents are corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The monthly dataset for the predictive regressions on the monthly RV of SP500 constituents spans the period from November 2002 till December 2017.

Panel A



Panel B

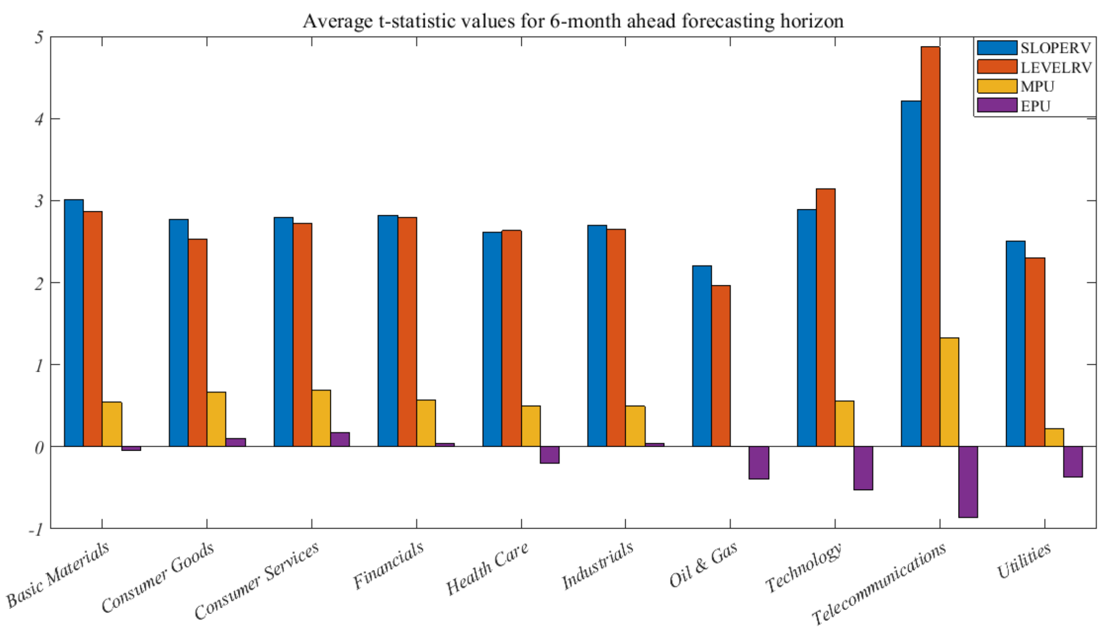
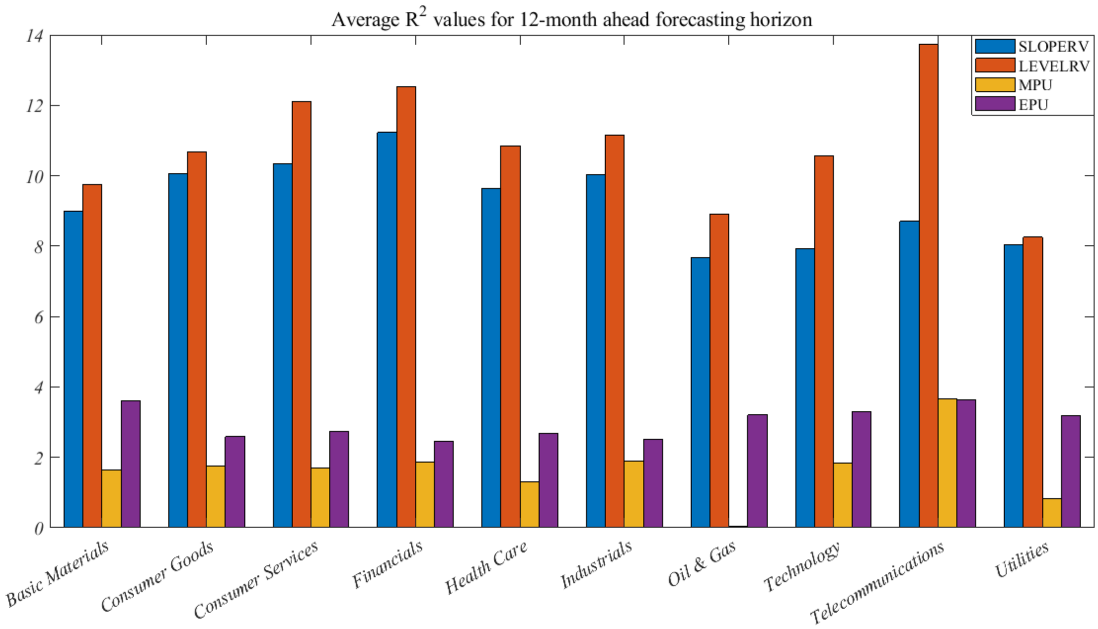


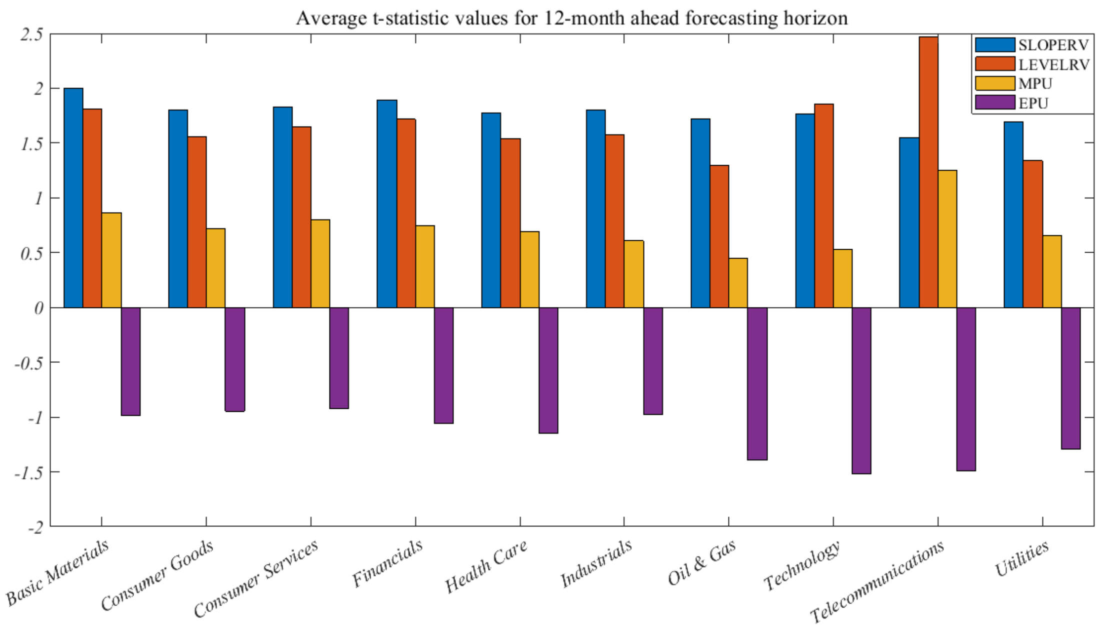
Figure 4.4. Predicting the RV of SP500 constituents for 12-month ahead

This figure shows the average R^2 values of the bivariate regressions (shown in Equation (4)) on the RV of the SP500 constituents, when using LEVELRV, SLOPERV, EPU and MPU in the right-hand side of the regression model. More specifically, in this table I report, for each industrial sector in the U.S. stock market, the average of the R^2 values for the SP500 constituents who belong to the same sector. Panel A reports the sectoral averages of the R^2 values, while panel B reports the respective averages of t-statistics. The t-statistics for the predictive regressions on S&P500 constituents are corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The monthly dataset for the predictive regressions on the monthly RV of SP500 constituents spans the period from November 2002 till December 2017.

Panel A



Panel B



In general, the results are in line with the regressions output that are obtained in the aggregate stock market volatility prediction, since both SLOPERV and LEVELRV exhibit higher average R^2 and t-statistic values than the EPU and MPU for all the forecast horizons. My Sectoral analysis results indicate that both LEVELRV and SLOPERV exhibit asymmetric predictability, amongst different sectors of the equities market. I find that volatility components can explain a large fraction of the volatility of Telecommunications industry, financial industry, consumer goods and consumer industries (more specifically the cyclical consumer goods and services), technology[36]. More specifically, my results indicate that the capital-intensive and cyclical industries volatility (like consumer industry, technology, telecommunications) can be strongly predicted from the yield curve volatility. This result is partially in line with a strand of the literature (Ehrmann and Fratzscher, 2004; Bernarke and Kuttner,2005; amongst others) who identify that similar industries[37] (like telecommunications, technologies and consumer cyclicals) are more responsive to changes in interest rates due to monetary policy announcements. Additionally, I find that the financial sector can be predicted from SLOPERV and LEVELRV, and especially in the long-term forecast horizon. I am the first to report that capital-intensive industries and cyclical industries volatility can strongly predicted by the volatility of the term structure of the interest rates.

[36] Additionally, I follow an identical analysis but instead of the averages R^2 and t-statistic values per industry, I report in tables the averages values per sector, in order to report the predictability of yield curve volatility in specific cyclical and capital-intensive sectors. For brevity, I include these results in the appendix section.

[37] Ehrmann and Fratzscher (2004) are following a different classification of SP500. For example, they categorize the consumer goods in cyclicals and non-cyclicals. Although, according to the further decomposition of SP500 that I provide (sectors of each industry), my results are similar. An example is that, amongst the consumer goods and consumer services that I have in my classification, the cyclical ones like General retailers, leisure goods, Travel and leisure exhibit the highest R^2 values.

When I estimate the RV of the constituents of SP500 using EPU and MPU as predictors, the regressions output is in line with the results on aggregate stock market volatility predictions. I find that the MPU is a stronger predictor of the RV of SP500 classified industries than EPU index. In line with the results of the previous subsection 4.2, SLOPERV provides stronger predictability than EPU and MPU indices for almost all the available forecast horizons.

4.5 Out-of-Sample Forecasting

In this section, I aim to provide additional robustness on my empirical findings, by estimating out-of-sample forecasts of the RV of SP500 index and its constituents' returns, using similar regression models with the previous subsection. More specifically, I use a dynamic recursive estimation scheme with an initial 5-year estimation window of monthly observations spanning from January 1990 to December 1994, hence the first forecast is being made for January 1995. The detailed steps of the out-of-sample setting are the following. Initially, I run an OLS predictive regression for h-months ahead (where h is the forecast horizon) in the initial 5-year estimation window. Then I use the estimated slope coefficients of the predictive regression to make a forecast for the following h-month ahead. The estimation window is then extended by one monthly period in order to obtain a new out-of-sample forecast. I ran the same forecasting regression models described in previous subsection and I make dynamic out-of-sample forecasts. Therefore, I estimate the squared error between the volatility forecasts and the actual volatility, and I use the mean-squared error of the forecast to estimate the respective out-of-sample R^2 values. I note that the observed R^2 values may be negative since the constant term is not used in the forecasting and consequently, a negative R^2 value means that the estimated forecasting model is not following the trend of the data.[38] I follow this method using similar samples and subsamples that I used in the in-sample analysis, except the post-crisis period subsample that covers the period of Jan 2002-Dec 2017. The post-crisis subsample that I used in the in-sample analysis contains almost 10-years and consequently, my rolling window method cannot use a sufficient dataset in order to perform adequate number of out-of-sample predictions for the available predicting horizons[39]. Inevitably, the small number of available observations will result poor out-of-sample estimations. Additionally, using the out-of-sample methodology in the post-crisis subsample, I cannot predict stock market volatility in the biggest fraction of ZLB period and financial crisis period, since the first out-of-sample prediction will be for observed stock market volatility on Jan/2012. So, in the out-of-sample framework, the post-crisis period subsample covers the period of Jan 2002-Dec 2017, in order to forecast stock market volatility during the period after the recent financial crisis. Hereby, I present the out-of-sample R^2 values when I estimate the volatility of S&P 500 index, in **Tables 4.8**. In the out-of-sample framework, I use the same bivariate and multiple regression models as they are described in previous subsections. The explanatory variables in the bivariate model are SLOPERV, LEVELRV, EPU, MPU and additionally the VIX index and lagged SP500RV. I additionally use these two variables as predictors of stock market volatility motivated by the relevant literature that identify their rich predictive information content about the subsequent stock market volatility, especially in an out-of-sample framework.

[38] The formula of R^2 is the following: $R^2 = 1 - \frac{SSE}{SST}$ where SSE is the sum of squares of residuals and SST is the total sum of squares. Therefore, in the out-of-sample setting the SSE can be larger than the SST in case that the constant term is not included in the forecasting model and the forecasts does not follow the trend of the dependent variable.

[39] For example, if I am going to use a 9month forecast horizon, I have to use the 5 years rolling window and then to predict the stock market volatility 9months ahead. So according to this, I make a prediction about 69 months ahead, which it means it is almost 6 years from the starting point. So, especially for long-term predicting horizons, there are not sufficient available predictions.

Table 4.10. Out-of-sample R^2s

Panel A: Full sample

Horizon (k)	*SLOPERV*	*LEVELRV*	*EPU*	*MPU*	*VIX*	*SP500RV*	*MULT*
1m	3.5%	-7.3%	-7.4%	-5.4%	51.6%	59.5%	56%
2m	-3.3%	-11.9%	-13.1%	-10.3%	33.3%	40.3%	33.7%
3m	-7.0%	-13.6%	-16.5%	-13.9%	23.4%	31.5%	20.6%
6m	-12.0%	-18.3%	-23.1%	-20.3%	3.5%	16.9%	-7.6%
9m	-20.8%	-27.0%	-31.0%	-28.4%	-9.9%	5.2%	-18.5%
12m	-24.0%	-32.7%	-37.8%	-35.8%	-22.6%	-7.4%	-10.3%

Panel B: Pre-crisis subsample (Jan/1990-Dec/2007)

Horizon (k)	*SLOPERV*	*LEVELRV*	*EPU*	*MPU*	*VIX*	*SP500RV*	*MULT*
1m	-21.0%	-25.7%	-24.8%	-22.7%	54.0%	60.3%	55.7%
2m	-27.0%	-28.2%	-31.6%	-28.2%	32.5%	38.7%	32.3%
3m	-32.0%	-33.1%	-35.6%	-34.3%	20.3%	27.5%	19.9%
6m	-43.7%	-42.5%	-46.7%	-45.0%	12.7%	18.4%	-2.2%
9m	-58.4%	-61.6%	-64.6%	-63.6%	-2.0%	5.9%	-16.8%
12m	-72.6%	-79.2%	-79.7%	-84.1%	-31.8%	-15.8%	-10.4%

Panel B: Post-crisis subsample (starting from Jan/2002)

Horizon (k)	*SLOPERV*	*LEVELRV*	*EPU*	*MPU*	*VIX*	*SP500RV*	*MULT*
1m	27.7%	14.3%	10.4%	-0.5%	49.7%	57.7%	51%
2m	19.7%	11.6%	4.5%	-4.6%	30.8%	39.2%	18.8%
3m	14.2%	12.8%	2.3%	-8.9%	21.1%	31.2%	-13.9%
6m	10.6%	9.1%	-12.1%	-21.6%	-8.4%	8.9%	-140%
9m	-8.1%	-3.5%	-18.4%	-25.0%	-15.6%	-5.5%	-214%
12m	-10.2%	-11.3%	-19.5%	-28.0%	-16.6%	-12.7%	-123%

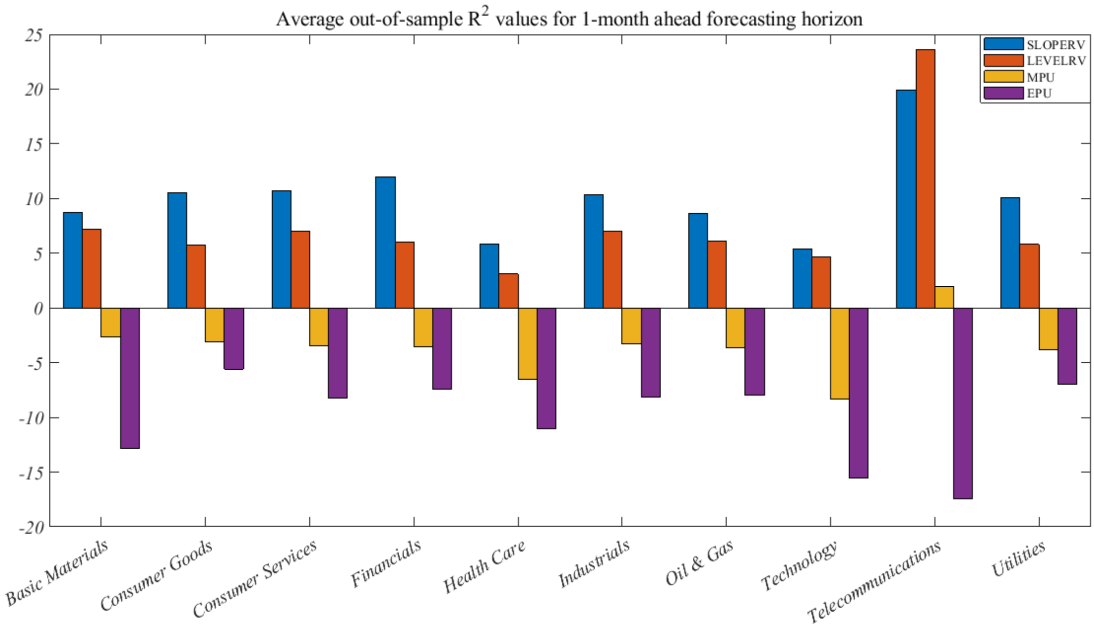
The estimated results are in line with in-sample analysis output. More specifically, between the volatility components of the yield curve (SLOPERV and LEVELRV), only the SLOPERV provide a positive R^2 (for 1-month forecast horizon), when I use all the available datasets. Additionally, while in the pre-crisis period the out-of-sample R^2 values when I use SLOPERV and LEVELRV as predictors of stock market volatility are negative, in the post-crisis subsample period they turn to positive. Interestingly, the LEVELRV exhibit 2 and 3 time lower out-of-sample R^2 values from the SLOPERV. Furthermore, the SLOPERV exhibits higher out-of-sample R^2 values from the VIX index and SP500RV in the mid-term forecast horizon. This result augment my basic argument that the SLOPERV is a strong predictor of the stock market volatility. My results show that the SLOPERV provide a rich information set about the time-varying dispersion of stock market returns

Additionally, I forecast the RV of the constituents of S&P 500 index, using the out-of-sample framework that I described above. I obtain the out-of-sample R^2 values by following the same method that I use for the out-of-sample aggregate stock market volatility forecasting. A problem that I face is that the decomposition of S&P 500 index contains the companies that were part of the index in November of 2017. As a result, many companies do not have values for all the available period of our sectoral analysis sample (Nov/2002-Nov/2017). For the in-sample analysis it is not a major issue, but the out-of-sample framework requires all the available observations, because, as I explain in section 4.5, a small number of available observations will inevitably result poor out-of-sample estimations. Therefore, in order to obtain consistent out-of-sample results, I include only the companies that contain values for all the available sectoral subsample (181 observations for the period that cover from Nov/2002 till Nov/2017). Amongst the constituents of SP500 that comprise our dataset, 421 companies have observations across the entire used sample. Therefore, I use only these 421 companies in my out-of-sample estimations on the volatility of the constituents of S&P 500 index. The **Figure 4.5** shows the average out-of-sample R^2 values, per industry for the estimated forecasting regression models on the RV of the constituents of SP500[40].

[40] In this section I include only the estimated results when I forecast the volatility of the S&P 500 constituents 1-month ahead. The out-of-sample results about the long-term horizon forecasting and the detailed out-of-sample R^2 values per sector and per industry, are presented in the appendix B.

Figure 4.5. Forecasting the RV of SP500 constituents (out-of-sample regression results)

Hereby, I show the out-of-sample R^2 values for the bivariate regression models (shown in Equation (4.1)) on the Realized Variance (RV) of the constituents of the SP500, when using LEVELRV, SLOPERV, EPU and MPU in the right-hand side of the regression equation. Specifically, I report, for each industrial sector in the U.S. stock market, the average of the out-of-sample R^2 values for the S&P500 constituents who belong to the industry. The monthly dataset for the predictive regressions on the monthly RV of SP500 constituents spans the period from November 2002 till December 2017.



The **Figure 4.5** verify that the SLOPERV and LEVELRV outperforms the EPU and MPU. The estimated results in the out-of-sample framework provide further robustness in the estimated in-sample sectoral analysis results, since they are similar. Specifically, the highest estimated out-of-sample R^2 values for the majority of the SP500 industries are obtained when I the SLOPERV as forecasting factor of the RV of the constituents of SP500, which result is in line with the corresponding results of the in-sample analysis. While the forecasting bivariate models in which the EPU and MPU are used as forecasting factors of the volatility of the firms, exhibit negative R^2 values, the bivariate model that includes SLOPERV in the right side of the equation, exhibit positive average R^2 values between almost 6% and 20% across varying industries of SP500.

4.6 VAR model

Following Bloom (2009) and Caggiano et al. (2014), I estimate a VAR model for the U.S. economy with a similar VAR ordering and identifying restrictions. More specifically, in my VAR model for the U.S. economy I make the assumption that shocks affect first the equity market, then consumer prices (inflation) and lastly quantities (Industrial production). I also assume that the monetary authority reacts last after observing the changes to the equity market, inflation and output. Hence, the monetary policy and economic policy variables are placed last in the VAR ordering. In more detail, I estimate a VAR model with the VAR ordering given in Equation (4.3) below:

$$Y_t = [SP500RV_t \;\; SP500RET_t \;\; INFL_t \; IPI_t \; FFR_t \; EPU_t \; MPU_t \; SLOPE_t \;\; SLOPERV_t] \tag{4.3}$$

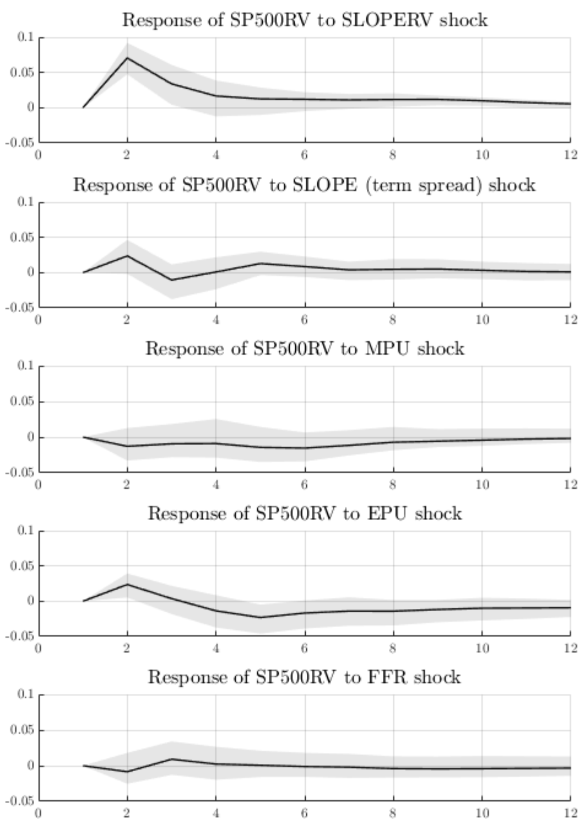
Where SP500RV is stock market volatility, SP500RET is stock market returns, INFL is inflation (monthly growth rate in the U.S. CPI index), FFR is the Fed funds rate, EPU is the Economic Policy Uncertainty index, MPU is the monetary policy uncertainty index, SLOPE is the slope of the term structure (defined as the difference of the U.S. 10-year government bond yield minus the 3-month U.S.-Treasury bill rate). Finally, the SLOPERV is the monthly volatility (realized variance) of the slope of the term structure of interest rates. Following Bloom (2009), I control for first and second moment shocks in the equity market by including both SP500RV and SP500RET as endogenous variables in the VAR model.

In this section I provide the results of the VAR analysis based on the estimated OIRFs of stock market volatility to different types of monetary policy, yield curve and economic policy uncertainty shocks. More specifically, I estimate the OIRFs of SP500RV to one standard deviation shock to SLOPERV, SLOPE, EPU, MPU and FFR shocks. **Figure 4.5** below shows the respective results, when I use the full sample and the post-crisis subsample.

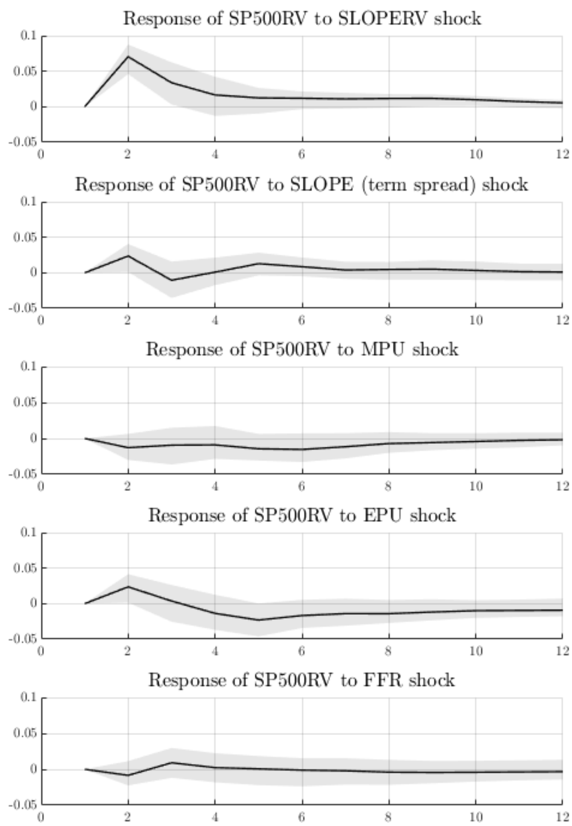
Figure 4.5. Estimated Orthogonalized Impulse Responses(OIRFs) ofstock marketRV to SLOPERV, SLOPE, EPU and MPU shocks.

The estimated OIRFs are obtained from the baseline 9-variable VAR model described in Equation (5). The shaded areas represent the 90% confidence intervals based on bootstrapped standard errors with 1000 repetitions.

Panel A: Full sample (Jan/1990-Dec/2017)



Panel B: post-crisis sample (Jan/2007-Dec/2017)



From **Figure 4.5,** I see that the only monetary policy related shock which results to a positive and statistically significant response of stock market volatility is the

SLOPERV shock. More specifically, a one standard deviation shock in the SLOPERV results to a persistent rise in stock market volatility of about 7 basis points 3 months after the initial shock. On the other hand, the effect of FFR, SLOPE, EPU and MPU shocks on stock market volatility is transitory and statistically insignificant.

4.7 Conclusions

The slope of the term structure of interest rates reflects the market expectations about the future path of the macroeconomy. Consequently, the volatility of the slope of the yield curve may reflect the dispersion of market expectations about the future macroeconomic state and outcomes. In this paper, I empirically verify the forecasting power of the volatility of the slope of the yield curve on stock market volatility. My empirical findings verify my claims which are based on a basic stock market valuation model, according to which the stock market price is the sum of the discounted (by the term structure of interest rates) expected cash-flows (dividend yields and capital gains).Thus, the volatility of the slope, affects stock market volatility through the following structurally different channels: Through greater uncertainty in the discount factor of future cash flows; and through greater uncertainty in the future cash flows and dividends in the stock market. In an efficient market, in which the macroeconomic fundamentals are fully reflected in asset prices, greater uncertainty about the future state of the macroeconomy should somehow be reflected in the stock market (as greater volatility in stock market prices). The policy implication behind these results, is that the stability (and not the steepness) of the slope of the yield curve may be an (indirect) but feasible target for monetary authorities, in case their objective is to reduce stock market turbulence.

Chapter 5

Option-implied expectations and the (non) neutrality of money

5.1 Introduction

The last years, the links amongst stock market performance and monetary policy have been extensively examined. A vast relevant literature starting with Thornbecke (1997) document a strong reaction of aggregate stock market returns to corresponding monetary policy news (Rigobon and Sack, 2003; Bernarke and Kuttner, 2005; Savor and Wilson, 2014; Brusa et al., 2015; Lucca and Moench, 2015; Cieslak et al., 2018; amongst others). While the Central Bank's target is traditionally inflation and unemployment, in many cases monetary policy decisions are made based on their expected impact on the equity market. In details, the recent findings in the literature have identified the systematic intervention of the Fed in the stock market during times of rising turbulence, volatility and meltdowns in the stock market (Rigobon and Sack, 2003; Kurov et al., 2016; Gu et al., 2018; Kurov et al., 2019; Cieslak and Vissing-Jorgensen, 2020). This behaviour of the Fed is characterized as Fed put (or Greenspans put), since the Fed intervenes by cutting interest rates in a falling market to prevent a severe meltdown (just like a protective put option does). In this chapter, Since the objective of the Fed is the management of market expectations, and, motivated by the findings in the literature about the risk-taking channel of monetary policy (Adrian and Shin, 2008; Borio and Zhu, 2012; Bekaert et al., 2013; Angeloni et al., 2015), I examine the impact of monetary policy on the option-implied expectations in the U.S. equity market.

I estimate the model-free version of option-implied moments (a model-free version of risk-neutral distribution) in order to proxy the investors' ex ante expectations. Many researchers use option-implied moments in their analysis, since option-implied information is inherently forward-looking and reflects investors' beliefs under the risk-neutral measure about the upcoming evolution of the underlying equities prices (Bates, 1991; Jackwerth and Rubinstein, 1996; Bakshi et al., 1997). More specifically, I use option data from the S&P 500 index in order to obtain higher option-implied moments of the return distribution[41], following the Bakshi et al., (2003) model-free methodology. Afterwards, I estimate the dynamic response of option-implied moments to monetary policy shocks, by using a Structural-VAR and reduced VAR models. In my analysis, I proxy the option-implied variance (IV), skewness (IS) and kurtosis (IK) of the return distribution of SP500, using option contracts with different maturities. Therefore, using risk neutral densities of the U.S. stock market that corresponds to varying horizons, I construct the term structure of option-implied moments, similatly to the term structure of interest rates[42]. I follow this approach because it allows me to examine if monetary policy affects asymmetrically investors' expectations and fears for different horizons in the future.

My empirical results show that the Fed can manage the investors' ex-ante expectations regarding the subsequent performance of U.S. equity market for both long-end and short-end horizon. More specifically, an expansionary monetary policy revises upward (downward) the short-end and long-end option-implied expectations regarding price (jump tail risk) in the U.S. equity market.

[41] More specifically, I calculate the IS and IK of the S&P 500 index return distribution. I may refer to option-implied moments as moments of the risk neutral density.
[42] I explain analytically the components of the term structure of option-implied moments (like IS and IK) that I estimate in my analysis in subsection 2.6.

The contribution of this chapter in the relevant literature is twofold. Firstly, in line with the results on the relevant literature (Bernarke and Kuttner, 2005; Bekaert et al., 2013; Triantafyllou and Dotsis, 2017; amongst others), my analysis shows that expansionary monetary policy revises upwards the expectations regarding to equity prices (risk neutral skewness becomes less negative). More specifically, when policy makers decide to follow a lax monetary policy in order to provide "protection" to financial markets, investors start revising upwardly their expectations about the subsequent stock market returns. A few other studies examine and empirically verify the "Greenspan put" phenomenon (Miller et al., 2001; Rigobon and Sack, 2003; Kurov et al., 2019; Cieslak and Vissing-Jorgensen, 2020), nevertheless I am the first to show the impact of "Fed put" on investors' expectations using higher moments of option-implied distribution of the SP500, that reflect a richer information set about investors' perception of subsequent stock market performance.

Secondly, in line with the results of a few relevant studies (Hanson and Stein, 2015; Kontonikas and Zekaite, 2018; Nakamura and Steinsson, 2018; amongst others), I find empirical evidence which are at odds with the standard monetary theory. Concretely, I find that, while the literature on monetary economics identifies the short-run impact of monetary policy on inflation expectations, my results demonstrate that the long-term option-implied expectations in the U.S. equity market are more responsive to monetary policy shocks. Hence, while the macroeconomics literature shows that the money is neutral in the long-run for the economy (see for example Lucas, 1972), I show that this is not the case for the U.S. equity market, by finding that long-term option-implied expectations are more sensitive to monetary policy shocks when compared with the monetary sensitivity of short-term option-implied expectations.

5.2 Descriptive statistics

Figure 5.1 and **Figure 5.2** plot the contemporaneous movements of Fed Fund rate with the level of IS and the level of IK respectively.

Figure 5.1. The level of IS and the FFR

In this figure, I plot the monthly time series of the level of IS and the FFR. The left vertical axis includes the values of the FFR and the right the values of the level of IS. The data covers the period from Jan/1996 to Jun/2019

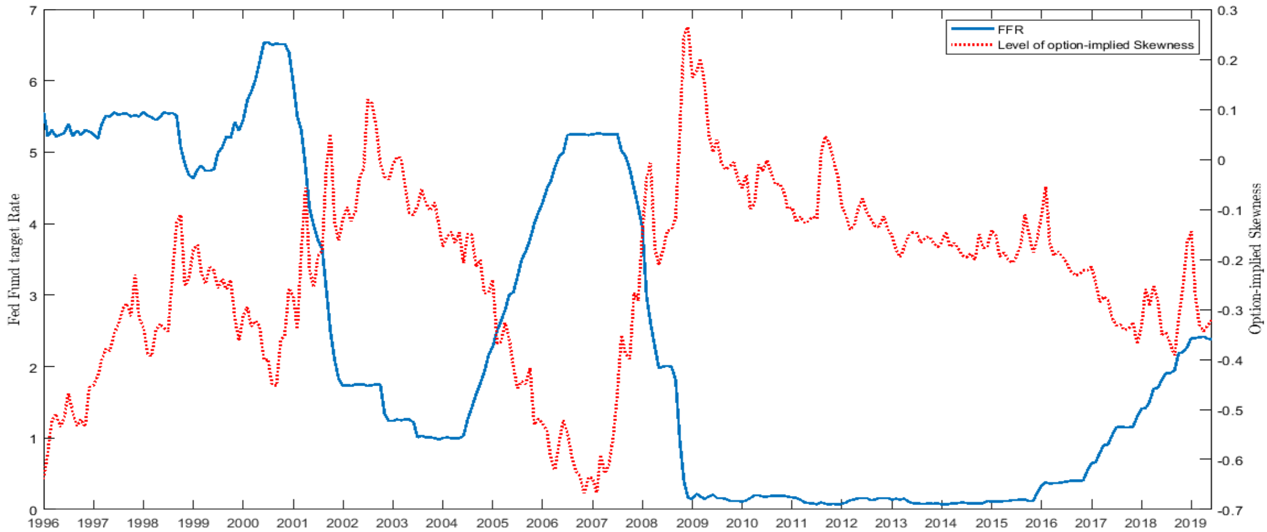
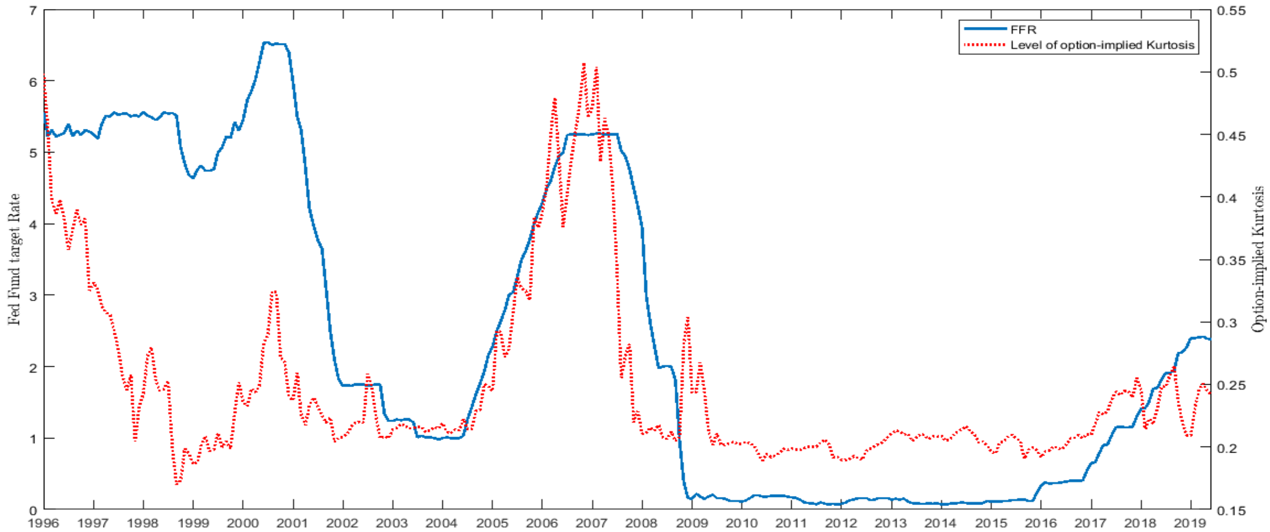


Figure 5.2. The level of IK and the Federal funds rate.

In this figure, I plot the monthly time series of the level of IK and the FFR. The left vertical axis includes the values of the FFR and the right the values of the level of IK. The data covers the period from Jan/1996 to Jun/2019



In general, I observe an opposite (analogue) direction movement between FFR and IS (IK). More specifically, the figures show that accommodative (contractionary) monetary policy is related to a higher (lower) level of IS and a lower (higher) level of IK. The pattern that I observe in **Figure 5.1** and **5.2**, is also documented in previous studies of the relevant literature, like the one conducted by Triantafyllou and Dotsis (2017) in which they find similar results about the relationship of IS in commodities markets and monetary policy stance. Additionally, Hattori *et al.* (2016) find similar results about the impact of the unconventional monetary policy on the jump tail risk of the stock market.

Moreover, I provide two more figures, **Figure 5.3** and **Figure 5.4**, in which I include the short-end and long-end components of the term structure of IS and IK instead of the level of IS and IK, respectively.

Figure 5.3. Short-end and long-end components of IS and the FFR

In this figure, I plot the monthly time series of the short-end and long-end components of IS and the FFR. The left vertical axis includes the values of the FFR and the right the values of IS. The data covers the period from Jan/1996 to Jun/2019

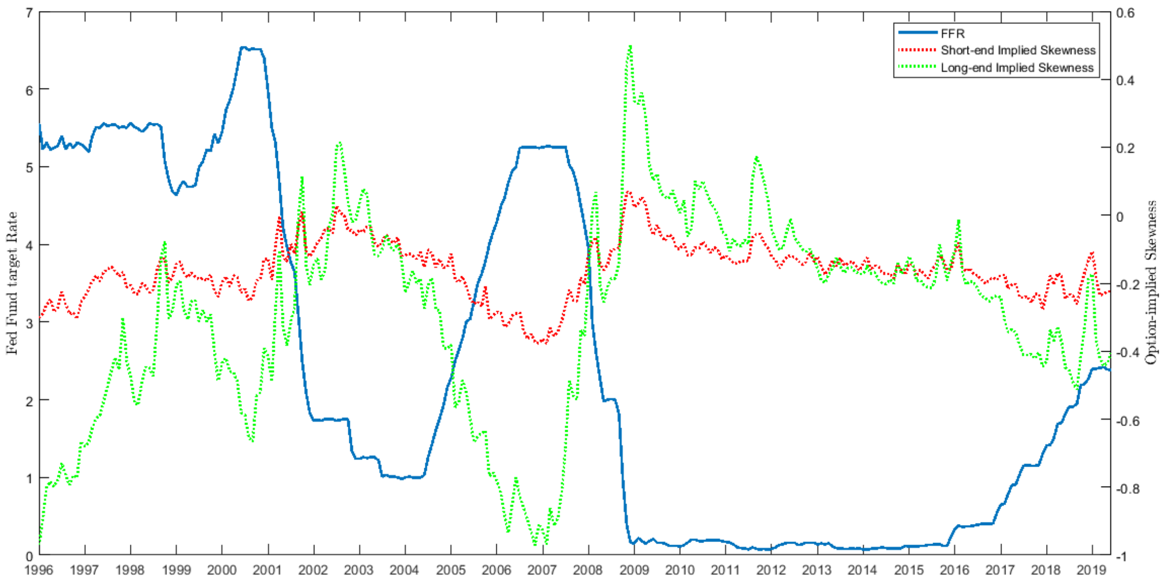
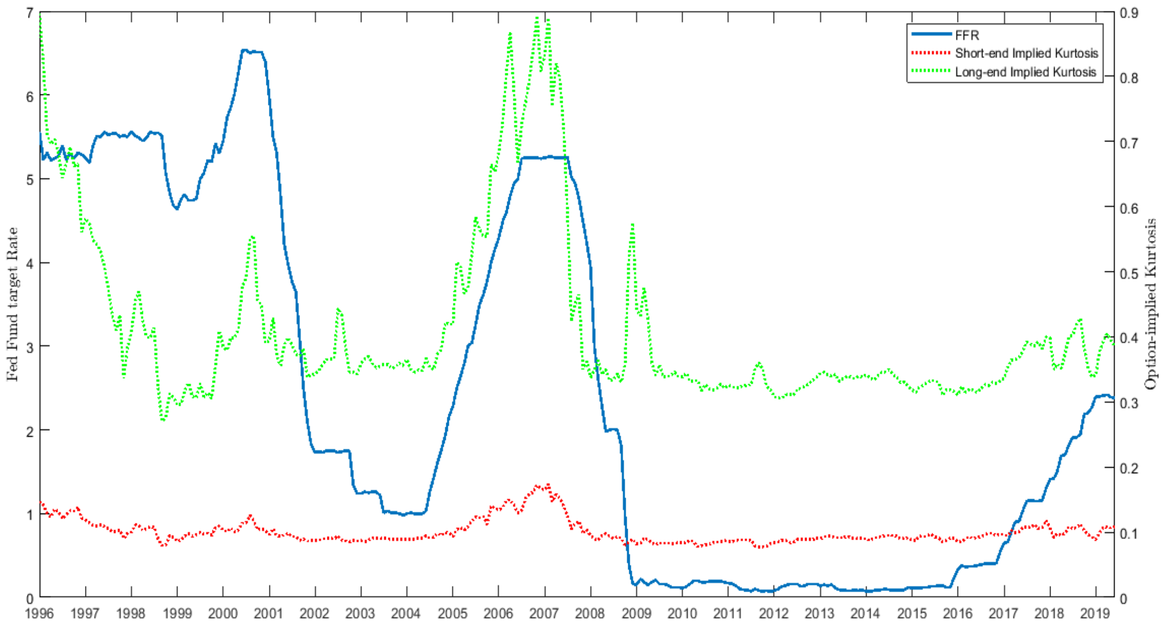


Figure 5.4. Short-end and long-end components of IK and the FFR

In this figure, I plot the monthly time series of the short-end and long-end components of IK and the FFR. The left vertical axis includes the values of the FFR and the right the values of IK. The data covers the period from Jan/1996 to Jun/2019



In **Figures 5.3** and **5.4**, I observe larger swings in the movement of the long-end components of option-implied moments (both IS and IK) compared to the movement of the short-end components, during periods that the level of FFR falls (or rises). This is a first indication that the long-end components of option-implied moments are more responsive to monetary policy shocks.

Finally, I present **Table 5.1** and **Table 5.2** that shows the descriptive statistics and the correlation respectively.

Table 5.1. Descriptive statistics

This table shows the descriptive statistics. All the time series have monthly frequency (except the TDR) and cover the period from January 1990 till December 2017.

	FFR	M1growth	INF	RIR	TDR	IS term spread	IS level	IS short-end	IS long-end	IK term spread	IK level	IK short-end	IK long-end	IV term spread	IV level	IV short-end	IV long-end	IPG	SLOPE
Mean	2.37	0.44	0.18	0.18	3.19	-0.20	-0.23	-0.16	-0.29	0.49	0.25	0.10	0.41	0.02	0.24	0.23	0.25	0.00	0.02
Median	6.54	5.75	1.22	40.01	6.33	0.70	0.26	0.07	0.50	1.14	0.51	0.17	0.90	0.20	1.42	1.71	1.13	0.02	0.04
Maximum	0.07	-3.32	-1.92	-3.68	-3.14	-0.97	-0.67	-0.38	-0.97	0.30	0.17	0.08	0.27	-1.08	0.08	0.06	0.09	-0.04	-0.01
Minimum	2.18	0.94	0.35	1.90	1.73	0.33	0.18	0.08	0.29	0.19	0.07	0.02	0.14	0.11	0.17	0.20	0.15	0.01	0.01
Std. Dev.	0.47	1.61	-0.89	0.35	-0.66	-0.40	-0.29	-0.07	-0.36	1.86	1.91	1.75	1.90	-5.09	3.11	3.58	2.56	-1.71	-0.06
Skewness	1.62	11.31	7.67	2.03	4.08	2.70	3.03	3.24	2.88	5.52	5.93	5.96	5.76	43.07	17.21	21.23	12.92	12.38	2.07
Kurtosis	2.37	0.44	0.18	0.18	3.19	-0.20	-0.23	-0.16	-0.29	0.49	0.25	0.10	0.41	0.02	0.24	0.23	0.25	0.00	0.02

Table 5.2. Correlation matrix

	FFR	M1growt h	INF	RIR	TDR	IS term spread	IS level	IS short-end	IS long-end	IK term spread	IK level	IK short-end	IK long-end	IV term spread	IV level	IV short-end	IV long-end	IPG	SLOPE
FFR	1.00																		
M1growth	-0.28	1.00																	
INF	0.08	0.02	1.00																
RIR	0.95	-0.25	0.03	1.00															
TDR	0.06	-0.02	-0.09	0.16	1.00														
IS term spread	-0.71	0.31	-0.12	-0.59	0.04	1.00													
IS level	-0.77	0.31	-0.13	-0.67	-0.04	0.97	1.00												
IS short-end	-0.76	0.29	-0.11	-0.70	-0.12	0.86	0.96	1.00											
IS long-end	-0.76	0.31	-0.13	-0.65	-0.01	0.99	0.99	0.93	1.00										
IK term spread	0.34	-0.31	0.15	0.23	-0.10	-0.80	-0.72	-0.59	-0.76	1.00									
IK level	0.43	-0.32	0.16	0.31	-0.11	-0.85	-0.79	-0.67	-0.82	0.99	1.00								
IK short-end	0.60	-0.35	0.14	0.49	-0.04	-0.91	-0.90	-0.83	-0.91	0.90	0.95	1.00							
IK long-end	0.39	-0.32	0.16	0.28	-0.11	-0.83	-0.76	-0.63	-0.79	1.00	1.00	0.93	1.00						
IV term spread	0.34	-0.18	0.09	0.32	0.33	-0.35	-0.49	-0.59	-0.43	-0.04	0.06	0.28	0.01	1.00					
IV level	-0.04	0.17	-0.09	0.08	0.11	0.67	0.59	0.47	0.62	-0.62	-0.64	-0.63	-0.63	-0.38	1.00				
IV short-end	-0.13	0.19	-0.09	-0.02	0.01	0.68	0.64	0.56	0.65	-0.53	-0.57	-0.62	-0.55	-0.58	0.97	1.00			
IV long-end	0.06	0.13	-0.07	0.19	0.21	0.61	0.49	0.33	0.54	-0.68	-0.67	-0.59	-0.67	-0.13	0.97	0.88	1.00		
IPG	0.12	-0.10	0.01	0.18	0.29	-0.18	-0.21	-0.24	-0.19	0.13	0.12	0.14	0.12	0.18	-0.08	-0.12	-0.03	1.00	
SLOPE	-0.92	0.18	-0.06	-0.89	0.00	0.50	0.60	0.63	0.57	-0.13	-0.23	-0.41	-0.19	-0.27	-0.16	-0.07	-0.25	0.00	1.00

5.3 Empirical analysis of Vector Autoregressive models

5.3.1 Analytical forms of SVARs and VARs models

My empirical analysis is comprised by a VAR framework. In details, I estimate several VAR and Structural VAR models in order to measure the impact of monetary policy stance on investors' expectations, following many relevant studies like Bekaert et al. (2013), Triantafyllou and Dotsis (2017), amongst others. My baseline model is a structural bivariate VAR model similar with Triantafyllou and Dotsis (2017). The bivariate VAR model has the form $Y_t = [MP_t \; IM_t]$ (5.1), where MP_t is the corresponding measure of monetary policy stance (i.e. FFR or RIR) and IM_t is the corresponding component of the term structure of option-implied moments (i.e. the level of the option-implied skewness or the short-end component of option-implied kurtosis).

Additionally, I estimate multivariate SVAR and VAR models in order to provide robustness in my empirical results. Firstly, similatly to Bekaert et al. (2013), I estimate 4 variables SVAR model of the form $Y_t = [IPG_t \; MP_t \; IS_t \; IV_t]$ (5.2), and the form $Y_t = [IPG_t \; MP_t \; IK_t \; IV_t]$[43] (5.3), where IPG_t is the industrial production growth, MP_t is the monetary policy stance variable, IS_t(IK_t) is component of the term structure of option-implied skewness(kurtosis) (for example the level of IS) and IV_t is the component of the term structure of option-implied variance. The industrial production growth is a business cycle indicator, and it is the most important control variable since it may affect simultaneously the monetary policy stance and the investors' expectations.

[43] Furthermore, I estimate the four variables SVAR model using a different ordering of the variables and different option-implied moments. For example, I use the same ordering as Triantafyllou and Dotsis (2017), or I replace the IS and IV with IK. I discuss the alternative ordering of the VAR specification in the robustness checks section.

Notwithstanding the fact that Structural VAR analysis provide interesting empirical insights about the impact of monetary policy to option-implied expectations, I additionally estimate a reduced-form VAR model without any specific restrictions, in order to ensure that the restrictions of the SVAR model do not influence the empirical results. Consequently, following Christiano et al. (1999) and Bekaert et al. (2013), I estimate a six variable monetary VAR model with the following ordering, first is the price level measure CPI, next is industrial production level (IPL), third is the fed fund rate, price level measure PPI is placed forth, and the components of IS (implied kurtosis) and IV are placed fifth and sixth respectively. The analytical form of the estimated six variable monetary VAR models, are the following: $Y_t = [CPI_t\ IPL_t\ FFR_t\ PPI_t\ IS_t\ IV_t]$ (5.4) and $Y_t = [CPI_t\ IPL_t\ FFR_t\ PPI_t\ IK_t\ IV_t]$ (5.5). In the estimated VAR specifications, the monetary policy variable is placed before the option-implied moments in order to capture the fact that asset markets are sensitive to monetary policy shocks, while the monetary authorities are neutral (or respond more sluggishly) to rising turbulence of the stock market. I estimate my SVAR models using short-run and long-run restrictions that I discuss in the next subsection. Since I use two and four variables in my SVAR models, I need to impose one and six restrictions respectively, for the exact identification of my models (I need N(N-1)/2 restrictions where N is the number of variables in each SVAR model). For Brevity, I include the multivariate SVAR and VAR models in the appendix (chapter 8). In general, the appendix includes multiple robustness checks like a subsample analysis and the estimation of the SVAR models described in equations 5.1-5.4 using varying measures of monetary policy stance.

5.3.2. Short-run and Long-run restrictions

I estimate a SVAR model using short-run restrictions. Similatly to Triantafyllou and Dotsis (2017), my short-run restrictions are that the market-based measures (option-implied moments) do not have a contemporaneous (short-run) effect on monetary policy and other macroeconomic variables. My selected restrictions are based on the premise that macroeconomic variables (like industrial production growth) and monetary policy have a sluggish response to changes in option-implied information. The SVAR models with the short run restriction are the following:

$$AY_t = \gamma + BY_{t-1} + \varepsilon_t \tag{5.6}$$

Where Y_t is the vector of variables (vectors described in equation 1 and 2), γ is the vector of constant terms and ε_t is the matrix with the independent structural shocks in my systems. Finally, A is a full rank matrix (2 x 2 or 4 x 4 depends on the model) which determines the endogeneity of the variables in each SVAR model and B is the short-run (feedback) response matrix in which I imply the contemporaneous restrictions, namely that option-implied moments do not have a short-run effect on monetary policy and macroeconomic variables. Consequently, the form of the feedback matrix based on the short-run restrictions is the following:

$$B = \begin{bmatrix} \beta_{11} & 0 & \cdots & 0 \\ \beta_{21} & & \ddots & \vdots \\ \vdots & & & 0 \\ \beta_{n1} & \beta_{n2} & \cdots & \beta_{n1} \end{bmatrix} \tag{5.7}$$

The long-run restrictions in my SVAR settings are based on the results of the relevant literature about the long-term money neutrality (Lucas, 1972; Barro, 1977; Bernarke and Mihov, 1998). More specifically, similatly to Triantafyllou and Dotsis (2017) and Bekaert et al. (2013), I restrict monetary policy to have zero long-run effect on real macroeconomic variables and option-implied moments. Following Blanchard and Quah (1989), the SVAR model with the long-run restrictions has the following long-run response matrix:

$$C = (I - A^{-1}B)^{-1}B^{-1} \tag{5.8}$$

My results are based on structural-form Impulse Response Function (SIRFs thereafter) for which, I estimate the 90% bootstrapped confidence intervals based on 1000 replications[44]. Finally, in my main analysis, I choose the optimal-length of my SVARs by following Akaike lag-length selection criterion (AIC).

5.3.3 SVAR analysis: The response of option-implied moments to MP shocks

In this section I discuss the empirical results of the bivariate Structural VAR models, while the rest models are discussed in the robustness checks section. As I discussed in previous subsections, my main goal is to identify the response of investors' expectations to monetary policy stance, and more specifically, to find if the responses of the short-

[44] Following the empirical approach of Triantafyllou and Dotsis (2017), and Bekaert et al. (2013), I estimate the bootstrapped confidence intervals using the 1000 of replications, but the results are unaltered when other number of replications are used. The results are available upon request.

term and long-term investors' expectations to monetary policy, differ. Consequently, I focus my main analysis in the responsiveness of option-implied moments to monetary policy shocks and not the reverse response. I present the results about the response of monetary policy to shocks of option-implied moments, in the following subsection and I discuss the results. As I discussed in previous subsection, I use the term spread, the level, the short-end and long end components of each term structure of option-implied moments, in order to obtain information about the term structure of risk neutral densities.

I use four different measures of monetary policy stance, FFR, RIR, M1growth and TRD. Following the empirical approach of Triantafyllou and Dotsis (2017) in this section I use FFR changes as measures of monetary policy shocks. In the robustness checks section, I present the results when I use the alternative measures of monetary policy stance and other subsamples (specifically samples before and after the recent financial crisis and the Zero-lower bound period).[45]

I present **Table 5.3**, that shows the sign of the statistically significant Structural Impulse Response Functions (SIRFs) generated by a negative one standard deviation shock in FFR for each SVAR model as discussed in previous section. Additionally, **Table 5.3** includes the time period (the months) in which the estimated SIRFs are statistically significant in a 90% confidence interval.

Additionally, I report the graphs of the SIRFs that show the responses of the term spread, the level, the short-end and the long-end components of the term structure of option-implied moments, to a negative one standard deviation shock in FFR. Precisely,

[45] I provide a subsample analysis in order to ensure that the different macroeconomic and monetary environment, and more specifically the Zero lower bound environment, does not affect the main results of my main analysis. In general, the main results and arguments are not affected by the subsample analysis.

Figure 5.5 demonstrate the SIRFs of the term spread and the level of the option-implied moments, while **Figure 5.6** plots the SIRFs of the short-end and long-end component of the option-implied moments.

Table 5.3. Structural-form Impulse Responses of the option-implied moments for bivariate SVARs

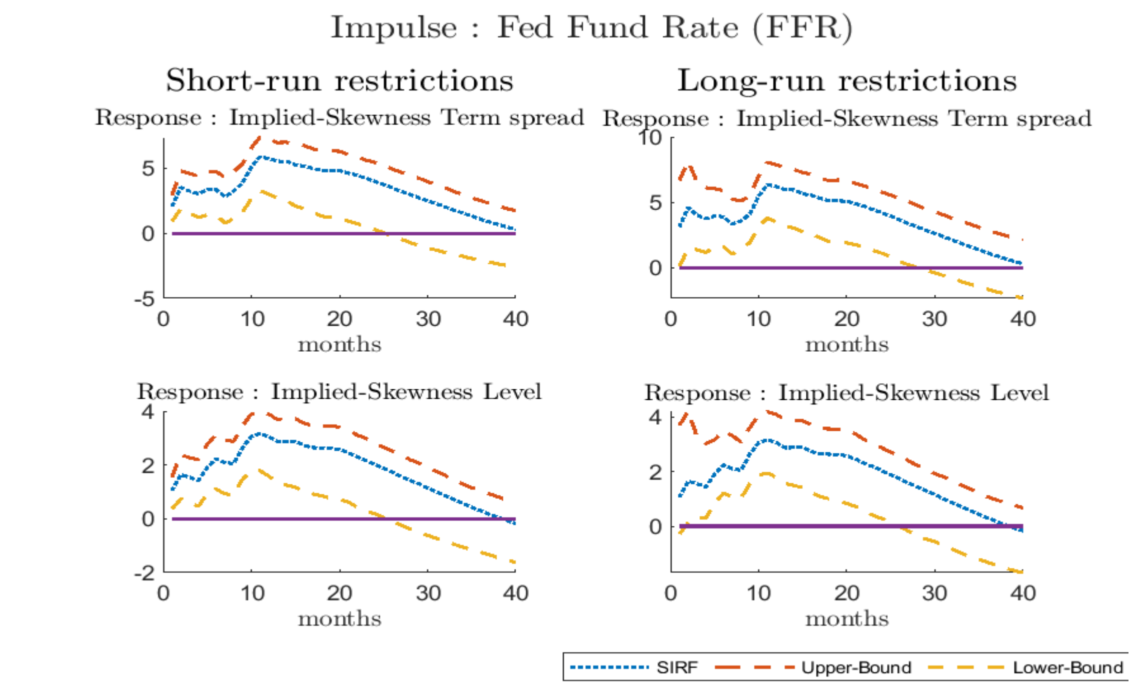
This table summarizes the results of the estimated bivariate SVAR models as I discussed in subsection 2.3. In details, Panel A (Panel B) present how many months the SIRFs that are generated by a negative (positive) one standard deviation shock in FFR (option-implied moment) are statistically significant in a 90% significance level. I estimate the bootstrapped standard errors of the computed SIRFS using 1000 replications. Additionally, I include the column sign, that indicates the sign of the statistically significant SIRFs.

The response of option-implied moments to a negative monetary policy shock			
Short-run restrictions		**Long-run restriction**	
Sign	**Significant from-to (month)**	**Sign**	**Significant from-to (month)**
Impulse: FFR, Response: Term spread of IS			
+	1-25	+	1-28
Impulse: FFR, Response: Level of IS			
+	1-25	+	1-25
Impulse: FFR, Response: Short-end of IS			
+	1-4,5-22	+	1-25
Impulse: FFR, Response: Long-end of IS			
+	1-26	+	1-26
Impulse: FFR, Response: Term spread of IK			
+	2-4	-	10-20
Impulse: FFR, Response: Level of IK			
-	8-15	-	7-20
Impulse: FFR, Response: Short-end of IK			
-	5,7-23	-	6-24
Impulse: FFR, Response: Long-end of IK			
+	2	-	9-21

Figure 5.5. SIRFs of the term spread and the level of IS-IK to negative FFR shocks (expansionary MP shocks), for the bivariate SVAR model

In this figure I plot the SIRFs of the term spread and the level of option-implied moments to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B

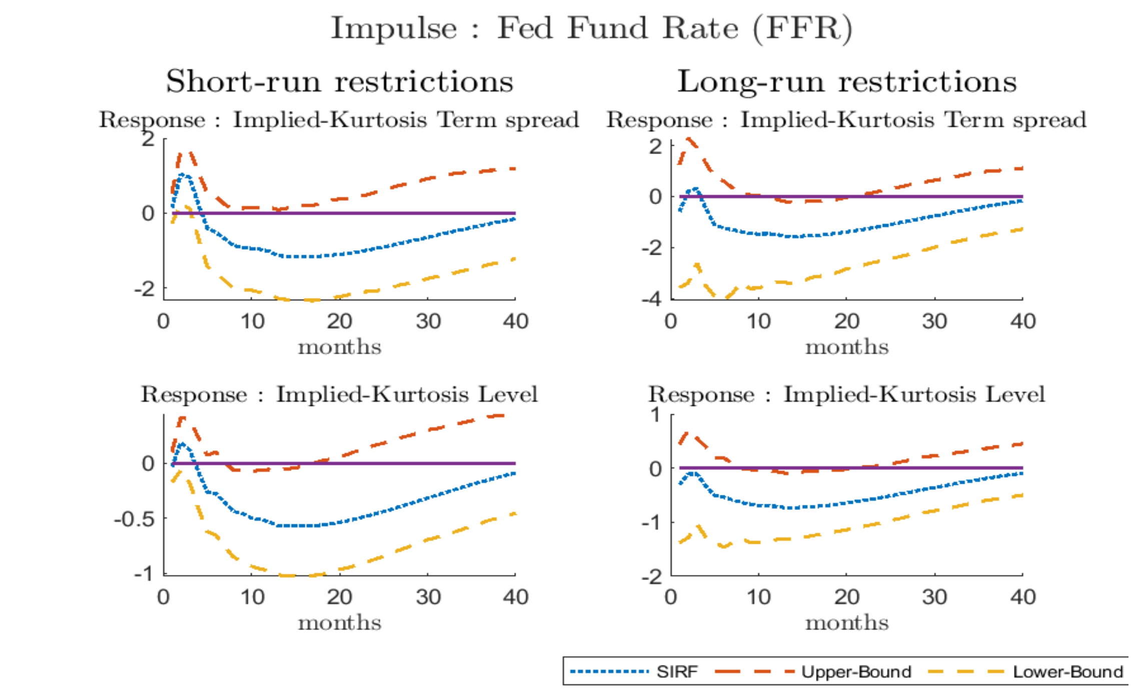
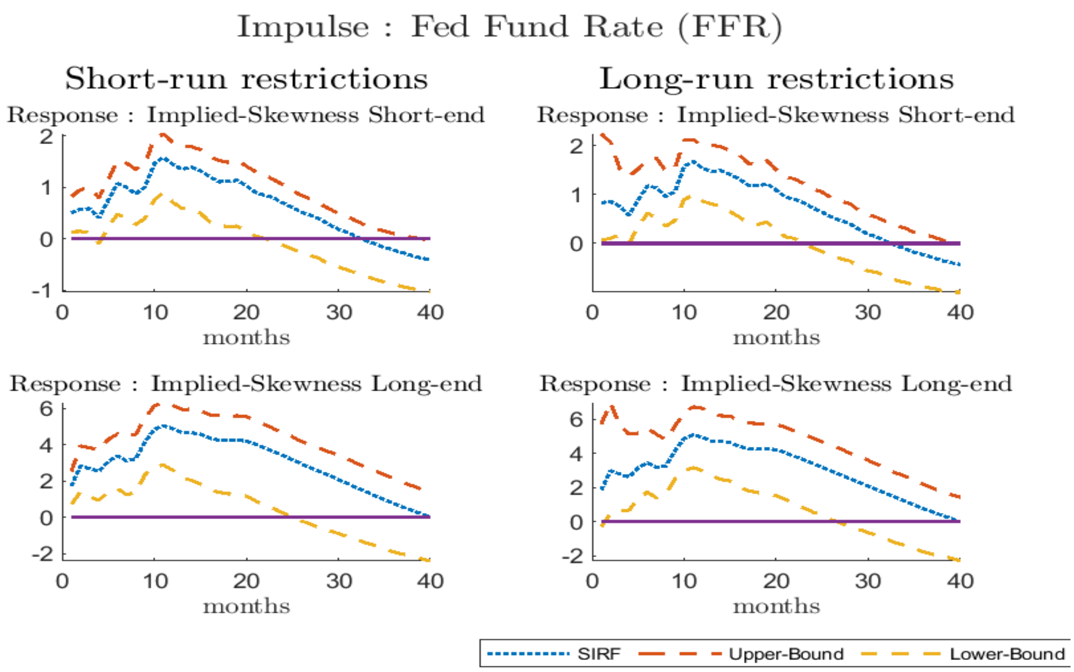


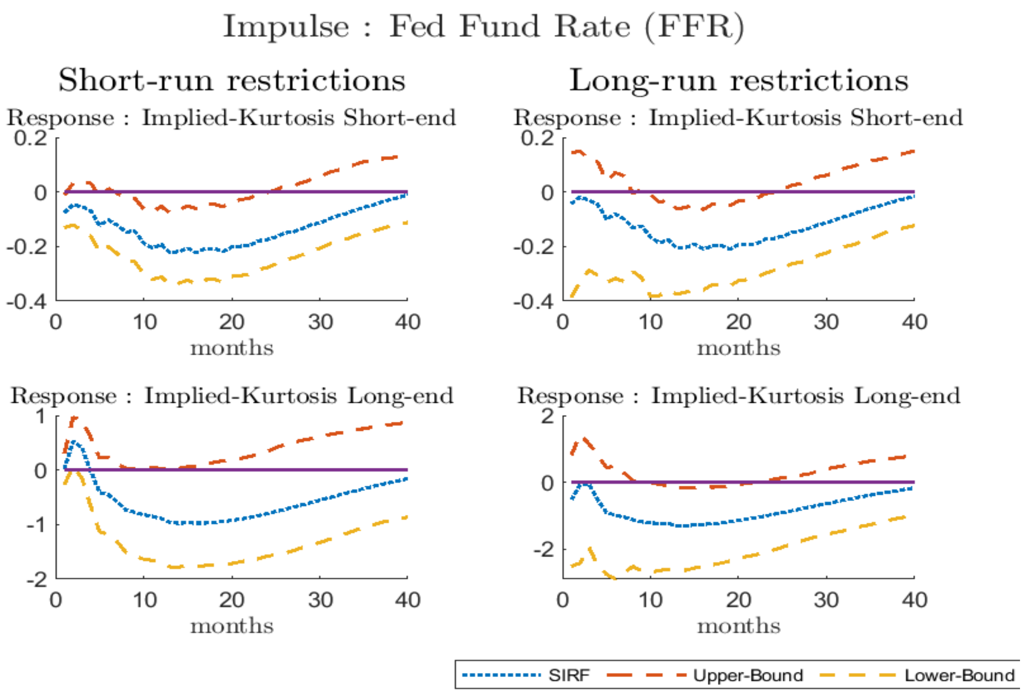
Figure 5.6. SIRFs of the short-end and the long-end IS-IK to negative FFR shocks (expansionary MP shocks), for the bivariate SVAR model

In this figure I plot the SIRFs of the short-end and the long-end components of option-implied moments to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B



I observe several interesting conclusions from the empirical results of the bivariate SVAR models. Initially, I notice that accommodative monetary policy (negative shock in FFR) results in an upward revision on investors' expectations about the subsequent stock market returns. Specifically, I find that the level of IS display an instant response (from the 1st month) to monetary policy shocks. The response is statistically significant for almost 2 years and reach its maximum value (2.5 basis points) after 11 months, for both models with short-run and long-run restrictions. This result is a first indication of the "Fed Put", since I find that accommodative monetary policy results in an upward revise of investors' expectations about the future state of the economy. My results are in line with the results of several relevant studies which examine the existence of "Fed put" during periods of economic turbulence, as well as its impact to financial markets[46]. More importantly, Triantafyllou and Dotsis (2017) find similar results about the reaction of IS of agricultural commodities market to monetary policy shocks, and Stotz (2019) documents a higher option-implied expected returns of S&P 500 index after accommodative monetary policy shock[47].

Furthermore, I observe that an expansionary monetary policy shock has a statistically significant negative effect in the level of option-implied kurtosis, irrespective of the applied restrictions (short-run or long-run). When I apply contemporaneous restrictions, the impact of monetary policy on the level of IK is positive and statistically insignificant for the first 4 months after the initial shock and it turns to negative after the 5th month. Specifically, the level of IK decreases by maximum 0.56 basis points after 18 months, with the impact being significant between lags 7 and 18 lags. I find that IK exhibits a slower response to monetary policy shocks compared to IS. This result

[46] For more details see Kurov et al. (2016), Gu et al. (2018), Cieslak and Vissing-Jorgensen (2020)

[47] Option-implied expected returns correspond to the mean of the risk neutral density, so it is correlated but not identical with the skewness of the risk neutral density.

reveals that monetary policy actions influence investors' perception about the probability of an extreme event to occur, and more specifically, that accommodative monetary policy contributes to the reduction of the jump tail risk of the stock market. Hattori et al. (2017) conclude that unconventional monetary policy tools reduce the jump tail risk during the zero-lower bound period. Nevertheless, I am the first to show the long-term dynamic response of option-implied kurtosis to a negative monetary policy shock, using a SVAR analysis.

Furthermore, the responsiveness of the term spread of option-implied moments (IS and IK) to monetary policy shocks, is a first indication that monetary policy actions have a distinct impact on short-term and long-term components of option-implied moments. The Table 1 provides interesting results about the impact of monetary policy shocks on the term spread of IS. In details, I find that an expansionary shock in monetary policy, has an immediate positive statistical impact on the term spread of IS that lasts for almost 24 months, regardless of the chosen applied restrictions in my model. Uncomplicated, this result suggests that a negative one standard deviation shock in FFR, increases the difference between the IS of 1-year maturity and 30-days maturity, option contracts. Therefore, this result is an indication that the long-term investors' expectations about the future returns of the stock market (proxied by IS of 1-year maturity) are more upwardly revised than the short-term investors' expectations, when an expansionary monetary policy shock occurs.

When I estimate the responsiveness of the term spread of IK to monetary policy shocks, the results are related to the applied restrictions of the SVAR model. When I apply short-run/long-run restrictions in the bivariate SVAR model, the statistically significant impact of lax monetary policy shock on the term spread of IK, is positive/negative between lags 2-4/8-20[48].

In addition, **Figure 5.6** provides novel and detailed results about the asymmetric response of long-term and short-term components of option-implied moments to monetary policy shocks. Specifically, I observe that a negative monetary policy shock has a stronger (in magnitude) and more long-lasting impact to long-term IS compared to short-term IS. When I apply short-run restrictions in my SVAR model, one standard deviation accommodative monetary policy shock causes a 0.016/0.044 change in short-end/long-end IS after 11 months. Moreover, the impact of lax monetary policy shock on short-end and long-end IS remain statistically significant from months 1 to 22 (except 5th month) and from months 1 to 26 respectively. The results are likewise when long-run restrictions are applied to the SVAR model. The results about the asymmetric impact of monetary policy on short-run and long-run IK are puzzling. When I apply short-run restrictions in the bivariate model, I find a more long-lasting statistically significant response of short-end IK to monetary policy shocks in comparison to the long-term kurtosis. The response of long-term IK to an accommodative monetary policy shock is positive and statistically significant in the first 2 months, and in the following months it turns to negative and statistically insignificant. Notwithstanding, the results are altered when I apply long-term restrictions in my SVAR model. I observe that the responses of short-term and long-term IK to a negative monetary policy shock, are statistically significant for almost the same period, but the impact of monetary policy shock on long-term IK is almost 6 times stronger. In details, the impact of

[48] In the robustness checks section, I find that multivariate SVAR model exhibit results more "persistent" about the impact of monetary policy on components of IK. I find negative statistically significant responses of the term spread of IK to expansionary monetary policy for both short-run and long-run SVAR models.

accommodative monetary policy shock on Short-end/long-end IK, remains statistically significant from 6-24/9-21 months and the maximum value of the impact is 2/12 basis points after 15/17 months.

The main conclusion that emerges from Figure 5.6 is that the long-term components of the term structure of option-implied moments are more responsive to monetary policy shocks than the short-end components. While the theory of monetary economics assume that real macroeconomic variables are immune to monetary policy actions in the long term, I find that investors' expectations about the long-term horizon exhibit a statistically significant response to monetary policy shocks. My empirical results provide a new perspective about the importance of monetary policy actions, since I find that policy makers are able to affect long-term investors' expectations.

5.3.4 SVAR analysis: The response of future monetary policy to option-implied expectations shocks

While it is not my target to empirically verify how monetary policy react to option-implied expectations, I provide results about the responsiveness of monetary policy to investors' expectations and fears about the future state of the economy. I present similar tables and figures with the previous subsection 5.2.3., in order to show the impact of option-implied moments on monetary policy. In details, similatly to **Table 5.3**, **Table 5.4** shows the sign of the statistically significant Structural Impulse Response Functions (SIRFs) generated by a negative(positive) one standard deviation shock in components of IS (IK) for each SVAR model as discussed in previous section. Furthermore, it includes the time period (the months) in which the estimated SIRFs are statistically significant in a 90% confidence interval. Furthermore, I include **figures 5.7** and **5.8** that demonstrate the SIRFs that correspond to the impact of the term spread and the level of the option-implied moments on monetary policy and the impact of the short-end and long-end components of the option-implied moments on monetary policy respectively.

Table 5.4. Structural-form Impulse Responses of the FFR for bivariate SVARs

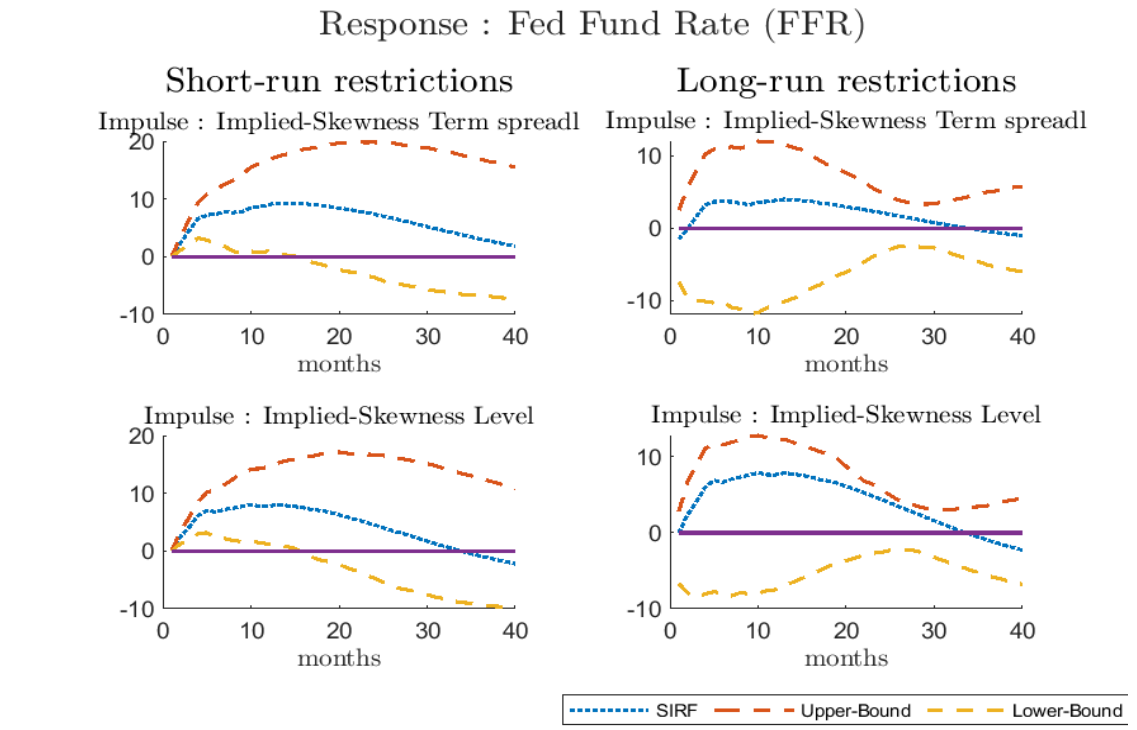
This table summarizes the results of the estimated bivariate SVAR models as I discussed in subsection 2.3. In details, the table present how many months the SIRFs that are generated by a negative (positive) one standard deviation shock in option-implied Skewness (kurtosis) are statistically significant in a 90% significance level. I estimate the bootstrapped standard errors of the computed SIRFS using 1000 replications, following Triantafyllou and Dotsis (2017) empirical approach. Additionally, I include the column sign, that indicates the sign of the statistically significant SIRFs.

The response of Fed Fund Rate to a negative/positive shock in IS/IK			
Short-run restrictions		**Long-run restriction**	
Sign	**Significant from-to (month)**	**Sign**	**Significant from-to (month)**
Impulse: Term spread of IS, Response: FFR			
-	1-15	\	\
Impulse: Level of IS, Response: FFR			
-	1-15	\	\
Impulse: Short-end of IS, Response: FFR			
-	1-18	\	\
Impulse: Long-end of IS, Response: FFR			
-	1-14	\	\
Impulse: Term spread of IK, Response: FFR			
+	1-20	\	\
Impulse: Level of IK, Response: FFR			
+	1-21	\	\
Impulse: Short-end of IK, Response: FFR			
+	1-16	\	\
Impulse: Long-end of IS, Response: FFR			
+	1-20	\	\

Figure 5.7. SIRFs of the FFR to a negative/positive shock of the term spread and the level of IS/IK, for the bivariate SVAR model

In this figure I plot the SIRFs of the FFR to a one standard deviation shock in the term spread and the level of option-implied moments. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B

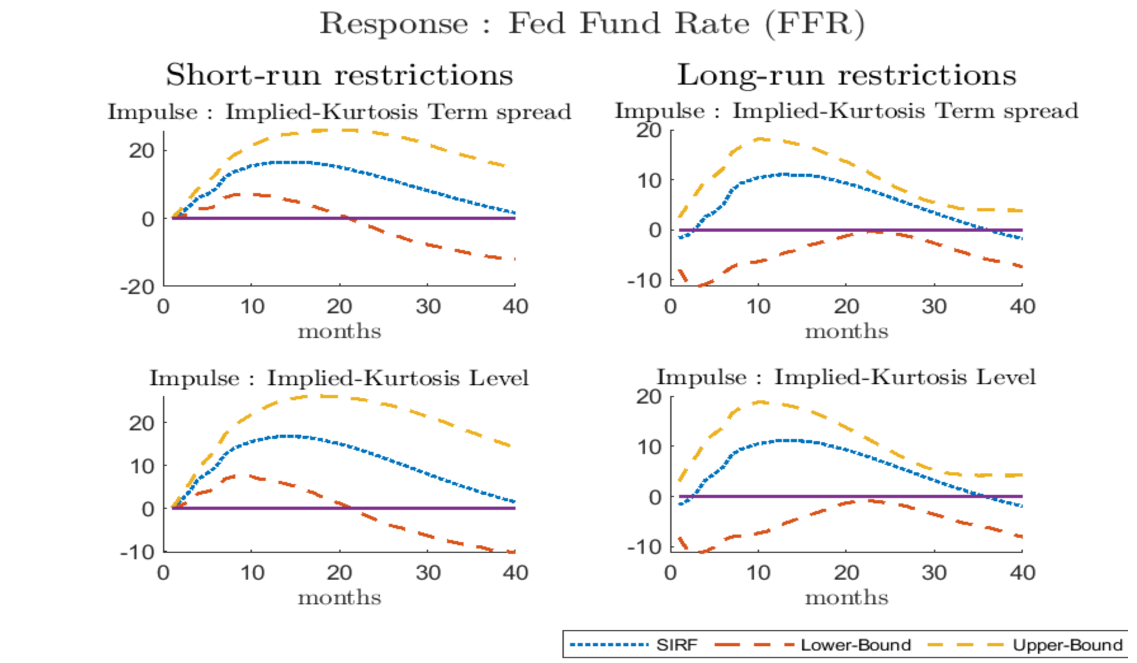
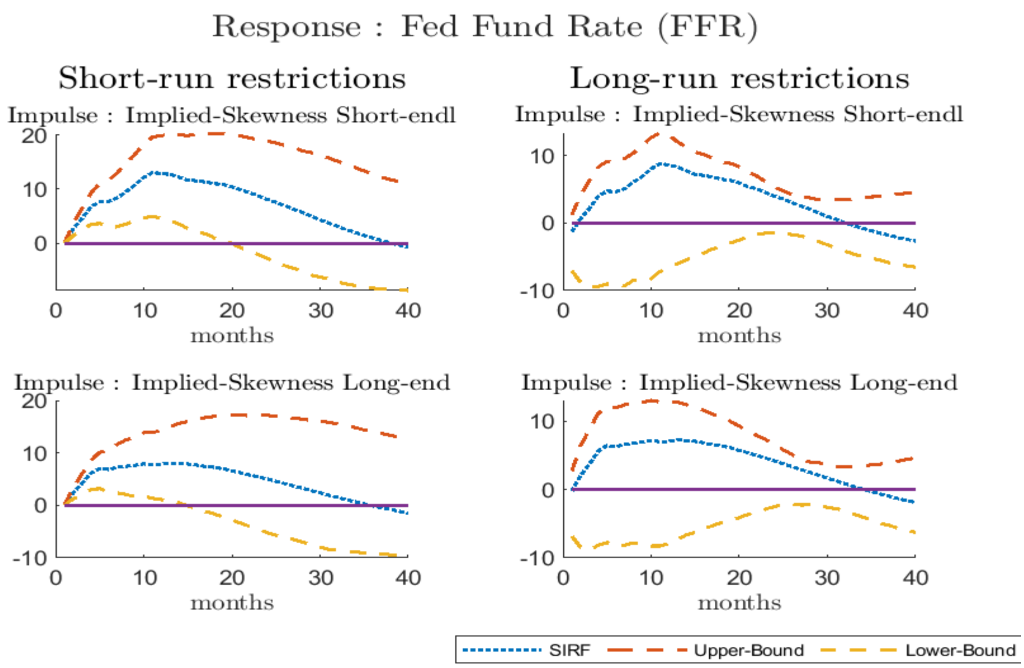


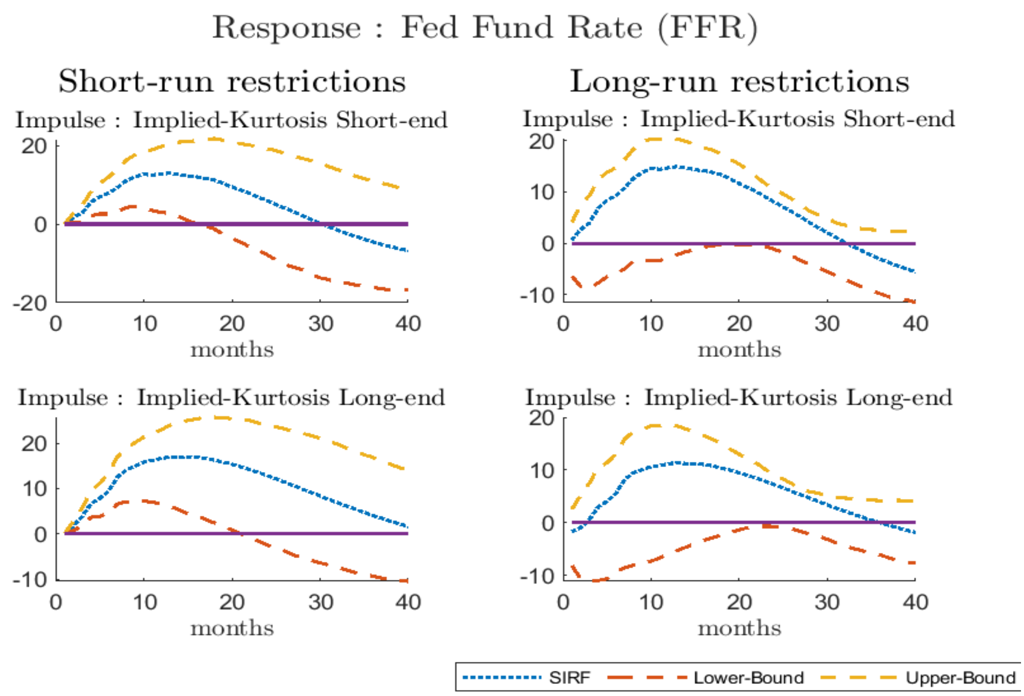
Figure 5.8. SIRFs of the FFR to a negative/positive shock of the short-end and the long-end of IS/IK, for the bivariate SVAR model

In this figure I plot the SIRFs of the FFR to a one standard deviation shock in the short-end and the long-end components of the option-implied moments. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B



I observe that the SVAR model with the long-run restrictions does not provide statistically significant SIRFs of the monetary policy stance. Triantafyllou and Dotsis (2017) find similar results about the response of FFR to shocks derived from option-implied moments of the agricultural commodities market. Notwithstanding the non-statistically significant results of the model with the applied long-run restrictions, the estimated SVAR model with the short-run restrictions applied provide interesting results. Specifically, I find that a negative shock in IS (an indication that investors expect bearish stock market) results an immediate and statistically significant increase to FFR for up to 15 months ahead from the initial shock. Similarly, I document that a positive shock in IK (an indication that investors predict a higher possibility of an extreme event to occur) cause an immediate increase to FFR and I observe that this impact remains statistically significant till 20 months after the initial shock. These results are puzzling since they indicate that when investors expect a subsequent poor performance of the stock market, monetary policy tends to be contractionary. In order to explain my results, I follow the argument of the David and Veronesi (2014). In their paper, they find similar results about the impact of option-implied expectations on subsequent short-term interest rates (a measure of monetary policy). Specifically, they find that a positive shock in a measure of downside-risk (put-to-call ratio) results a statistically significant increase on future short-term interest rates for a long period after the initial shock. They provide a dynamic equilibrium model in order to explain this phenomenon, and they conclude that beliefs and expectations about economy drive both option prices and monetary policy stance through the forward-looking Taylor rule. In simple words, they claim that expectations about the future state of the economy drives both option prices and the conducted monetary policy, and consequently option prices lead monetary policy.

Finally, when it comes to the response of monetary policy to shocks in the short-end and long-end components of option-implied moments, I find similar results about the impact of short-end and long-end option-implied moments on FFR.

I discuss in details, the empirical evidence of this subsection about the impact of option-implied moments on monetary policy, in the following subsection in which I estimate a regression predicting model similar with Triantafyllou and Dotsis 2017. My purpose is to ensure that the argument of David and Veronesi (2014) about the predictability of option-implied moments on subsequent monetary policy is robust and it is can explain the empirical results of this subsection. Additionally, I discuss more about the relevant results in the robustness checks section and in the appendix.

5.4 Predicting Subsequent monetary policy rate using option-implied moments

As I mention in the previous subsection, I attempt to verify the claim of David and Veronesi (2014), by using a predictive regression analysis. I estimate a predictive regression model in which I predict the future monetary policy path using option-implied moments. I follow this empirical approach motivated by the seminal paper of David and Veronesi (2014). The predictive regression model is similar with Triantafyllou and Dotsis (2017) and has the following equation:

$$FFR_t = a + b_1 IV_{t-k} + b_1 IS_{t-k} + u_t \tag{5.9}$$

Where FFR is the Fed Fund rate at month t, IV_{t-k} is the component of the term structure of IV (for example the level of IV), the IS_{t-k} is the component of the IS and finally k corresponds to the predicting horizon. In order to provide robustness in my empirical results, I run a multiple predictive regression model that I use macroeconomic indicators as control variables. Specifically, the predictive regressionmodel has the following form:

$$FFR_t = a + b_1SLOPE_{t-k} + b_1IPG_{t-k} + b_1INF_{t-k} + b_1IV_{t-k} + b_1IS_{t-k} + u_t \tag{5.10}$$

Where SLOPE is the term spread of the yield curve, IPG is the industrial production growth and INF is the monthly inflation rate.

In the end, I estimate similar regression models with equations (5.9) and (5.10) but instead of the components of the IS I include the components of IK. The predicting models that include the option-implied kurtosis are described by the following equations:

$$FFR_t = a + b_1IV_{t-k} + b_1IK_{t-k} + u_t \tag{5.11}$$

$$FFR_t = a + b_1SLOPE_{t-k} + b_1IPG_{t-k} + b_1INF_{t-k} + b_1IV_{t-k} + b_1IK_{t-k} + u_t \tag{5.12}$$

In this section, I empirically verify that ex-ante investors' expectations are able to predict the subsequent level of the monetary policy rate, following the argument of

David and Veronesi (2014) and Triantafyllou and Dotsis (2017). The following **Tables 5.5** and **5.6** includes the results of the estimated regression model of the equation (5.9), and equation (5.10), respectively.

Table 5.5. Predicting the monetary policy (Fed funds rate) with the level of IV and IS

This table shows the predictive regressions on monthly monetary policy stance (Fed funds rate), using as explanatory variables lagged values of the level of IV and IS. My predicting horizon ranges from 1 to 24 months. IV is option-implied variance, IS option-implied skewness. The t-statistics reported in the relevant lines are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. I forecast the future monetary policy stance k months ahead (k = 1, 3, 6, 12, 24).

Horizon (k)		***k=1***	***k=3***	***k=6***	***k=12***	***k=24***
Const	Coef.	-2.453***	-2.407***	-2.288***	-1.596*	0.291
	t-stat	(-4.35)	(-3.81)	(-3.36)	(-1.81)	(0.19)
Level of IV	Coef.	7.596***	7.282***	6.871***	5.389**	2.068
	t-stat	(4.08)	(3.55)	(3.23)	(2.24)	(0.64)
Level of IS	Coef.	-13.19***	-13.25***	-13.01***	-11.28***	-5.862
	t-stat	(-14.40)	(-11.53)	(-9.24)	(-5.20)	(-1.52)
% R^2		70.9	72.9	72.1	57.6	18.7

Table 5.6. Predicting the monetary policy (Fed funds rate) with the level of IV, IS and other macroeconomic variables.

This table shows the predictive regressions on monthly monetary policy stance (Fed funds rate), using as explanatory variables lagged values of the level of IV and IS, the term spread of U.S. yield curve, the industrial production growth of U.S. and the monthly inflation rate. My predicting horizon ranges from 1 to 24 months. The t-statistics reported in the relevant lines are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. I predict the future monetary policy stance k months ahead (k = 1, 3, 6, 12, 24).

Horizon (k)		***k=1***	***k=3***	***k=6***	***k=12***	***k=24***
Const	Coef.	-0.824	-1.063	-1.437	-1.877	-0.651
	t-stat	(-1.00)	(-1.15)	(-1.42)	(-1.58)	(-0.38)
Term spread	Coef.	-51.81***	-44.85**	-31.18	-0.0679	18.87
	t-stat	(-3.16)	(-2.43)	(-1.47)	(-0.00)	(0.37)
IPG	Coef.	32.02**	40.10***	48.62***	55.87***	54.08*
	t-stat	(2.23)	(3.33)	(3.82)	(2.88)	(1.80)
INF	Coef.	0.672**	0.696***	0.592***	0.396	0.216
	t-stat	(2.47)	(3.00)	(2.83)	(1.41)	(0.87)
Level of IV	Coef.	6.839***	6.791***	6.759***	6.106***	3.218
	t-stat	(4.71)	(4.15)	(3.72)	(2.89)	(1.15)
Level of IS	Coef.	-9.894***	-10.36***	-10.93***	-11.11***	-6.866*
	t-stat	(-7.28)	(-6.80)	(-6.30)	(-4.82)	(-1.82)
% R^2		74.9	76.8	75.4	60.7	22.1

The estimated results show that the IS (more specifically the level of the IS) is a robust predictor of subsequent FFR. In details the predicting model that includes the level of IV and IS as predictors of future FFR explains the larger fraction of the variability of the subsequent FFR, since the estimated R^2 values are 70.2, 72.9, 72.1, 57.6 for a 1,3,6 and 12 months forecast horizon respectively. The estimated coefficients of the level of IS are statistically significant in a 1% significance level for forecast horizons ranging from 1 up to 12 months. Finally, I observe that even when I include macroeconomic control variables in my predicting model, the level of IS remain a highly statistically significant predictor of subsequent FFR.

Furthermore, **Table 5.7** and **5.8** include the results of the estimated regression models of the equation (5.11) and (5.12) respectively.

Table 5.7. Predicting the monetary policy (Fed funds rate) with the level of IV and IK

This table shows the predictive regressions on monthly monetary policy stance (Fed funds rate), using as explanatory variables lagged values of the level of IV and IK. My predicting horizon ranges from 1 to 24 months. IV is option-implied variance and IK is option-implied kurtosis. The t-statistics reported in the relevant lines are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. I forecast the future monetary policy stance k months ahead (k = 1, 3, 6, 12, 24).

Horizon (k)		***k=1***	***k=3***	***k=6***	***k=12***	***k=24***
Const	Coef.	-2.697***	-2.698***	-2.581**	-1.650	0.823
	t-stat	(-3.40)	(-2.85)	(-2.50)	(-1.34)	(0.42)
Level of IV	Coef.	1.018	0.711	0.432	-0.244	-1.063
	t-stat	(0.59)	(0.35)	(0.20)	(-0.11)	(-0.53)
Level of IK	Coef.	19.46***	19.68***	19.33***	15.95***	6.177
	t-stat	(9.17)	(7.46)	(6.35)	(3.79)	(0.92)
% R^2		37.8	39.7	39.5	29.4	6.7

Table5.8. Predicting the monetary policy (FFR) with the level of IV, IK and other macroeconomic variables.

This table shows the predictive regressions on monthly monetary policy stance (Fed funds rate), using as explanatory variables lagged values of the level of IV and IK, the term spread of U.S. yield curve, the industrial production growth of U.S. and the monthly inflation rate. My predicting horizon ranges from 1 to 24 months. The t-statistics reported in the relevant lines are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. I predict the future monetary policy stance k months ahead (k = 1, 3, 6, 12, 24).

Horizon (k)		***k=1***	***k=3***	***k=6***	***k=12***	***k=24***
Const	Coef.	1.236	1.103	1.012	1.168	2.241
	t-stat	(1.54)	(1.09)	(0.83)	(0.68)	(1.05)
Term spread	Coef.	-121.5***	-118.2***	-111.2***	-87.66**	-46.21
	t-stat	(-9.53)	(-7.02)	(-4.99)	(-2.43)	(-0.96)
IPG	Coef.	50.90***	59.60***	67.84***	75.13***	65.82**
	t-stat	(2.84)	(3.72)	(3.99)	(3.16)	(2.00)
INF	Coef.	0.651***	0.676***	0.579**	0.354	0.182
	t-stat	(2.61)	(3.15)	(2.50)	(1.02)	(0.52)
Level of IV	Coef.	2.467***	2.206**	1.878	1.019	-0.173
	t-stat	(2.65)	(2.07)	(1.58)	(0.67)	(-0.09)
Level of IK	Coef.	9.589***	10.06***	10.21***	8.729	2.347
	t-stat	(4.28)	(3.47)	(2.84)	(1.64)	(0.34)
% R^2		67	68.2	65.8	48.3	15

My results show that the level of IK is a strong predictor of future FFR. The estimated coefficient of the level of IK are statistically significant in a 1% significance level for almost all the estimated predicting horizons, and the estimated R^2 values are 37.8, 39.7, 39.5, 29.4 for a 1,3,6 and 12 months forecast horizon respectively. Furthermore, I find that the results remain unaltered in the inclusion of other macroeconomic control variables. The estimated results of the predictive regression models are in line with the empirical results of the David and Veronesi (2014) and Triantafyllou and Dotsis (2017). In details, similatly to the estimated results of the SVAR model, I find that the level of the IS/IK predicts negatively/positively the subsequent FFR. In simple words this result means that when investors expect bearish stock market or they estimate a higher probability of extreme event to occur, policy makers conduct contractionary monetary policy. My results confirm the claim of David and Veronesi (2014) who emphasize that option prices embody a rich information content about the subsequent FFR.

5.5 Conclusion

Briefly, in my paper I document the impact of monetary policy on investors' expectations and fears. Specifically, by using higher moments of the option-implied distribution, I find that lax monetary policy results in an upward revision on investors' expectations about the future state of the economy. My empirical results provide further insights about the risk-taking channel of monetary policy, and they clearly demonstrate that investors start revising upwardly their expectations about the subsequent stock market returns when the monetary policy is accommodative. More importantly, I provide novel results about the long-term non money neutrality on option markets. I am the first to show that policy makers are not only able to influence investors' expectations about the subsequent market performance, but more significantly, they are capable of shaping expectations about the long-term horizon.

My results have a potential important policy implementation, since I provide evidence that policy makers are qualified to influence not only ex-ante expectations about the short-term horizon, but mainly, investors' beliefs about the long-term horizons.

Chapter 6

Conclusions-suggestions for future research

In this thesis I empirically verify the strong predictive information content of macroeconomic uncertainty and yield curve volatility about the subsequent stock market volatility, as well as the "maturity-varying" impact of monetary policy to investors' ex-ante expectations about the future state of equities market.

In the first chapter I document the strong predictability of latent macroeconomic uncertainty on subsequent stock market volatility and price jumps, especially during the period after the recent financial crisis of 2007 that many relevant studies find tighter macro-finance linkages (Hubrich and Tetlow, 2015; Caldara et al., 2016; Prieto et al., 2016). In details, latent macroeconomic uncertainty outperforms other measures that commonly are commonly used as predictors of stock market volatility like VIX index and EPU, MPU measures of Baker et al. (2016), for long-term forecast horizons. Additionally, the latent macroeconomic uncertainty explains a large fraction of equities price jumps. My empirical results are in line with several strands of the literature who find a time-varying macro-finance linkage (Hubrich and Tetlow, 2015; Caldara et al., 2016; Prieto et al., 2016)., a strong relation amongst macroeconomic and monetary policy news, with stock market volatility and price jumps (Pastor and Veronesi, 2012; Asgharian and Hou, 2013; Corradi et al., 2013; Engle et al., 2013; Conrad and Loch, 2015; Liu and Zhang, 2015; Amengual and Xiu, 2018; Kaminska and Roberts-Sklar, 2018). Interestingly, I find that latent macroeconomic uncertainty strongly outperforms VIX index when it comes to volatility prediction of companies in the financial sector.

One possible suggestion for future research, would be the time-varying impact of latent macroeconomic uncertainty on investors' expectations and jump tail risk. I believe that interesting results will emerge from the specific research, since we will be able to empirically verify how investors' expectations and fears about the future state of the stock market, react to high levels of macroeconomic uncertainty under varying macroeconomic and monetary regimes. The specific research will help us to understand in depth, the time-varying macro-finance linkages and more specifically, to which extent investors consider the macroeconomic uncertainty when they "discount" the future path of stock prices.

Additionally, the emerging cryptocurrency market introduced a new era in trading. The last years, a growing part of the global market capitalization is allocated to cryptocurrencies and there is a new possible research field regarding the trading patterns, volatility spillovers amongst the stock, commodity, and cryptocurrency markets. The possible linkage between macroeconomic uncertainty and cryptocurrency market volatility is now examined yet. Future research could shed light about the linkages of macroeconomic fundamentals, monetary policy and cryptos volatility.

In the second chapter of my thesis, I empirically verify the strong predictive information content of yield curve volatility on stock market volatility. More specifically, I find that the realized variance of the slope of the yield curve outperforms other measures of economic and monetary policy uncertainty (EPU and MPU measures of Baker et al. (2016)) when it comes to stock market volatility prediction. My empirical results suggest that the predictability of SLOPERV is substantially increased during the period after the recent financial crisis of 2007 that coincides with the zero-lower bound period. More interestingly, I find that yield curve volatility has a stronger impact on the price volatility of cyclical and capital-intensive industries that according to a relevant strand of the literature (Ehrmann and Fratzscher (2004), Bernarke and Kuttner (2005) amongst others) these companies are more sensitive to monetary policy news, and consequently, interest rates changes. My analysis provides interesting results with important policy implementations, since I find that the variation of the term structure of interest rates is a strong predictor of the long-term stock market volatility, especially during period of financial and macroeconomic distress.

A suggested idea for future research is the empirical examination of the predictability of the volatility of the slope of the yield curve on future economic activity. My argument is based on the premise that since the term spread of the yield curve reflects investors' beliefs about the state of the economy, therefore the second moments of the slope of the yield curve reflects the dispersion of expectations that is strongly affects future real economic activity likewise other measures of uncertainty.

Finally, in the last chapter of my thesis, I document the "maturity-varying" response of the option-implied expectations to monetary policy news. In details, I find that the investors' expectations and fears about the long-end horizon are more sensitive to monetary policy shocks. My novel results are partially at odds with the standard monetary theory, likewise a few other similar studies (Hanson and Stein 2015, Kontonikas and Zekaite 2018, Nakamura and Steinsson 2018). Nevertheless, the estimations do not directly challenge the validity of the standard monetary theory. Further research is needed to understand in depth, the risk-taking channel of monetary policy, and the underlying economic mechanism that explains this long-term money non-neutrality of ex-ante investors' expectations. The trading pattern in which investors borrowing in lower rates and invest in risky assets with higher return (carry trades) would be a possible explanation of the specific observed phenomenon. A possible research idea is the examination of the reaction of stocks' cost of carry to monetary policy shocks. Specifically, it can be estimated the cost of carry for varying maturities of the future contracts that are used for the cost of carry estimation. In this way, it can be constructed the term structure of cost of carries in order to examine the impact of monetary policy on long-end and short-end cost of carries. Further research about this possible mechanism that is related to the risk-taking channel of monetary policy, could be investigated, and it will be helpful to understand the underlying mechanism of this long-term non-neutrality of money on investors' ex-ante expectations.

7. 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.

Adrian, T., & Shin, H. S. (2008). Financial intermediaries, financial stability, and monetary policy. *FRB of New York staff report*, (346).

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

Andersen, T. G., Bollerslev, T., and Diebold, F. X. (2007). 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., & Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of financial economics,* 61(1), 43-76.

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

Ang, A., & Piazzesi, M. (2003). A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables. *Journal of Monetary economics*, *50*(4), 745-787.

Angeloni, I., Faia, E., & Duca, M. L. (2015). Monetary policy and risk taking. *Journal of Economic Dynamics and Control*, *52*, 285-307.

Antonakakis, N., Chatziantoniou, I., & Filis, G. (2014). Dynamic spillovers of oil price shocks and economic policy uncertainty. *Energy Economics*, *44*, 433-447.

Antonakakis, N., Chatziantoniou, I., and Filis, G. (2013). Dynamic co-movements of stock market returns, option-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.

Arrow, K. J. (1964). The role of securities in the optimal allocation of risk-bearing. *The review of economic studies*, *31*(2), 91-96.

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

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of finance*, *61*(4), 1645-1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of economic perspectives*, *21*(2), 129-152.

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

Bakshi, G., Cao, C., & Chen, Z. (1997). Empirical performance of alternative option pricing models. *The Journal of finance*, *52*(5), 2003-2049.

Bakshi, G., Kapadia, N., & Madan, D. (2003). Stock return characteristics, skew laws, and the differential pricing of individual equity options. *The Review of Financial Studies*, *16*(1), 101-143.

Bali, T. G., & Murray, S. (2013). Does risk-neutral skewness predict the cross-section of equity option portfolio returns?. *Journal of Financial and Quantitative Analysis*, *48*(4), 1145-1171.

Bali, T. G., Hu, J., & Murray, S. (2019). Option-implied volatility, skewness, and kurtosis and the cross-section of expected stock returns. *Georgetown McDonough School of Business Research Paper*.

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.

Barro, R. J. (1977). Unanticipated money growth and unemployment in the United States. *The American Economic Review*, *67*(2), 101-115.

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

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 U.S. and UK. *Journal of Banking and Finance,* 19(7), 1191-1210.

Beckmeyer, H., Branger, N., & Grünthaler, T. (2019). The Fed Call: FOMC Announcements and Stock Market Uncertainty. *Available at SSRN.*

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

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

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

Berger, D., & Turtle, H. J. (2015). Sentiment bubbles. *Journal of financial markets*, *23*, 59-74.

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.

Black, F. (1976). The pricing of commodity contracts. *Journal of financial economics*, *3*(1-2), 167-179.

Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy, 81* (May-June).

Blanchard, O. J., & Quah, D. (1989). The dynamic effects of aggregate demand and supply disturbances. *The American Economic Review*, 655-673

Blanchard, O. J., & Watson, M. W. (1982). Bubbles, rational expectations and financial markets.

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

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., & Terry, S. J. (2018). Really uncertain business cycles. *Econometrica*, *86*(3), 1031-1065.

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

Borio, C., & Zhu, H. (2012). Capital regulation, risk-taking and monetary policy: a missing link in the transmission mechanism?. *Journal of Financial stability*, *8*(4), 236-251.

Breeden, D. T., & Litzenberger, R. H. (1978). Prices of state-contingent claims implicit in option prices. *Journal of business*, 621-651.

Brusa, F., Savor, P. G., & Wilson, M. I. (2015). One central bank to rule them all. *Said Business School WP*, *13*.

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.

Campbell, J. Y. (1986). Bond and stock returns in a simple exchange model. *The Quarterly Journal of Economics*, *101*(4), 785-803.

Canina, L., and Figlewski, S. (1993). The informational content of option-implied volatility. *Review of Financial Studies,* 6(3), 659-681.

Chen, L., Da, Z., & Zhao, X. (2013). What drives stock price movements?. *The Review of Financial Studies*, *26*(4), 841-876.

Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of business*, 383-403.

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.

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of financial Economics*, 10(4), 407-432.

Cremers, M., Fleckenstein, M., & Gandhi, P. (2021). Treasury yield option-implied volatility and real activity. *Journal of Financial Economics*, *140*(2), 412-435.

Christensen, B. J., and Prabhala, N. R. (1998). The relation between option-implied and realized volatility1. *Journal of Financial Economics*, 50(2), 125-150.

Christiano, L. J., Eichenbaum, M., & Evans, C. L. (1999). Monetary policy shocks: What have I learned and to what end?. *Handbook of macroeconomics*, *1*, 65-148.

Cieslak, A., & Povala, P. (2016). Information in the term structure of yield curve volatility. *The Journal of Finance*, *71*(3), 1393-1436.

Cieslak, A., Morse, A., & Vissing-Jorgensen, A. (2018). Stock returns over the FOMC cycle. *Journal of Finance, forthcoming*.

Cieslak, A., & Vissing-Jorgensen, A. (2020). *The economics of the Fed put* (No. w26894). National Bureau of Economic Research.

Clements, A. (2007). S&P 500 option-implied volatility and monetary policy announcements. *Finance Research Letters*, *4*(4), 227-232.

Cochrane, A. (2007). *Understanding urban policy: a critical approach*. Blackwell.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of finance*, *66*(4), 1047-1108.

Connolly, R., Dubofsky, D., & Stivers, C. (2018). Macroeconomic uncertainty and the distant forward-rate slope. *Journal of Empirical Finance*, *48*, 140-161.

Conrad, J., Dittmar, R. F., & Ghysels, E. (2013). Ex ante skewness and expected stock returns. *The Journal of Finance*, *68*(1), 85-124.

Conrad, C., and K. Loch (2015). Anticipating Long-Term Stock Market Volatility. *Journal of Applied Econometrics,* 30(7), 1090-1114

Coroneo, L., Giannone, D., & Modugno, M. (2016). Unspanned macroeconomic factors in the yield curve. *Journal of Business & Economic Statistics*, *34*(3), 472-485.

Corradi, V., Distaso, W., and Mele, A. (2013). Macroeconomic determinants of stock volatility and volatility premiums. *Journal of Monetary Economics*, 60(2), 203-220.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics,* 7(2), 174-196.

Cox, J. C., & Ross, S. A. (1976). The valuation of options for alternative stochastic processes. *Journal of financial economics*, *3*(1-2), 145-166.

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of financial Economics*, *10*(4), 407-432.

Creal, D. D., & Wu, J. C. (2017). Monetary policy uncertainty and economic fluctuations. *International Economic Review*, *58*(4), 1317-1354.

D'Amico, S., & Farka, M. (2011). The Fed and the stock market: An identification based on intraday futures data. *Journal of Business & Economic Statistics*, *29*(1), 126-137.

David, A., & Veronesi, P.,(2014). Investors' and Central Bank's Uncertainty Embedded in Index Options. *The Review of Financial Studies*, 27(6), 1661–1716.

Debreu, G. (1959). *Theory of value: An axiomatic analysis of economic equilibrium* (Vol. 17). Yale University Press.

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., & Grossman, H. I. (1988). Explosive rational bubbles in stock prices?. *The American Economic Review*, *78*(3), 520-530.

Diebold, F. X., Piazzesi, M., & Rudebusch, G. D. (2005). Modeling bond yields in finance and macroeconomics. *American Economic Review*, *95*(2), 415-420.

Diebold, F. X., Rudebusch, G. D., & Aruoba, S. B. (2006). The macroeconomy and the yield curve: a dynamic latent factor approach. *Journal of econometrics*, *131*(1-2), 309-338.

Doshi, H., Jacobs, K., & Liu, R. (2018). Macroeconomic determinants of the term structure: Long-run and short-run dynamics. *Journal of Empirical Finance, 48,* 99-122.

Du, B., Fung, S., & Loveland, R. (2018). The informational role of options markets: Evidence from FOMC announcements. *Journal of Banking & Finance, 92*, 237-256.

Ebens, H. (1999). Realized stock volatility. Department of Economics, Johns Hopkins University.

Ehrmann, M., & Fratzscher, M. (2004). Taking stock: Monetary policy transmission to equity markets. *Journal of Money, Credit and Banking*, 719-737.

Elder, J. (2018). Oil price volatility: Industrial production and special aggregates. *Macroeconomic Dynamics,* 1-14

Elder, J., and Serletis, A. (2010). Oil price uncertainty. *Journal of Money, Credit and Banking*, 42(6), 1137-1159.

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., & Rangel, J. G. (2008). The spline-GARCH model for low-frequency volatility and its global macroeconomic causes. *The Review of Financial Studies*, *21*(3), 1187-1222

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.

Estrella, A., & Hardouvelis, G. A. (1991). The term structure as a predictor of real economic activity. *The journal of Finance*, *46*(2), 555-576.

Evans, K. P. (2011). Intraday jumps and U.S. macroeconomic news announcements. *Journal of Banking and Finance,* 35(10), 2511-2527.

Fama, E. F. (1990). Stock returns, expected returns, and real activity. *The journal of finance*, *45*(4), 1089-1108.

Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of financial economics*, *25*(1), 23-49.

Fernandez-Perez, A., Frijns, B., & Tourani-Rad, A. (2017). When no news is good news–The decrease in investor fear after the FOMC announcement. *Journal of Empirical Finance*, *41*, 187-199.

Figlewski, S. (2008). Estimating the option-implied risk neutral density.

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

Gorodnichenko, Y., & Weber, M. (2016). Are sticky prices costly? Evidence from the stock market. *American Economic Review*, *106*(1), 165-99.

Gospodinov, 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

Goto, S., & Valkanov, R. I. (2002). The Fed's effect on excess returns and inflation is much bigger than you think. *Available at SSRN 307133*.

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.

Guo, H., and Kliesen, K. L. (2005). Oil price volatility and U.S. macroeconomic activity. Review-Federal Reserve Bank of Saint Louis, 87(6), 669.

Gürkaynak, R. S., Sack, B., & Swanson, E. (2005). The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models. *American economic review*, *95*(1), 425-436.

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

Han, B. (2008). Investor sentiment and option prices. *The Review of Financial Studies*, *21*(1), 387-414.

Hanson, S. G., & Stein, J. C. (2015). Monetary policy and long-term real rates. *Journal of Financial Economics*, *115*(3), 429-448.

Hardouvelis, G. A. (1987). Macroeconomic information and stock prices. *Journal of Economics and Business*, *39*(2), 131-140.

Hattori, M., Schrimpf, A., & Sushko, V. (2016). The response of tail risk perceptions to unconventional monetary policy. *American Economic Journal: Macroeconomics*, *8*(2), 111-36.

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

Hull, J.C. (2009). *Options, Futures and Other Derivatives.* Pearson – Prentice Hall 7th ed.

Ioannidou, V., Ongena, S., & Peydró, J. L. (2015). Monetary policy, risk-taking, and pricing: Evidence from a quasi-natural experiment. *Review of Finance*, *19*(1), 95-144.

Jackwerth, J. C., & Rubinstein, M. (1996). Recovering probability distributions from option prices. *The journal of Finance*, *51*(5), 1611-1631.

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

Jiang, G. J., Konstantinidi, E., & Skiadopoulos, G. (2012). Volatility spillovers and the effect of news announcements. *Journal of Banking & Finance*, *36*(8), 2260-2273.

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

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

Kang, W., & Ratti, R. A. (2013). Oil shocks, policy uncertainty and stock market return. Journal of International Financial Markets, Institutions and Money, 26, 305-318.

Kiley, M. T. (2014). The response of equity prices to movements in long-term interest rates associated with monetary policy statements: before and after the zero lower bound. *Journal of Money, Credit and Banking*, *46*(5), 1057-1071.

Kontonikas, A., MacDonald, R., & Saggu, A. (2013). Stock market reaction to fed funds rate surprises: State dependence and the financial crisis. *Journal of Banking & Finance*, *37*(11), 4025-4037.

Kontonikas, A., & Zekaite, Z. (2018). Monetary policy and stock valuation: structural VAR identification and size effects. *Quantitative Finance*, *18*(5), 837-848.

Kraus, A., & Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. *The Journal of finance*, *31*(4), 1085-1100.

Kurov, A., & Gu, C. (2016). Monetary policy and stock prices: Does the “Fed Put” work when it is most needed?. *Journal of Futures Markets*, *36*(12), 1210-1230.

Kurov, A., Olson, E., & Gulnara, R. (2019). When Does the Fed Care About Stock Prices?. *Available at SSRN 3234977*.

Kurov, A., Sancetta, A., Strasser, G., & Wolfe, M. H. (2019). Price drift before U.S. macroeconomic news: Private information about public announcements?. Journal of Financial and Quantitative Analysis, 54(1), 449-479.

Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. Journal of monetary economics, 47(3), 523-544.

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

Laopodis, N. T. (2013). Monetary policy and stock market dynamics across monetary regimes. *Journal of International Money and Finance*, *33*, 381-406.

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

Lucas Jr, R. E. (1972). Expectations and the Neutrality of Money. *Journal of economic theory*, *4*(2), 103-124.

Lucca, D. O., & Moench, E. (2015). The pre-FOMC announcement drift. *The Journal of finance*, *70*(1), 329-371.

Merton, R. C. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of financial economics*, 8(4), 323-361.

Maio, P. (2013). The “Fed model” and the predictability of stock returns. *Review of Finance*, 17(4), 1489-1533.

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.

Miller, M. H., Weller, P. A., & Zhang, L. (2001). Moral Hazard and the U.S. Stock Market: The Idea of 'Greenspan Put'.

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

Nakamura, E., & Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: the information effect. *The Quarterly Journal of Economics*, *133*(3), 1283-1330.

Neumann, M., & Skiadopoulos, G. (2013). Predictable dynamics in higher-order risk-neutral moments: Evidence from the S&P 500 options. *Journal of Financial and Quantitative Analysis*, 947-977.

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.

Patelis, A. D. (1997). Stock return predictability and the role of monetary policy. *the Journal of Finance*, *52*(5), 1951-1972.

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.

Pindyck, R. S. (1984). Uncertainty in the theory of renewable resource markets. *The Review of Economic Studies*, 51(2), 289-303.

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.

Rigobon, R., & Sack, B. (2003). Measuring the reaction of monetary policy to the stock market. *The quarterly journal of Economics*, *118*(2), 639-669.

Rigobon, R., & Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics*, *51*(8), 1553-1575.

Rosa, C. (2011). Words that shake traders: The stock market's reaction to central bank communication in real time. *Journal of Empirical Finance*, *18*(5), 915-934.

Rubinstein, M. E. (1973). The fundamental theorem of parameter-preference security valuation. *Journal of Financial and Quantitative Analysis*, 61-69.

Savor, P., & Wilson, M. (2014). Asset pricing: A tale of two days. *Journal of Financial Economics*, *113*(2), 171-201.

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). Alternative tests of rational expectations models: The case of the term structure. *Journal of Econometrics*, *16*(1), 71-87.

Stotz, O. (2019). The response of equity prices to monetary policy announcements: Decomposing the announcement day return into cash-flow news, interest rate news, and risk premium news. *Journal of International Money and Finance*, *99*, 102069.

Thorbecke, W. (1997). On stock market returns and monetary policy. *The Journal of Finance*, *52*(2), 635-654.

Triantafyllou, A., & Dotsis, G. (2017). Option-implied expectations in commodity markets and monetary policy. *Journal of International Money and Finance*, *77*, 1-17.

Vähämaa, S., & Äijö, J. (2011). The Fed's policy decisions and option-implied volatility. *Journal of Futures Markets*, *31*(10), 995-1010.

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

8. Appendix

A. Stock market volatility and jumps in times of uncertainty.

I provide additional robustness to my OLS and VAR results by varying different aspects of my empirical design. In more detail, I evaluate the robustness of my findings by estimating the same set of VAR models used in the main analysis employing alternative VAR orderings and allowing for more lags in the model. My main results remain unaltered. Moreover, I estimate the same VAR models in which I use MU3 and MU12 instead of MU1 as endogenous variables in the 4-variable VAR model and my results remain unaltered. Hence, my findings are independent of the choice of the Jurado et al. (2015) latent macroeconomic uncertainty series. Additionally, I include a set of alternative macroeconomic variables like U.S. industrial production, unemployment and short-term interest rates who 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 my 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 OLS and VAR settings. I lastly provide additional robustness checks and more analytical results for my regression models on the volatility and tail risk of individual equity prices which I present on Subsection 3.4. My additional forecasting regressions on S&P constituents clearly show that the MU is a robust common volatility and jump tail risk predictor for individual equity prices which belonging to different sectors-industries with the highest predictive power still remaining for the stocks which belong to the financial and banking sector. I lastly provide robustness to my OLS predictive regressions by showing the robust predictive power of multiple OLS regression models.

Table A1 below shows the results of the Augmented Dickey-Fuller (ADF) tests for the time series variables.

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
JV	-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
Defspr	-3.221**	0.018

The unit root tests shown in **Table A1** reject the hypothesis of a unit root for all of my time series variables at the 5% significance level. Moreover, **Tables A2** and A**3** below show the results of my univariate regression models (shown in Equations 5 and 6) on stock market volatility and jumps for the pre-2007 (January 1990-December 2006) period.

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

This table show the output of the bivariate predictive regressions on stock market volatility. The corresponding forecast horizons are 1-month, 3-months, and 12-months ahead. The panel A to E show the estimation output of the predicting model when MU, VIX, RV, EPU and MPU is used as explanatory variable respectively.

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. Predicting stock market price jumps variation for the pre-crisis period (Jan 1990-Dec 2006)

This table show the output of the bivariate predictive regressions on stock market price jump variation. The corresponding forecast horizons are 1-month, 3-months, and 12-months ahead. The panel A to E show the estimation output of the predicting model when MU, VIX, JV, EPU and MPU is used as explanatory variable respectively.

Panel A

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

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

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

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

$$JV_t = b_0 + b_1 JV_{t-k} + \varepsilon_t$$

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

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

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

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

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.

The regression results shown in **Tables A2** and A**3** clearly show that the forecasting power of MU has deteriorated in the pre-crisis period (when compared with the respective forecasting power on the post-2007 period). My additional results on the forecasting regression models for the pre-crisis period show that, while the MU 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 A4** to **A7** show the regression results of the multiple regression models in which I additionally control for macroeconomic determinants of stock market volatility and price jumps like the Fed fund rate (Bekaert et al., 2013; among others), the U.S. Industrial Production Index growth (IPI) and the U.S. unemployment rate (UNEMP) (Schwert, 1989; Paye, 2012; among others).

Table A4. Predicting RV in pre-crisis period when controlling for macroeconomic fundamentals.

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (RV) when controlling for macroeconomic fundamentals. The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. $RV_t = b_0 + b_1 MU(k)_{t-k-1} + b_2 RV_{t-k} + b_3 JV_{t-k} + b_4 VIX_{t-k} + b_5 EPU_{t-k} + b_6 MPU_{t-k} + b_7 Defspr_{t-k} + b_8 FFR_{t-k} + b_9 IPI_{t-k} + b_{10} UNEMP_{t-k} + \varepsilon_t$

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)
JV	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)
Defspr	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 Predicting JV in pre-crisis period when controlling for macroeconomic fundamentals.

This table shows the results of multiplepredictive regressions of the U.S. stock market jump variation (JV) when controlling for macroeconomic fundamentals. The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator.

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

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)
JV	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)
Defspr	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 A4. Predicting RV in post-crisis period when controlling for macroeconomic fundamentals.

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (RV) when controlling for macroeconomic fundamentals. The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator.

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

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)
JV	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)
Defspr	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. Predicting JV in post-crisis period when controlling for macroeconomic fundamentals.

This table shows the results of multiple predictive regressions of the U.S. stock market jump variation (JV) when controlling for macroeconomic fundamentals. The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator.

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

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)
JV	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)
Defspr	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

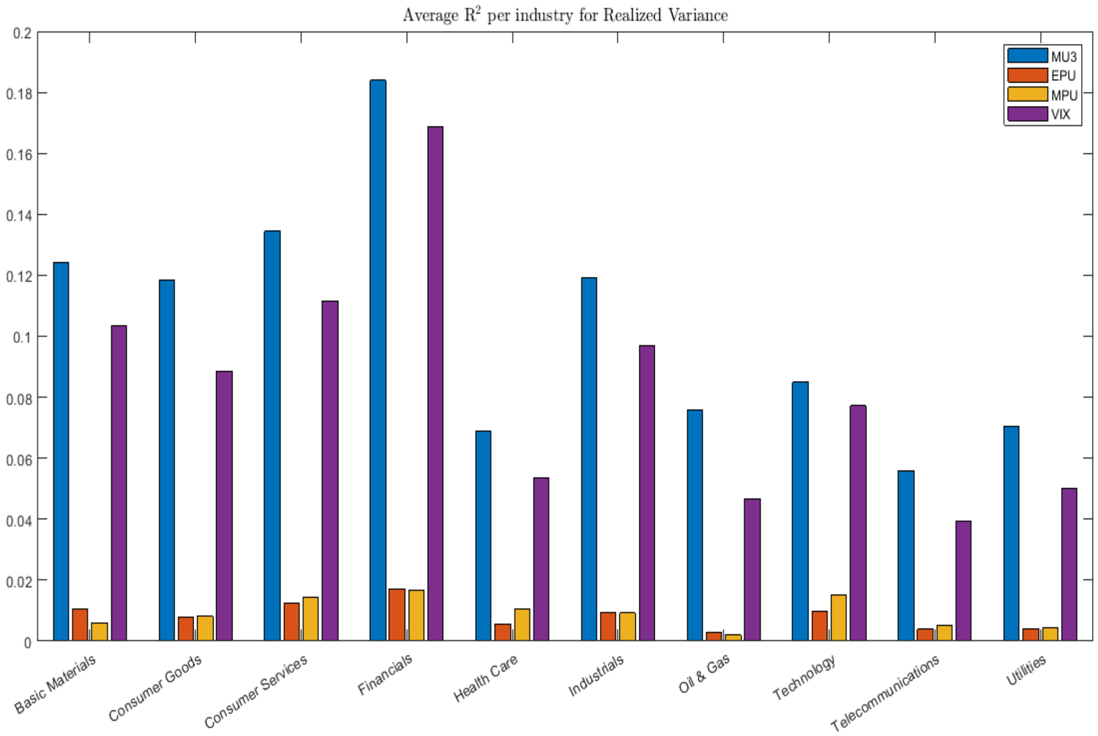
*, ** and *** denote statistical significance at 10%, 5% and 1% respectively. The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

The results shown in **Tables A4** to **A7** show that my main findings regarding the predictive power of the MU 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.

Figures A1 to **A4** show the respective results (average sectoral R^2s and t-statistics) of my bivariate regression models on the realized variance (RV) and price jumps (JUMPS) of S&P500 constituents for 3-month and 12-month forecast horizon respectively.

Figure A1. Average R^2 values and t-statistics when forecasting RV 3 months ahead

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 MU3, the VIX index, EPU and MPU as predictors. In more detail, the bar chart shows the average R^2s and t-statistics for the univariate regressions on the JUMP of the stocks which belong to different sectors. The forecast 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.



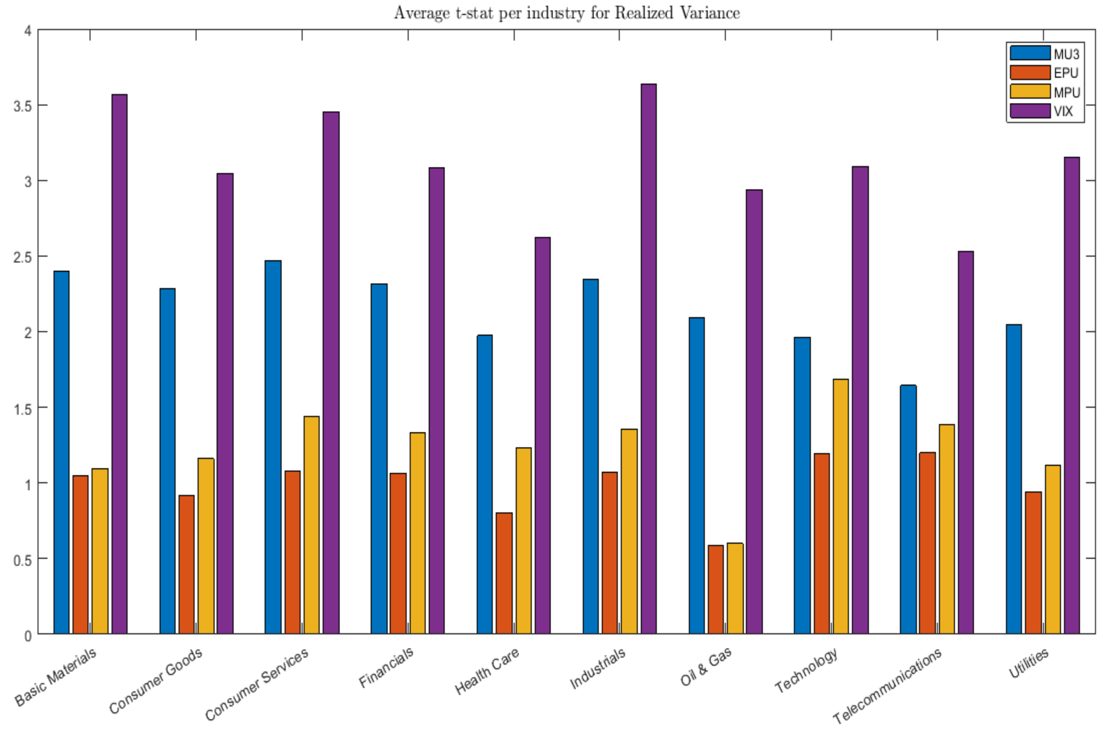
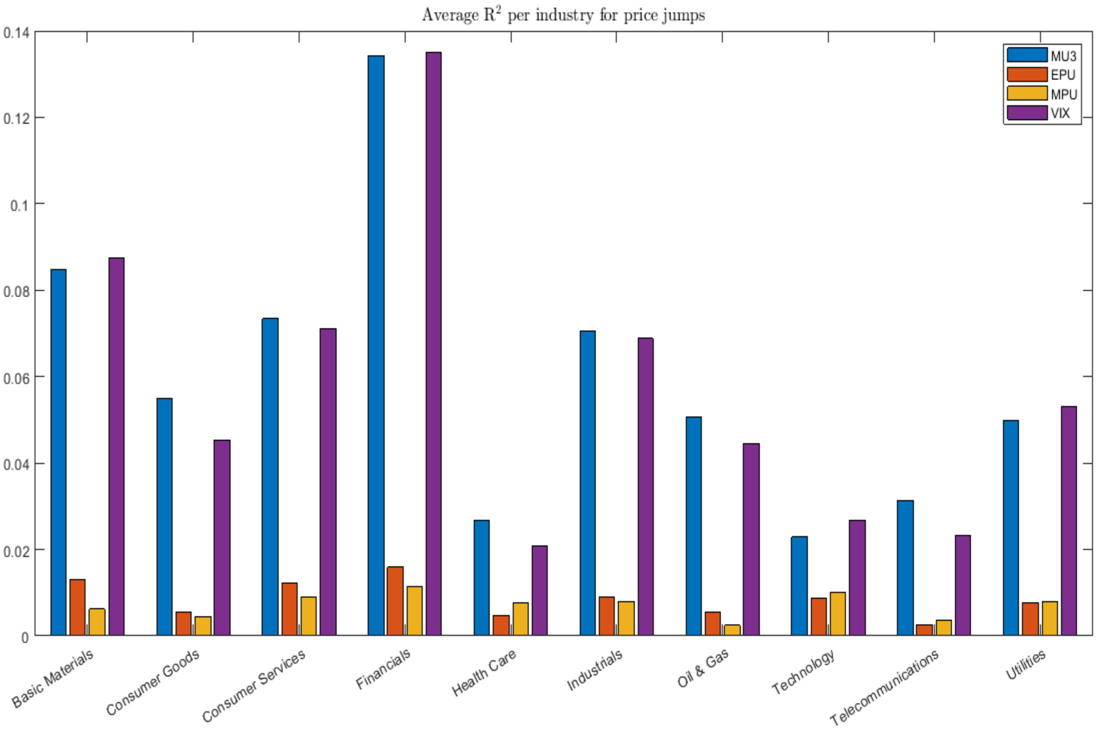


Figure A2. Average R^2 values and t-statistics when forecasting JV 3 months ahead

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 MU3, the VIX index, EPU and MPU as predictors. In more detail, the bar chart shows the average R^2s and t-statistics for the univariate regressions on the JUMP of the stocks which belong to different sectors. The forecast 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.



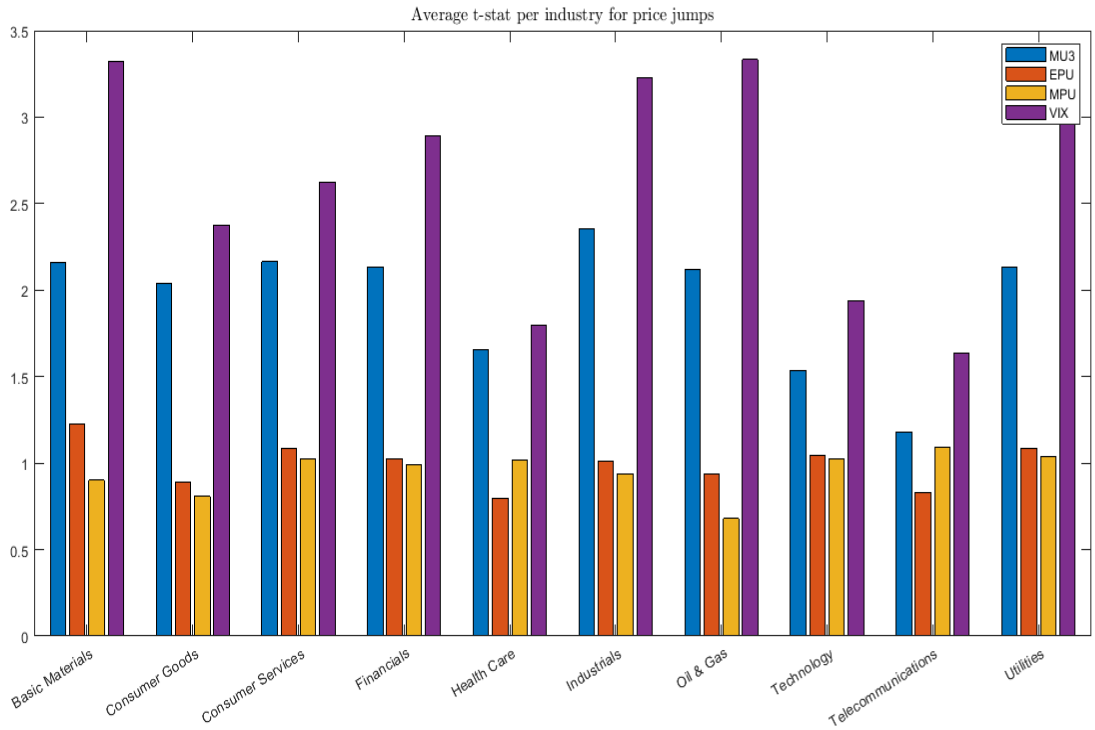
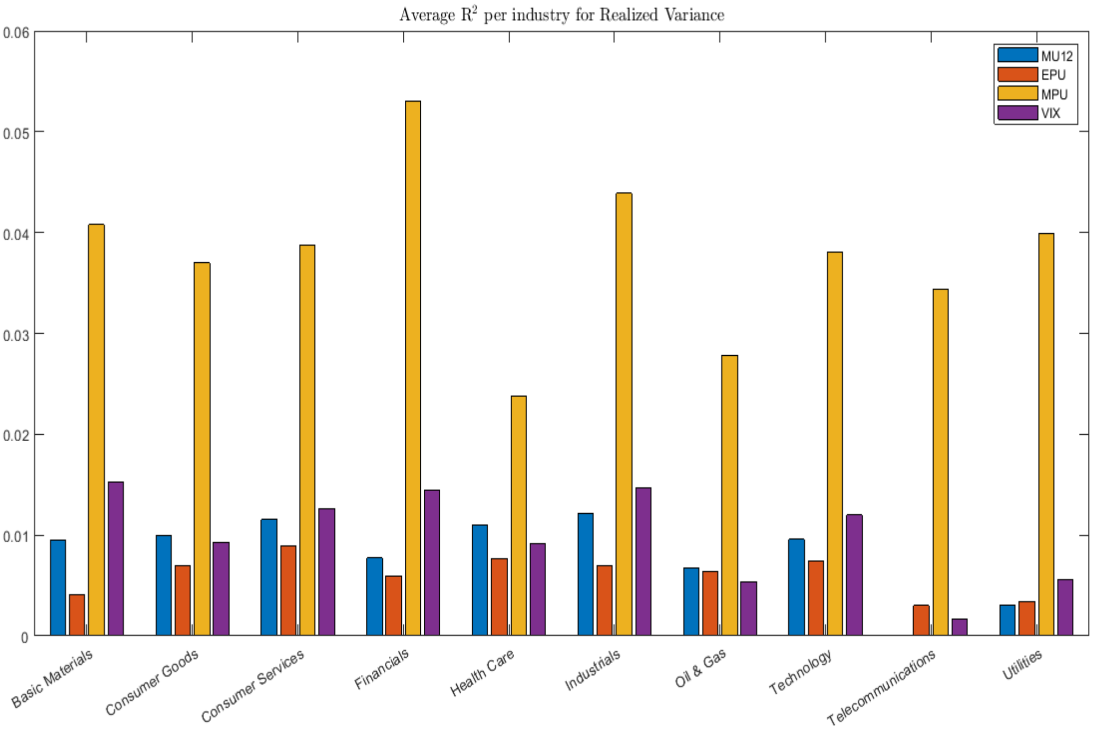


Figure A3. Average R^2 values and t-statistics when forecasting RV 12 months ahead

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 MU12, the VIX index, EPU and MPU as predictors. In more detail, the bar chart shows the average R^2s and t-statistics for the univariate regressions on the RV of the stocks which belong to different sectors. The forecast 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.



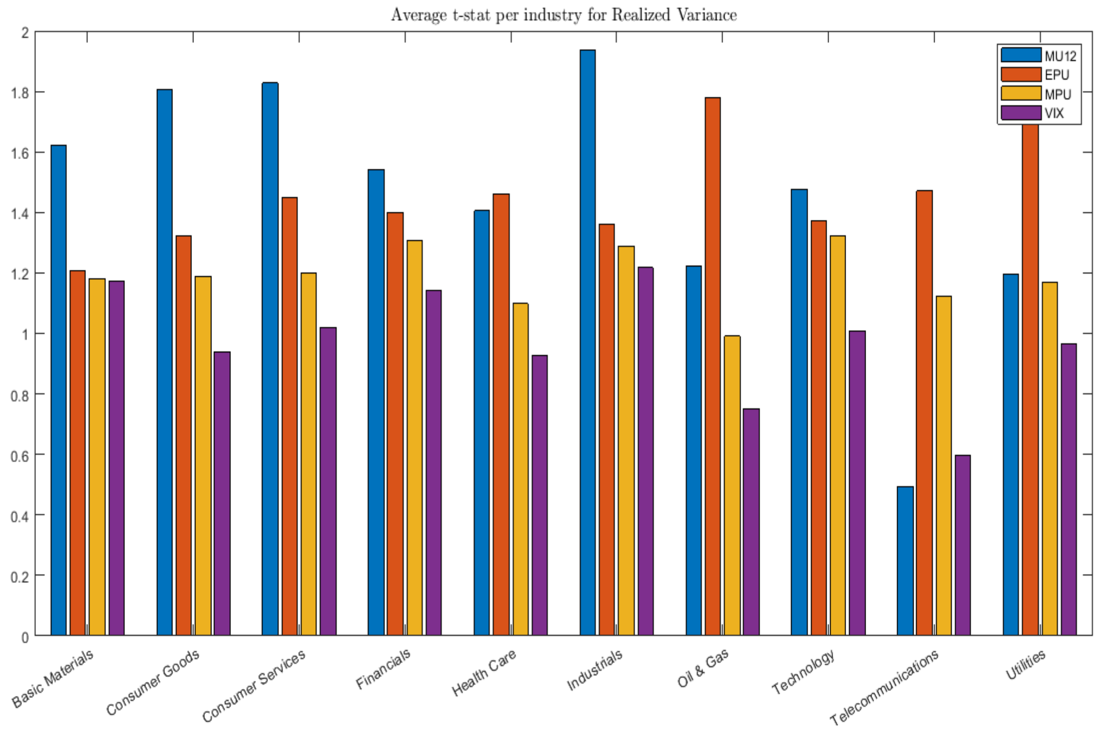
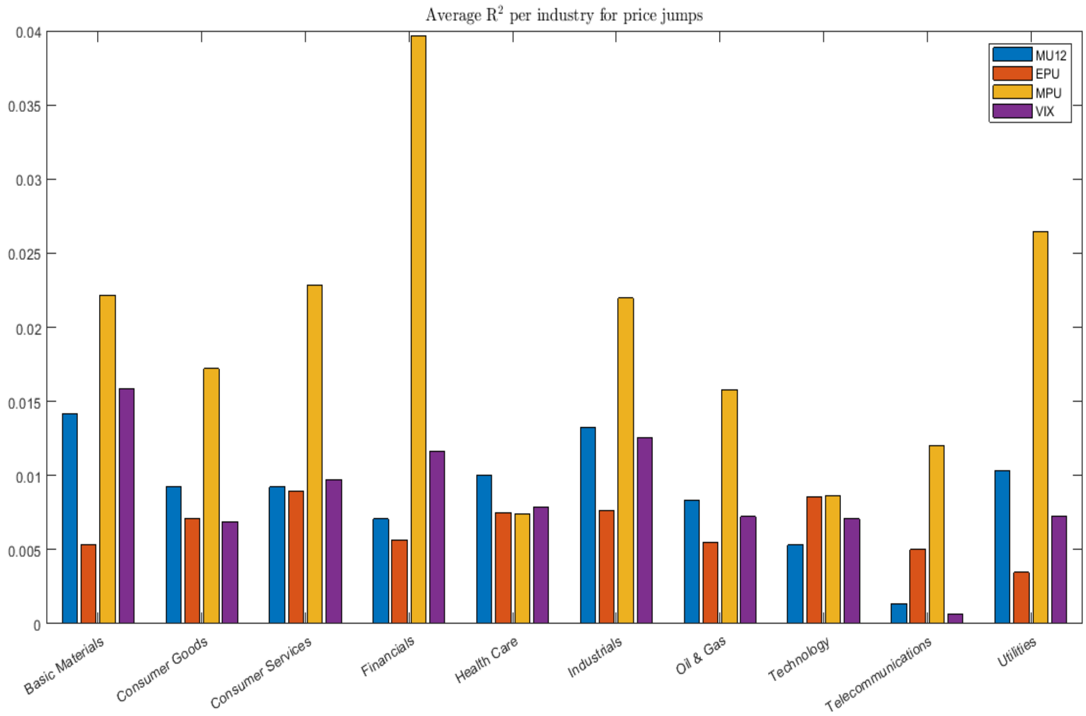
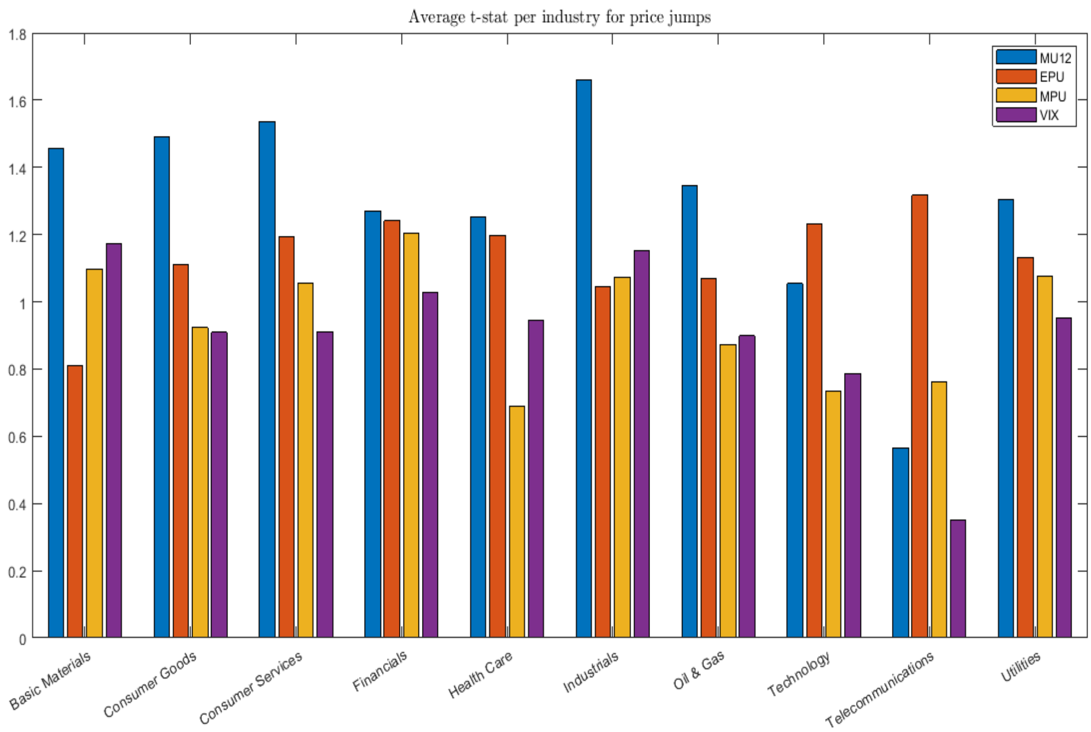


Figure A4. Average R^2 values and t-statistics when forecasting JV 12 months ahead

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 forecast 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.





The figures A1 to A4 show that my main findings and conclusions regarding the predictive power of the MU on S&P500 constituents remain robust when having 3-month (instead of one-month) forecast horizon. For example, the MU still outperforms the VIX for volatility and jump tail risk forecasts having a 3-month horizon. Moreover, the forecasting power of the MU 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 is significantly diminished for 12-month forecast horizon.

I lastly provide robustness to my 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) as my proxy for latent macroeconomic uncertainty on the VAR model. **Figures A5** to A**12** below show the respective OIRFs for these VAR models.

Figure A5. 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 forecast horizon (MU3) shock.The estimated responses are obtained from the baseline 4-variable 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).

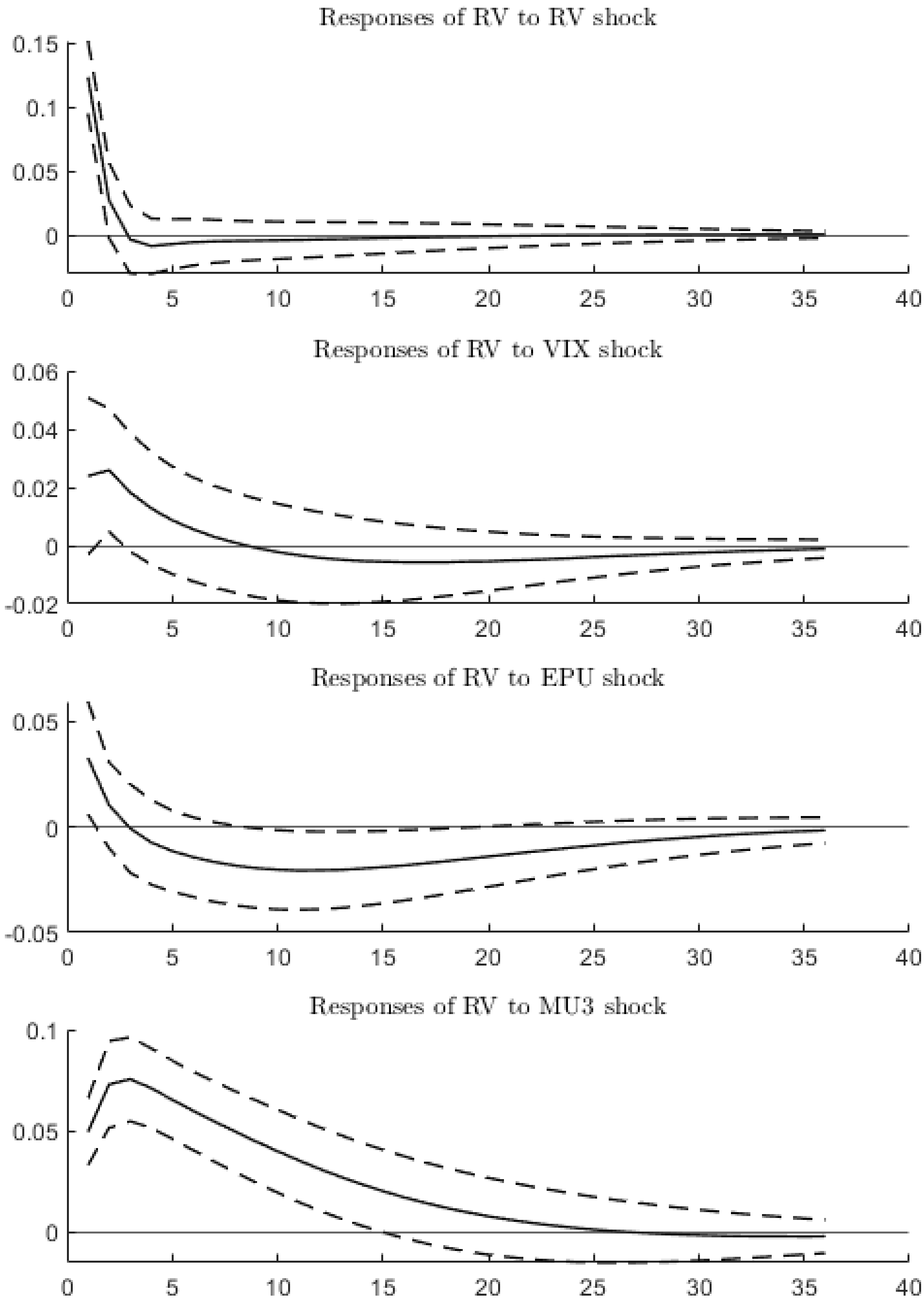


Figure A6. Orthogonalized Impulse Response Functions (OIRFs) of stock market volatility to uncertainty shocks (using MU12 instead of MU1)

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 forecast horizon (MU12) shock.The estimated responses are obtained from the baseline 4-variable 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).

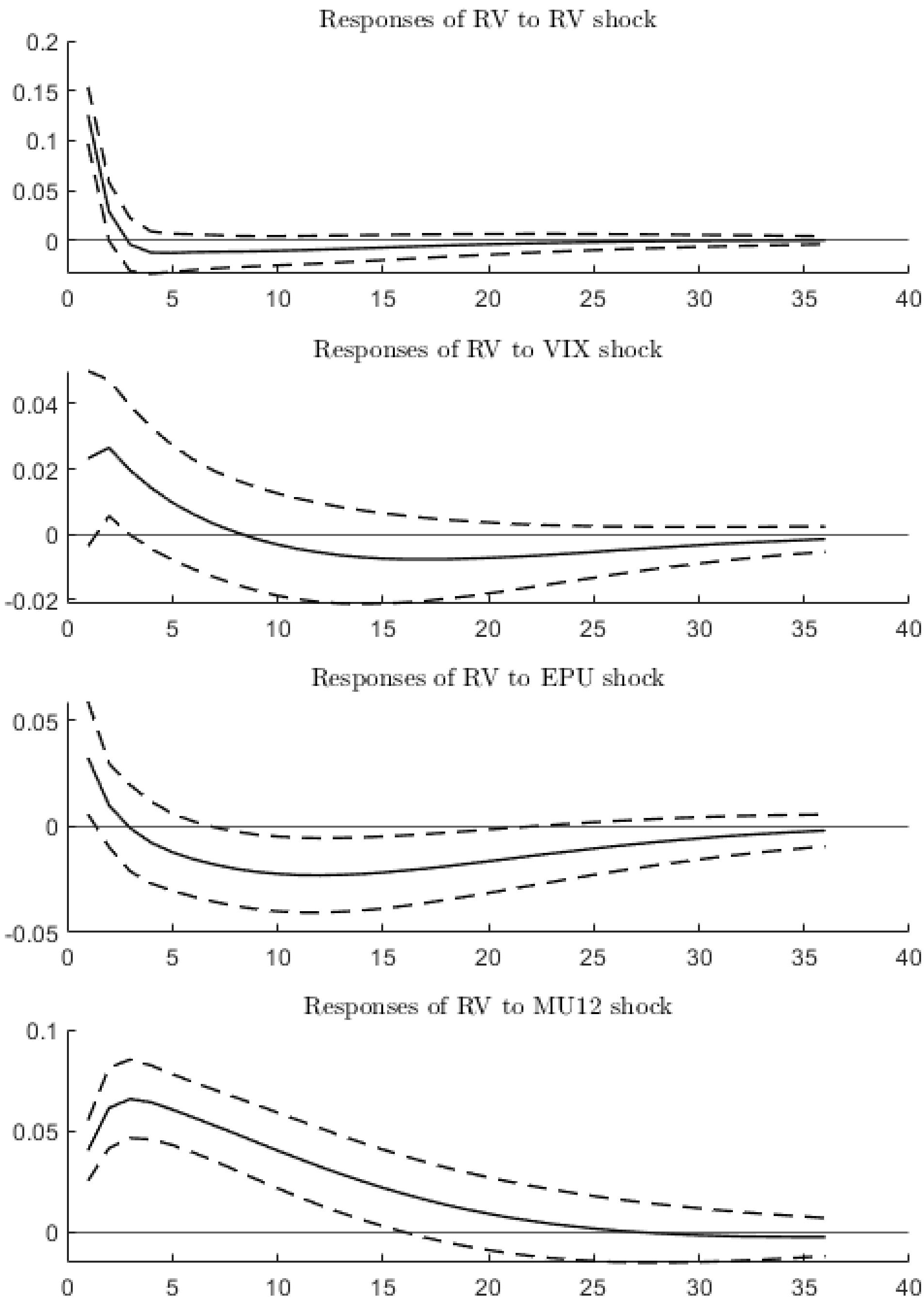


Figure A7. Orthogonalized Impulse Response Functions (OIRFs) of stock market volatility to uncertainty shocks in the post-crisis period. (using MU3 instead of MU1)

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 forecast horizon (MU3) shock.The estimated responses are obtained from the baseline 4-variable 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).

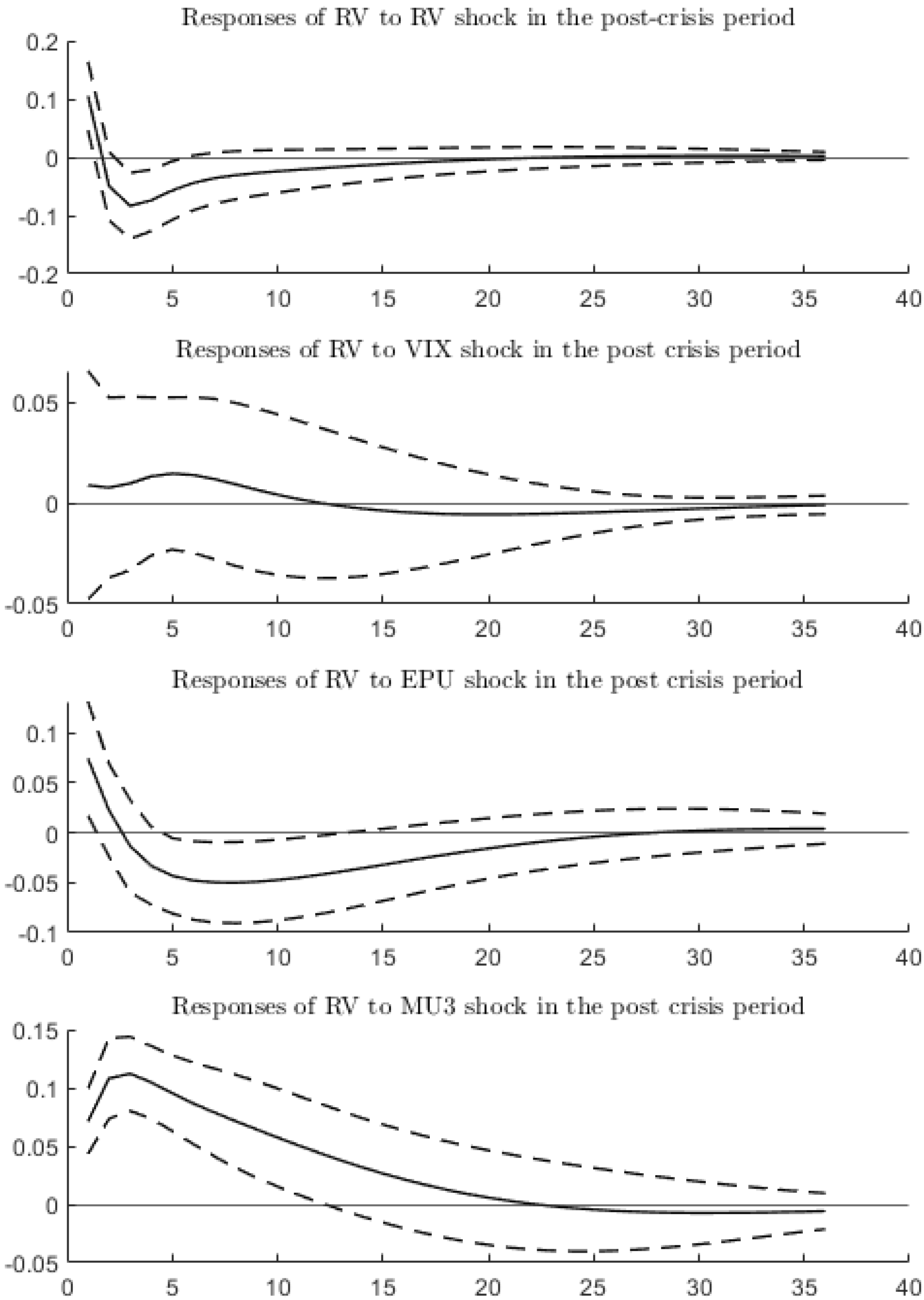


Figure A8. Orthogonalized Impulse Response Functions (OIRFs) of stock market volatility to uncertainty shocks in the post-crisis period. (using MU12 instead of MU1)

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 forecast horizon (MU12) shock.The estimated responses are obtained from the baseline 4-variable 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).

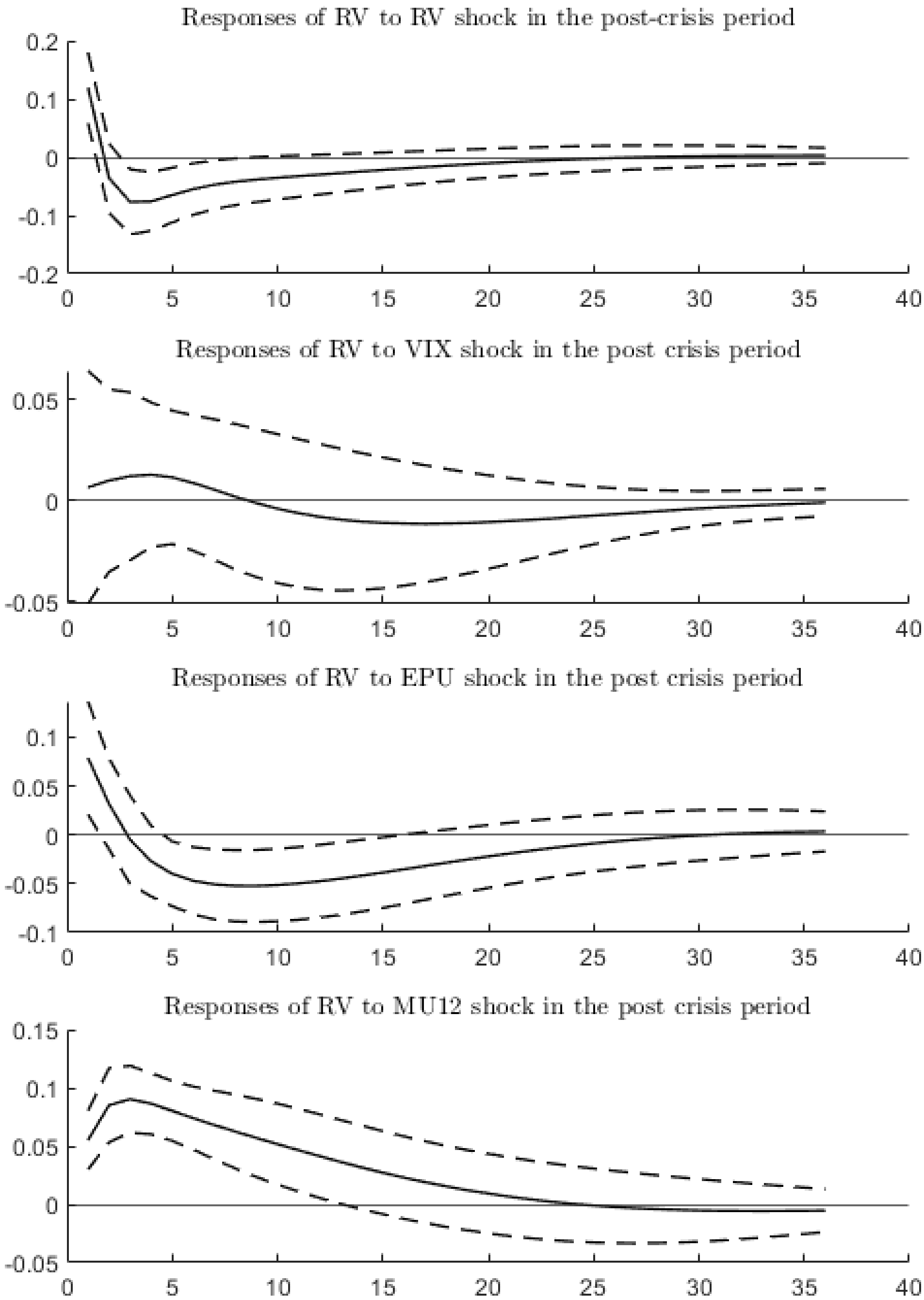


Figure A9. Orthogonalized Impulse Response Functions (OIRFs) of stock market price jumps (JUMP) to uncertainty shocks. (using MU3 innstead of MU1)

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 forecast horizon (MU3) shock.The estimated responses are obtained from the baseline 4-variable 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).

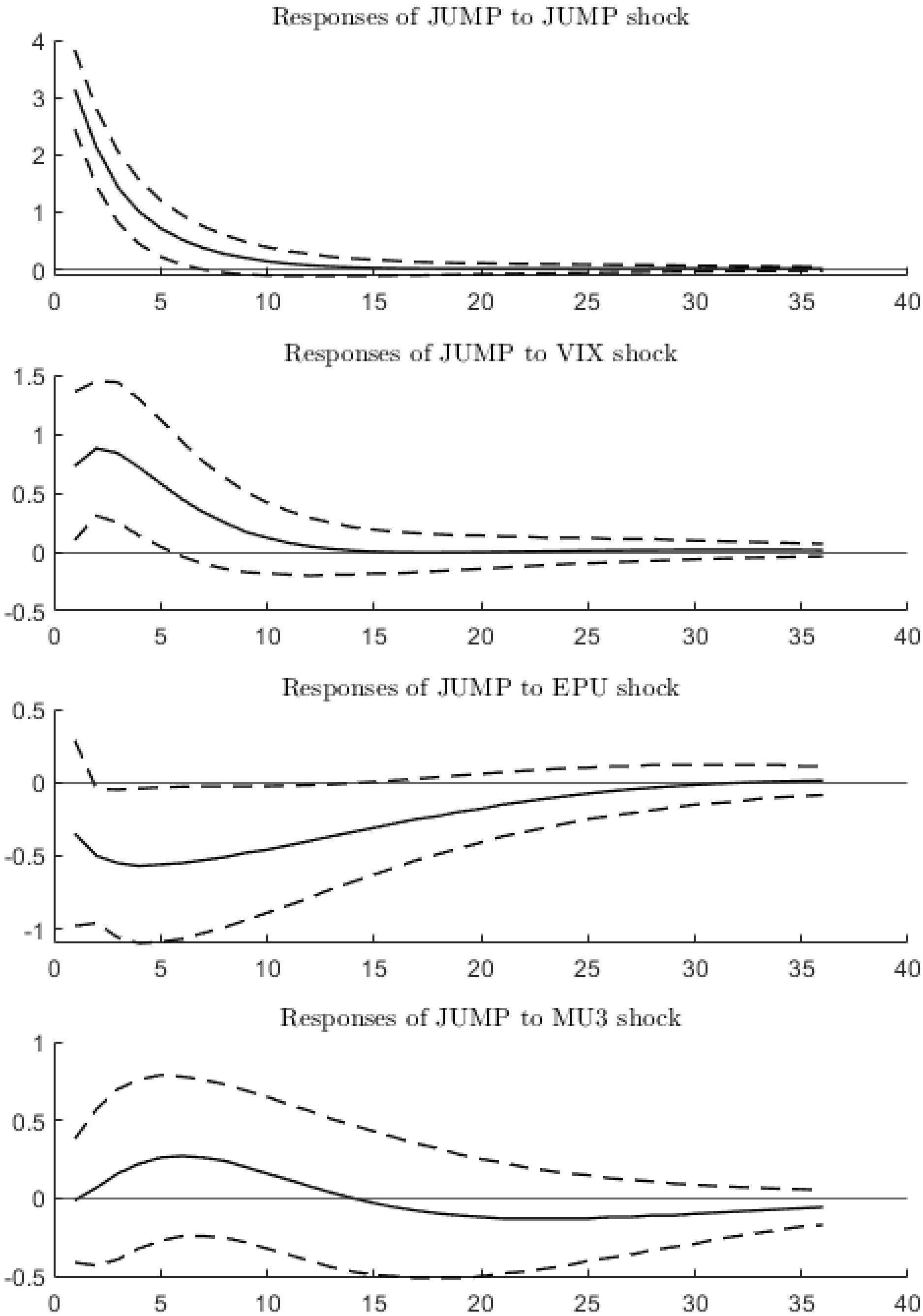


Figure A10. Orthogonalized Impulse Response Functions (OIRFs) of stock market price jumps (JUMP) to uncertainty shocks. (using MU12 innstead of MU1)

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 forecast horizon (MU12) shock.The estimated responses are obtained from the baseline 4-variable 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).

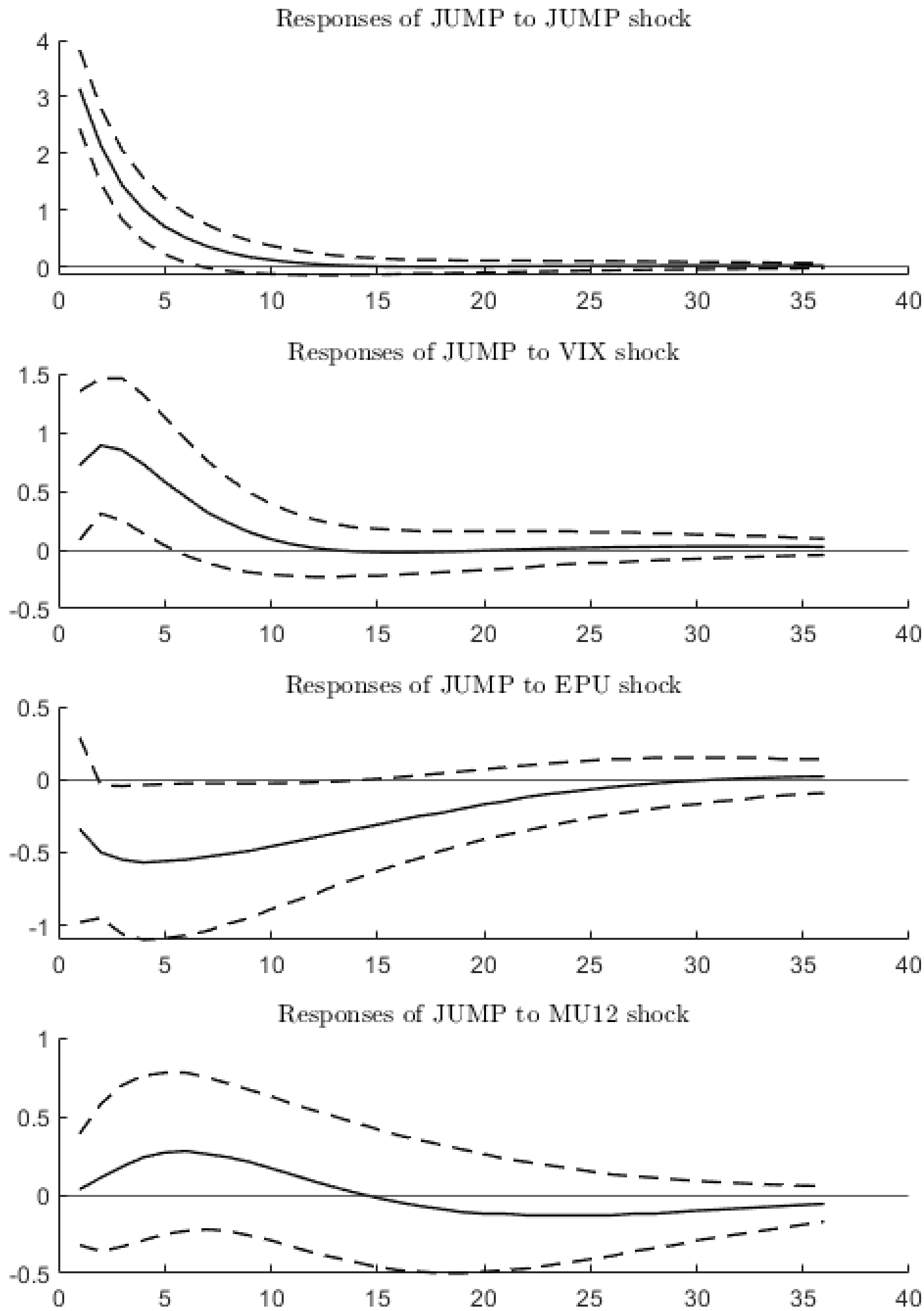


Figure A11. Orthogonalized Impulse Response Functions (OIRFs) of stock market price jumps (JUMP) to uncertainty shocks in the post-crisis period (using MU3 instead of MU1)

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 forecast horizon (MU3) shock.The estimated responses are obtained from the baseline 4-variable 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).

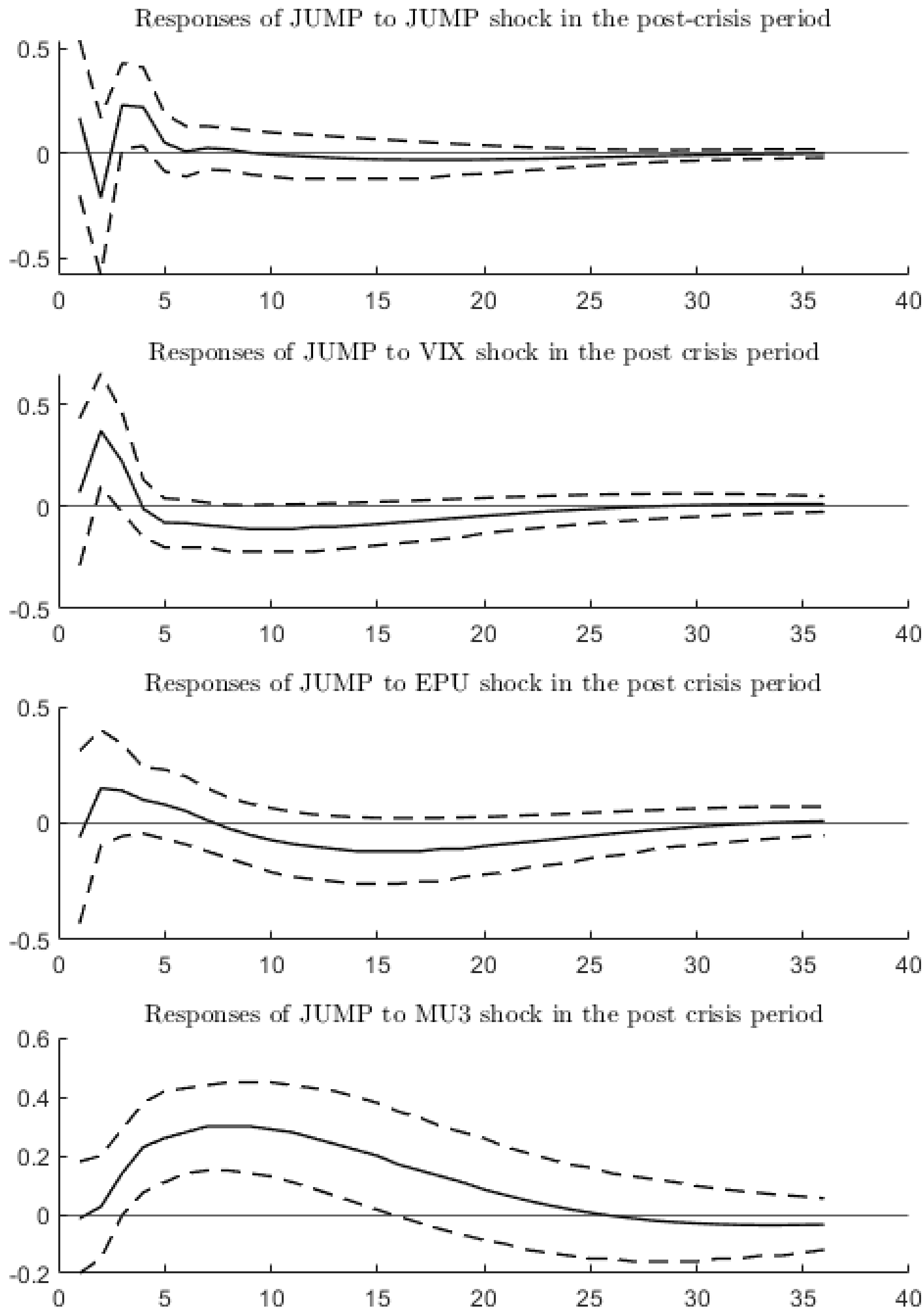
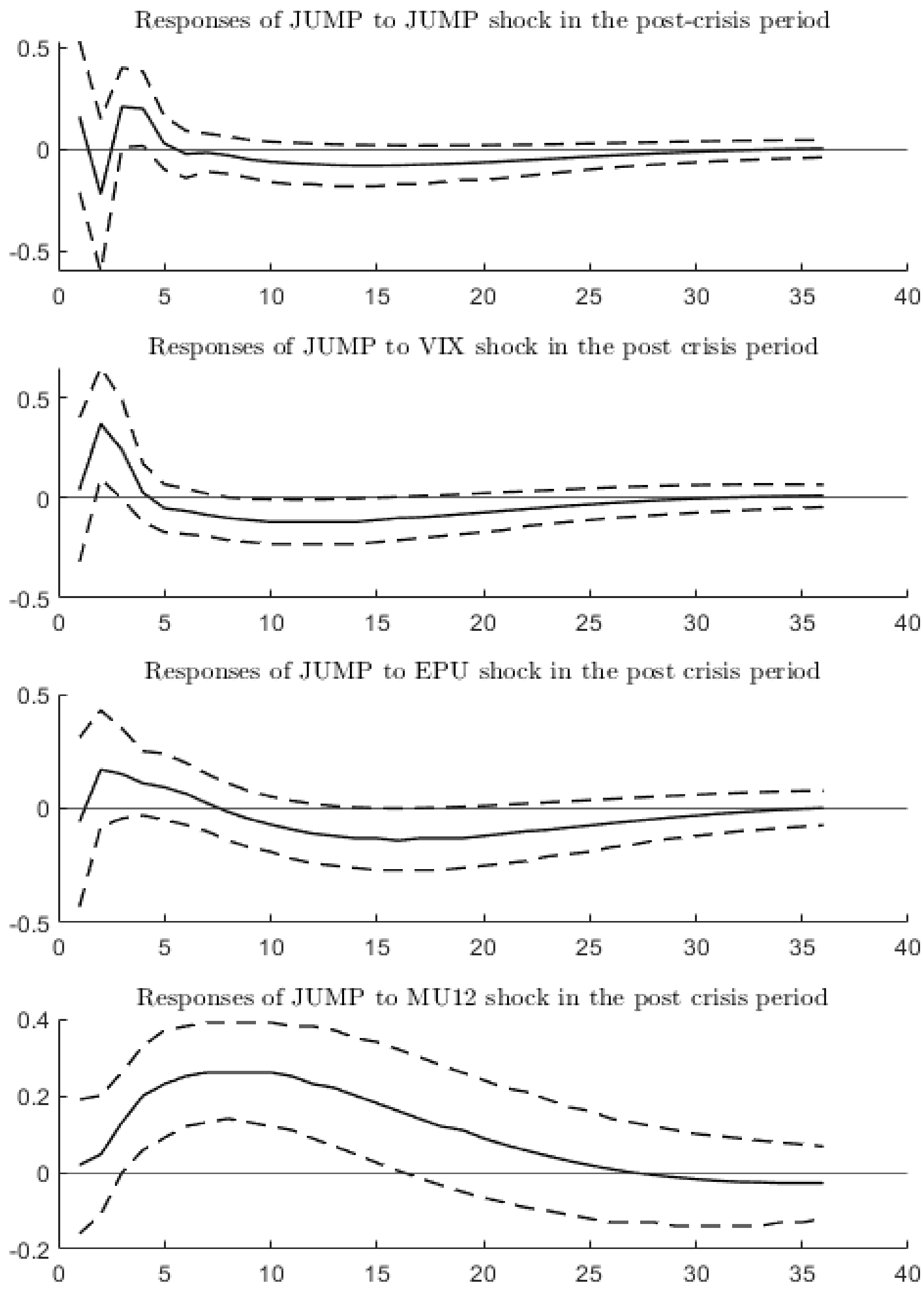


Figure A12. Orthogonalized Impulse Response Functions (OIRFs) of stock market price jumps (JUMP) to uncertainty shocks in the post-crisis period (using MU12 instead of MU1)

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 forecast horizon (MU12) shock.The estimated responses are obtained from the baseline 4-variable 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).



Figures A5 to **A12** show that my VAR results remain unaltered when using MU3 or MU12 as endogenous variable in the VAR model. Hence, my estimated OIRFs are independent of the choice of the MU in the VAR model.

B. The term structure of interest rates as predictor of stock market volatility

Hereby, I present my robustness checks, as it is discussed through the chapter 4., I include the **Tables B1-B3** and **Tables B4-B6** that show the average R^2 and t-statistic values per sector and per industry respectively, when we predict the volatility of the S&P 500 index constituents. I include these tables in order to show detailed results, about the asymmetric predictability of the yield curve volatility on the volatility of firms that comprise S&P 500 index, according to industry-specific characteristics. Additionally, the **Tables B7-B15** contain 3 additional multiple predictive regression models, when I use all the available dataset, the pre-crisis period subsample and the post-crisis period subsample. I follow this approach in order to ensure that SLOPERV remain a robust predictor of stock market volatility independently of the selection of the control variables in the regression model. The specific forms of the regression models are described in **Tables B7-B15**

Finally, I present the detailed out-of-sample estimations when I forecast the volatility of the constituents of S&P 500 index. The **Table B16 - B18** contain the average estimated out-of-sample R^2 values per industry and per sector when I forecast the volatility of the S&P 500 index constituents, using all the predictors that is used in the main paper, for 3 different forecast horizons (1-month,6month and 12-month forecast horizon).

Table B1. Average R^2 values (percentage values) per sector and industry for the bivariate regression models on the Realized Variance of S&P500 constituents, for 1-month forecast horizon.

Average R^2 values per Factor h=1 (h= forecast horizon)	EPU	MPU	LEVELRV	SLOPERV
Basic Materials	**2.73**	**6.80**	**11.95**	**13.60**
Chemicals	2.65	6.97	12.10	13.89
Forestry & Paper	-0.55	7.74	16.36	10.97
Industrial Metals & Mining	5.20	7.72	8.98	12.95
Mining	-0.42	0.89	14.50	14.51
Consumer Goods	**4.92**	**6.30**	**12.00**	**15.63**
Automobiles & Parts	2.40	6.41	12.13	15.08
Beverages	1.46	5.40	13.60	16.95
Food Producers	5.68	6.53	12.00	15.03
Household Goods & Home Construction	5.91	4.91	8.50	14.20
Leisure Goods	8.68	7.07	8.80	14.46
Personal Goods	5.36	8.05	15.65	17.80
Tobacco	2.48	2.05	12.01	15.86
Consumer Services	**4.56**	**6.55**	**13.93**	**16.70**
Food & Drug Retailers	2.54	6.22	8.56	8.48
General Retailers	3.07	7.09	16.76	18.28
Media	6.86	6.12	12.83	16.22
Travel & Leisure	5.42	6.27	12.59	17.37
Financials	**4.86**	**6.06**	**13.48**	**18.05**
Banks	8.39	7.73	14.40	19.17
Financial Services (Sector)	2.30	6.27	14.60	17.04
Life Insurance	8.47	6.69	10.99	19.97
Nonlife Insurance	3.53	5.75	11.46	16.66
Real Estate Investment & Services	0.48	9.53	23.98	26.71
Real Estate Investment Trusts	5.10	4.77	13.18	18.20
Health Care	**3.86**	**5.15**	**11.18**	**13.35**
Health Care Equipment & Services	3.63	5.30	12.53	14.49
Pharmaceuticals & Biotechnology	4.19	4.95	9.28	11.74
Industrials	**4.35**	**6.37**	**12.48**	**15.34**
Aerospace & Defense	5.84	7.34	12.24	15.52
Construction & Materials	5.07	6.62	12.78	16.03
Electronic & Electrical Equipment	7.20	5.99	9.38	16.58
General Industrials	3.87	6.92	12.49	16.83
Industrial Engineering	3.39	6.78	13.73	16.65
Industrial Transportation	1.89	3.45	10.67	10.92
Support Services	3.56	6.59	14.08	14.58
Oil & Gas	**2.57**	**3.58**	**11.29**	**12.68**
Oil & Gas Producers	1.97	4.26	12.27	13.79
Oil Equipment & Services	3.89	2.08	9.13	10.23
Technology	**3.26**	**5.99**	**12.69**	**13.48**
Software & Computer Services	3.87	6.44	12.69	13.84
Technology Hardware & Equipment	2.67	5.55	12.69	13.14
Telecommunications	**0.37**	**10.09**	**23.57**	**20.99**
Fixed Line Telecommunications	0.37	10.09	23.57	20.99
Utilities	**3.86**	**4.88**	**11.95**	**13.60**
Electricity	4.32	4.82	12.10	13.89
Gas, Water & Multiutilities	2.70	5.02	16.36	10.97
Grand Total	**4.16**	**5.93**	**8.98**	**12.95**

Table B2. Average R^2 values (percentage values) per sector and industry for the bivariate regression models on the Realized Variance of S&P500 constituents, for 6-month forecast horizon.

Average R^2 values per Factor h=6 (h= forecast horizon)	EPU	MPU	LEVEL RV	SLOPE RV
Basic Materials	**1.55**	**0.57**	**14.32**	**10.79**
Chemicals	0.15	0.78	14.85	11.94
Forestry & Paper	1.64	0.74	17.69	8.52
Industrial Metals & Mining	6.81	-0.01	12.43	9.01
Mining	3.89	-0.60	9.70	3.51
Consumer Goods	**1.59**	**0.85**	**15.12**	**13.24**
Automobiles & Parts	0.91	0.53	16.04	12.00
Beverages	-0.04	0.44	17.18	14.58
Food Producers	1.71	1.44	16.16	12.35
Household Goods & Home Construction	3.02	0.50	11.44	13.74
Leisure Goods	1.60	0.83	10.41	10.58
Personal Goods	1.40	0.96	17.44	15.35
Tobacco	1.73	0.39	16.31	11.66
Consumer Services	**1.72**	**1.07**	**16.57**	**13.95**
Food & Drug Retailers	2.65	2.58	10.11	8.08
General Retailers	1.09	1.30	19.02	14.71
Media	2.59	0.04	14.61	12.56
Travel & Leisure	1.65	1.06	16.68	15.63
Financials	**1.33**	**0.94**	**17.31**	**15.00**
Banks	2.65	1.07	18.76	17.32
Financial Services (Sector)	0.79	1.05	17.29	12.78
Life Insurance	1.56	0.54	16.47	17.95
Nonlife Insurance	0.38	0.44	16.70	14.87
Real Estate Investment & Services	0.34	0.07	27.69	20.13
Real Estate Investment Trusts	1.51	1.13	16.70	14.91
Health Care	**1.78**	**0.44**	**14.17**	**11.59**
Health Care Equipment & Services	2.03	0.29	15.09	12.26
Pharmaceuticals & Biotechnology	1.42	0.64	12.87	10.66
Industrials	**1.41**	**1.15**	**15.24**	**12.93**
Aerospace & Defense	2.67	0.44	13.24	12.42
Construction & Materials	1.63	0.62	14.73	12.67
Electronic & Electrical Equipment	1.62	0.63	14.19	15.10
General Industrials	0.51	0.52	14.50	14.03
Industrial Engineering	0.83	0.92	16.36	13.74
Industrial Transportation	0.73	1.47	13.39	8.85
Support Services	1.59	2.42	17.68	12.87
Oil & Gas	**0.83**	**-0.27**	**15.33**	**10.03**
Oil & Gas Producers	1.00	0.33	13.75	10.49
Oil Equipment & Services	0.45	-1.59	18.80	9.01
Technology	**1.68**	**1.40**	**15.00**	**10.63**
Software & Computer Services	2.00	0.58	15.16	11.66
Technology Hardware & Equipment	1.36	2.19	14.85	9.64
Telecommunications	**0.33**	**1.63**	**27.43**	**19.50**
Fixed Line Telecommunications	0.33	1.63	27.43	19.50
Utilities	**2.31**	**0.13**	**12.97**	**11.05**
Electricity	2.63	0.16	13.20	11.31
Gas, Water & Multiutilities	1.53	0.06	12.39	10.40
Grand Total	**1.54**	**0.84**	**15.61**	**12.82**

Table B3. Average R^2 values (percentage values) per sector and industry for the bivariate regression models on the Realized Variance of S&P500 constituents, for 12-month forecast horizon.

Average R^2 values per Factor h=12 (h= forecast horizon)	EPU	MPU	LEVELRV	SLOPERV
Basic Materials	**3.62**	**1.65**	**9.76**	**8.98**
Chemicals	1.68	1.27	9.47	9.34
Forestry & Paper	9.53	-0.49	11.03	3.63
Industrial Metals & Mining	9.93	4.07	11.97	10.68
Mining	3.94	1.37	5.58	4.67
Consumer Goods	**2.59**	**1.76**	**10.68**	**10.05**
Automobiles & Parts	2.37	2.68	12.59	10.93
Beverages	2.94	1.23	10.84	9.39
Food Producers	2.61	1.36	10.53	9.12
Household Goods & Home Construction	2.52	2.35	8.15	9.69
Leisure Goods	1.10	0.99	7.52	9.28
Personal Goods	2.91	1.19	12.20	10.95
Tobacco	4.51	4.54	16.39	13.45
Consumer Services	**2.73**	**1.70**	**12.11**	**10.35**
Food & Drug Retailers	1.66	0.82	7.03	4.92
General Retailers	4.03	1.72	13.18	10.11
Media	2.36	2.12	10.64	11.16
Travel & Leisure	1.63	1.63	13.23	11.61
Financials	**2.47**	**1.86**	**12.53**	**11.23**
Banks	1.85	1.59	12.64	13.50
Financial Services (Sector)	3.11	1.37	10.42	9.18
Life Insurance	0.55	2.14	13.84	14.53
Nonlife Insurance	2.75	0.81	11.48	10.53
Real Estate Investment & Services	4.68	1.15	17.50	11.83
Real Estate Investment Trusts	2.54	2.90	14.45	11.30
Health Care	**2.68**	**1.32**	**10.85**	**9.65**
Health Care Equipment & Services	3.08	1.38	10.86	9.71
Pharmaceuticals & Biotechnology	2.12	1.22	10.83	9.55
Industrials	**2.51**	**1.89**	**11.16**	**10.02**
Aerospace & Defense	1.94	0.92	8.78	8.99
Construction & Materials	3.65	0.92	9.27	8.58
Electronic & Electrical Equipment	0.70	2.38	12.11	12.47
General Industrials	1.69	1.32	11.51	11.24
Industrial Engineering	2.75	1.83	13.03	10.50
Industrial Transportation	3.53	2.04	8.57	6.55
Support Services	3.07	2.93	12.67	10.57
Oil & Gas	**3.21**	**0.05**	**8.92**	**7.67**
Oil & Gas Producers	3.94	0.36	9.29	8.41
Oil Equipment & Services	1.59	-0.64	8.11	6.05
Technology	**3.29**	**1.83**	**10.56**	**7.92**
Software & Computer Services	3.43	1.62	10.49	8.73
Technology Hardware & Equipment	3.17	2.03	10.62	7.14
Telecommunications	**3.63**	**3.67**	**13.72**	**8.70**
Fixed Line Telecommunications	3.63	3.67	13.72	8.70
Utilities	**3.18**	**0.82**	**8.26**	**8.03**
Electricity	3.48	0.80	8.47	8.14
Gas, Water & Multiutilities	2.43	0.88	7.73	7.75
Grand Total	**2.77**	**1.60**	**11.08**	**9.75**

Table B4. Average t-statistic values (percentage values) per sector and industry for the bivariate regression models on the Realized Variance of S&P500 constituents, for 1-month forecast horizon.

Average t-statistic values per Factor h=1 (h= forecast horizon)	EPU	MPU	LEVELRV	SLOPERV
Basic Materials	**0.97**	**1.87**	**2.19**	**2.49**
Chemicals	1.09	1.86	2.16	2.58
Forestry & Paper	-0.11	2.60	2.82	4.62
Industrial Metals & Mining	1.29	2.11	2.35	1.48
Mining	-0.38	0.56	1.55	2.32
Consumer Goods	**1.09**	**1.76**	**2.04**	**2.33**
Automobiles & Parts	0.57	1.78	1.98	2.66
Beverages	0.89	1.73	2.17	2.51
Food Producers	1.08	1.82	2.03	2.37
Household Goods & Home Construction	1.25	1.40	1.58	1.35
Leisure Goods	1.75	2.03	1.87	1.85
Personal Goods	1.37	2.11	2.32	2.97
Tobacco	-0.44	0.54	3.23	3.02
Consumer Services	**1.07**	**1.79**	**2.05**	**2.55**
Food & Drug Retailers	0.72	1.84	1.69	1.85
General Retailers	0.93	1.93	2.18	2.93
Media	1.27	1.65	1.95	2.52
Travel & Leisure	1.19	1.68	2.05	2.30
Financials	**1.04**	**1.65**	**2.07**	**2.34**
Banks	1.56	2.08	2.35	2.66
Financial Services (Sector)	0.68	1.68	2.21	2.66
Life Insurance	1.56	1.77	2.03	1.98
Nonlife Insurance	1.06	1.62	1.64	1.86
Real Estate Investment & Services	0.65	2.03	2.57	3.66
Real Estate Investment Trusts	0.95	1.34	1.99	2.13
Health Care	**0.78**	**1.74**	**1.88**	**2.43**
Health Care Equipment & Services	0.88	1.76	1.99	2.53
Pharmaceuticals & Biotechnology	0.63	1.70	1.73	2.27
Industrials	**0.90**	**1.76**	**1.95**	**2.49**
Aerospace & Defense	1.06	2.03	1.95	2.40
Construction & Materials	0.86	1.79	1.91	2.65
Electronic & Electrical Equipment	1.49	1.65	1.94	1.87
General Industrials	1.11	2.01	1.87	2.30
Industrial Engineering	1.02	1.87	2.09	2.48
Industrial Transportation	0.71	1.26	1.24	1.91
Support Services	0.43	1.66	2.24	3.16
Oil & Gas	**0.73**	**1.43**	**1.61**	**2.24**
Oil & Gas Producers	0.82	1.39	1.73	2.30
Oil Equipment & Services	0.55	1.52	1.35	2.10
Technology	**0.49**	**1.71**	**2.29**	**2.97**
Software & Computer Services	0.52	1.82	2.35	3.06
Technology Hardware & Equipment	0.47	1.61	2.23	2.88
Telecommunications	**0.64**	**2.32**	**3.47**	**4.37**
Fixed Line Telecommunications	0.64	2.32	3.47	4.37
Utilities	**1.10**	**1.57**	**1.93**	**2.31**
Electricity	1.17	1.55	1.94	2.34
Gas, Water & Multiutilities	0.93	1.64	1.90	2.24
Grand Total	**0.92**	**1.71**	**2.02**	**2.48**

Table B5. Average t-statistic values (percentage values) per sector and industry for the bivariate regression models on the Realized Variance of S&P500 constituents, for 6-month forecast horizon.

Average t-statistic values per Factor h=6 (h= forecast horizon)	EPU	MPU	LEVEL RV	SLOPE RV
Basic Materials	**-0.05**	**0.54**	**2.86**	**3.01**
Chemicals	0.01	0.47	2.99	3.17
Forestry & Paper	-1.61	1.24	4.62	3.02
Industrial Metals & Mining	0.68	0.91	2.13	2.82
Mining	-1.30	-0.36	1.66	1.40
Consumer Goods	**0.10**	**0.67**	**2.53**	**2.77**
Automobiles & Parts	-0.22	0.54	3.08	3.11
Beverages	-0.30	0.55	2.68	3.07
Food Producers	-0.12	0.65	2.64	2.56
Household Goods & Home Construction	0.85	0.50	1.81	2.83
Leisure Goods	0.86	0.93	1.83	2.15
Personal Goods	0.02	0.89	2.75	2.89
Tobacco	-1.37	0.49	3.36	2.52
Consumer Services	**0.17**	**0.69**	**2.72**	**2.79**
Food & Drug Retailers	0.13	0.84	2.53	2.76
General Retailers	-0.22	0.76	3.09	2.86
Media	0.43	0.56	2.54	2.74
Travel & Leisure	0.48	0.65	2.44	2.74
Financials	**0.04**	**0.57**	**2.80**	**2.82**
Banks	0.50	0.89	2.92	2.91
Financial Services (Sector)	-0.50	0.40	2.99	2.76
Life Insurance	0.75	0.70	2.58	2.78
Nonlife Insurance	-0.03	0.47	2.53	2.81
Real Estate Investment & Services	-0.92	0.65	4.99	3.76
Real Estate Investment Trusts	0.17	0.58	2.66	2.81
Health Care	**-0.20**	**0.50**	**2.63**	**2.62**
Health Care Equipment & Services	-0.24	0.47	2.76	2.72
Pharmaceuticals & Biotechnology	-0.15	0.54	2.46	2.48
Industrials	**0.04**	**0.49**	**2.64**	**2.70**
Aerospace & Defense	0.12	0.55	2.55	2.49
Construction & Materials	-0.25	0.40	2.62	2.18
Electronic & Electrical Equipment	0.85	0.80	2.36	3.13
General Industrials	0.12	0.64	2.63	2.85
Industrial Engineering	0.39	0.73	2.72	2.92
Industrial Transportation	-0.50	-0.10	1.71	1.58
Support Services	-0.30	0.37	3.22	3.12
Oil & Gas	**-0.40**	**0.01**	**1.97**	**2.21**
Oil & Gas Producers	-0.48	0.07	2.34	2.36
Oil Equipment & Services	-0.22	-0.14	1.13	1.87
Technology	**-0.52**	**0.56**	**3.15**	**2.89**
Software & Computer Services	-0.41	0.64	3.48	3.12
Technology Hardware & Equipment	-0.63	0.48	2.83	2.66
Telecommunications	**-0.86**	**1.33**	**4.87**	**4.22**
Fixed Line Telecommunications	-0.86	1.33	4.87	4.22
Utilities	**-0.36**	**0.23**	**2.30**	**2.50**
Electricity	-0.32	0.20	2.27	2.47
Gas, Water & Multiutilities	-0.47	0.30	2.38	2.58
Grand Total	**-0.08**	**0.52**	**2.68**	**2.73**

Table B6. Average t-statistic values (percentage values) per sector and industry for the bivariate regression models on the Realized Variance of S&P500 constituents, for 12-month forecast horizon.

Average t-statistic values per Factor h=12 (h= forecast horizon)	EPU	MPU	LEVEL RV	SLOPE RV
Basic Materials	**-0.99**	**0.87**	**1.81**	**2.00**
Chemicals	-0.93	0.72	1.91	1.98
Forestry & Paper	-3.66	0.21	2.36	1.26
Industrial Metals & Mining	-0.19	1.77	1.49	2.52
Mining	-1.40	0.72	0.93	1.42
Consumer Goods	**-0.95**	**0.72**	**1.56**	**1.80**
Automobiles & Parts	-1.02	0.65	1.91	2.03
Beverages	-1.15	0.69	1.71	1.85
Food Producers	-1.25	0.60	1.57	1.68
Household Goods & Home Construction	-0.35	0.83	0.95	1.73
Leisure Goods	-0.24	0.64	1.03	1.72
Personal Goods	-1.11	0.72	1.89	1.80
Tobacco	-1.94	1.48	2.30	2.29
Consumer Services	**-0.92**	**0.80**	**1.64**	**1.83**
Food & Drug Retailers	-0.85	0.57	1.10	1.31
General Retailers	-1.33	0.79	1.93	1.80
Media	-0.49	0.93	1.62	1.98
Travel & Leisure	-0.73	0.79	1.45	1.90
Financials	**-1.06**	**0.74**	**1.72**	**1.89**
Banks	-0.63	0.84	1.77	2.07
Financial Services (Sector)	-1.43	0.66	1.61	1.69
Life Insurance	-0.53	0.89	1.66	2.08
Nonlife Insurance	-1.29	0.55	1.49	1.83
Real Estate Investment & Services	-1.82	0.83	2.35	1.69
Real Estate Investment Trusts	-0.97	0.82	1.89	1.97
Health Care	**-1.15**	**0.69**	**1.54**	**1.78**
Health Care Equipment & Services	-1.25	0.74	1.59	1.78
Pharmaceuticals & Biotechnology	-1.01	0.64	1.47	1.78
Industrials	**-0.98**	**0.61**	**1.57**	**1.80**
Aerospace & Defense	-0.61	0.62	1.44	1.75
Construction & Materials	-1.35	0.54	1.57	1.50
Electronic & Electrical Equipment	-0.60	0.56	1.49	1.85
General Industrials	-0.92	0.54	1.54	1.92
Industrial Engineering	-0.55	1.04	1.46	1.99
Industrial Transportation	-1.58	-0.14	1.04	1.31
Support Services	-1.24	0.74	2.02	1.99
Oil & Gas	**-1.39**	**0.44**	**1.30**	**1.72**
Oil & Gas Producers	-1.45	0.46	1.50	1.86
Oil Equipment & Services	-1.26	0.42	0.85	1.41
Technology	**-1.52**	**0.53**	**1.86**	**1.77**
Software & Computer Services	-1.50	0.74	2.02	1.91
Technology Hardware & Equipment	-1.54	0.33	1.70	1.64
Telecommunications	**-1.49**	**1.25**	**2.47**	**1.55**
Fixed Line Telecommunications	-1.49	1.25	2.47	1.55
Utilities	**-1.29**	**0.65**	**1.34**	**1.69**
Electricity	-1.30	0.63	1.33	1.69
Gas, Water & Multiutilities	-1.28	0.71	1.36	1.71
Grand Total	**-1.10**	**0.68**	**1.62**	**1.81**

Table B7. Predicting RV using multiple regression model

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (SP500RV). The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 to December 2017. The estimated multiple predictive regression model is given below:

$$\begin{aligned} LN(RV_t) = b_0 &+ b_1 INF_{t-h} + b_2 LN(RV_{t-h}) + b_3 SLOPE_{t-h} + b_4 LN(SLOPERV)_{t-h} \\ &+ b_5 LN(EPU)_{t-h} + b_6 LN(MPU)_{t-h} + b_7 Defspr_{t-h} + b_8 IPG_{t-h} \\ &+ b_9 LN(OILRV_{t-k}) + \varepsilon_t \end{aligned}$$

Sample		***1m***	***2m***	***3m***	***6m***	***9m***	***12m***
Const	Coef.	-1.23	-1.28	-0.45	-0.0972	-1.561	-0.0598
	t-stat	(-1.40)	(-1.02)	(-0.29)	(-0.05)	(-0.91)	(-0.03)
INF	Coef.	13.76*	20.97*	32.85*	39.32*	31.39	21.88
	t-stat	(1.70)	(1.73)	(1.80)	(1.70)	(1.32)	(1.02)
RV	Coef.	0.743***	0.635***	0.594***	0.553***	0.530***	0.447***
	t-stat	(15.32)	(10.46)	(8.66)	(8.48)	(7.51)	(6.31)
SLOPE	Coef.	-2.748	-2.874	-1.541	-6.186	-16.35***	-20.88***
	t-stat	(-0.81)	(-0.58)	(-0.24)	(-0.83)	(-2.67)	(-3.59)
SLOPERV	Coef.	-0.00227	-0.0125	-0.00619	0.0552	0.0551	0.114*
	t-stat	(-0.05)	(-0.26)	(-0.13)	(0.96)	(0.87)	(1.92)
EPU	Coef.	-0.199	-0.362	-0.580*	-0.499	-0.100	-0.576
	t-stat	(-0.97)	(-1.25)	(-1.71)	(-1.17)	(-0.24)	(-1.51)
MPU	Coef.	-0.0828	-0.114	-0.0869	-0.212	-0.288*	-0.0781
	t-stat	(-0.96)	(-1.12)	(-0.83)	(-1.52)	(-1.90)	(-0.59)
Defspr	Coef.	20.03**	24.52**	24.49*	19.08	8.497	11.49
	t-stat	(2.31)	(2.22)	(1.88)	(1.23)	(0.58)	(0.84)
IPG	Coef.	-7.798	-14.42	-12.73	-9.184	-11.90	-0.958
	t-stat	(-0.80)	(-1.49)	(-1.42)	(-0.97)	(-1.64)	(-0.13)
OILRV	Coef.	-0.0501	-0.0540	-0.0200	-0.0596	-0.0968	-0.0561
	t-stat	(-1.48)	(-1.09)	(-0.31)	(-0.80)	(-1.23)	(-0.64)
% adj. R^2		62.3	47.7	41.2	33.7	30.5	31.4

Table B8. Predicting RV using multiple regression model

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (SP500RV). The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 to December 2017. The estimated multiple predictive regression model is given below:

$$LN(RV_t) = b_0 + b_1 LN(RV_{t-h}) + b_3 SLOPE_{t-h} + b_4 LN(SLOPERV)_{t-h} + b_5 LN(EPU)_{t-h} + b_6 LN(MPU)_{t-h} + b_7 Defspr_{t-h} + b_8 IPG_{t-h} + \varepsilon_t$$

Sample		***1m***	***2m***	***3m***	***6m***	***9m***	***12m***
Const	Coef.	-0.563	-0.565	-0.202	0.674	-0.319	0.632
	t-stat	(-0.72)	(-0.54)	(-0.17)	(0.47)	(-0.23)	(0.46)
RV	Coef.	0.744***	0.635***	0.592***	0.551***	0.527***	0.443***
	t-stat	(14.96)	(10.23)	(8.53)	(8.26)	(6.97)	(6.04)
SLOPE	Coef.	-1.431	-1.505	-1.297	-4.870	-14.01**	-19.63***
	t-stat	(-0.42)	(-0.31)	(-0.21)	(-0.67)	(-2.17)	(-3.05)
SLOPERV	Coef.	-0.00145	-0.0109	-0.00268	0.0592	0.0574	0.116*
	t-stat	(-0.03)	(-0.23)	(-0.06)	(1.01)	(0.86)	(1.89)
EPU	Coef.	-0.284	-0.447	-0.580*	-0.574	-0.255	-0.656*
	t-stat	(-1.44)	(-1.61)	(-1.89)	(-1.42)	(-0.65)	(-1.86)
MPU	Coef.	-0.0404	-0.0671	-0.0642	-0.155	-0.205	-0.0304
	t-stat	(-0.49)	(-0.68)	(-0.64)	(-1.14)	(-1.43)	(-0.24)
Defspr	Coef.	14.89*	18.11*	18.65	9.879	-1.880	4.951
	t-stat	(1.81)	(1.81)	(1.58)	(0.67)	(-0.13)	(0.36)
IPG	Coef.	-7.171	-13.93	-13.18	-8.895	-10.64	-0.327
	t-stat	(-0.73)	(-1.43)	(-1.46)	(-0.92)	(-1.47)	(-0.05)
% adj. R^2		62.2	47.4	40.8	32.7	29.5	31.2

Table B9. Predicting RV using multiple regression model

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (SP500RV). The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 to December 2017. The estimated multiple predictive regression model is given below:

$$LN(RV_t) = b_0 + b_1 INF_{t-h} + b_2 VIX_{t-h} + b_3 SLOPE_{t-h} + b_4 LN(SLOPERV)_{t-h} + b_5 LN(EPU)_{t-h} + b_6 LN(MPU)_{t-h} + b_7 Defspr_{t-h} + b_8 IPG_{t-h} + b_9 LN(OILRV_{t-k}) + \varepsilon_t$$

Sample		***1m***	***2m***	***3m***	***6m***	***9m***	***12m***
Const	Coef.	-5.900***	-5.287***	-4.198***	-3.574*	-4.887***	-2.874
	t-stat	(-6.22)	(-4.15)	(-2.80)	(-1.95)	(-2.78)	(-1.58)
Inflation	Coef.	30.45**	35.63**	45.87**	50.77**	41.89	29.88
	t-stat	(2.30)	(2.30)	(2.22)	(2.00)	(1.54)	(1.22)
VIX	Coef.	8.920***	7.753***	7.085***	6.207***	5.881***	4.662***
	t-stat	(10.40)	(8.09)	(7.10)	(5.34)	(4.31)	(3.63)
TermSpread	Coef.	-3.423	-3.297	-2.283	-7.621	-17.86***	-22.62***
	t-stat	(-0.76)	(-0.59)	(-0.34)	(-1.00)	(-2.79)	(-3.82)
SLOPERV	Coef.	0.0370	0.0184	0.0239	0.0910	0.0908	0.148**
	t-stat	(0.82)	(0.37)	(0.48)	(1.44)	(1.29)	(2.49)
EPU	Coef.	-0.470*	-0.590*	-0.791**	-0.685	-0.274	-0.717*
	t-stat	(-1.85)	(-1.81)	(-2.15)	(-1.49)	(-0.62)	(-1.76)
MPU	Coef.	-0.0316	-0.0765	-0.0465	-0.172	-0.249	-0.0381
	t-stat	(-0.33)	(-0.68)	(-0.41)	(-1.15)	(-1.55)	(-0.27)
BAA	Coef.	13.09	17.58	19.16	16.67	6.499	11.61
	t-stat	(1.06)	(1.23)	(1.17)	(0.84)	(0.32)	(0.66)
Ind prod growth	Coef.	-5.275	-12.41	-10.08	-6.453	-9.228	1.462
	t-stat	(-0.42)	(-1.04)	(-0.90)	(-0.55)	(-1.08)	(0.17)
Oil RV	Coef.	0.0325	0.0179	0.0478	0.000387	-0.0393	-0.00923
	t-stat	(0.78)	(0.35)	(0.71)	(0.01)	(-0.48)	(-0.10)
% adj. R^2		57.8	44.9	38.3	30.1	27	28.2

Table B10. Predicting RV using multiple regression model, during the pre-crisis period

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (SP500RV). The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 to December 2006. The estimated multiple predictive regression model is given below:

$$\begin{aligned} LN(RV_t) = b_0 &+ b_1 INF_{t-h} + b_2 LN(RV_{t-h}) + b_3 SLOPE_{t-h} + b_4 LN(SLOPERV)_{t-h} \\ &+ b_5 LN(EPU)_{t-h} + b_6 LN(MPU)_{t-h} + b_7 Defspr_{t-h} + b_8 IPG_{t-h} \\ &+ b_9 LN(OILRV_{t-k}) + \varepsilon_t \end{aligned}$$

Sample		***1m***	***2m***	***3m***	***6m***	***9m***	***12m***
Const	Coef.	-2.930**	-2.444	-2.003	-2.339	-1.727	1.577
	t-stat	(-2.33)	(-1.44)	(-1.00)	(-1.32)	(-1.07)	(0.97)
INF	Coef.	24.88**	15.23	9.988	3.691	-25.38	-24.19
	t-stat	(2.07)	(0.89)	(0.48)	(0.17)	(-0.91)	(-0.96)
RV	Coef.	0.708***	0.584***	0.496***	0.503***	0.539***	0.477***
	t-stat	(11.24)	(6.91)	(5.09)	(6.67)	(6.98)	(5.70)
SLOPE	Coef.	-8.749**	-9.151*	-10.83	-16.27**	-19.05***	-21.87***
	t-stat	(-2.27)	(-1.65)	(-1.62)	(-2.26)	(-3.10)	(-3.81)
SLOPERV	Coef.	-0.0699	-0.104*	-0.0874*	-0.0708	-0.0669	0.0437
	t-stat	(-1.30)	(-1.88)	(-1.78)	(-1.20)	(-1.32)	(0.86)
EPU	Coef.	-0.00710	-0.304	-0.387	-0.568	-0.438	-1.259***
	t-stat	(-0.02)	(-0.73)	(-0.79)	(-1.32)	(-1.08)	(-3.57)
MPU	Coef.	-0.105	-0.137	-0.201	-0.0827	-0.191	0.0563
	t-stat	(-0.92)	(-1.02)	(-1.32)	(-0.63)	(-1.43)	(0.52)
Defspr	Coef.	35.35***	47.05***	53.84***	49.82**	28.68	28.21
	t-stat	(3.62)	(3.32)	(3.04)	(2.59)	(1.61)	(1.36)
IPG	Coef.	3.332	-0.0851	-0.0246	8.471	-16.94**	-5.720
	t-stat	(0.39)	(-0.01)	(-0.00)	(0.88)	(-2.05)	(-0.56)
OILRV	Coef.	-0.0294	0.0164	0.0633	-0.0740	-0.0970	-0.0777
	t-stat	(-0.55)	(0.24)	(0.85)	(-0.93)	(-1.09)	(-1.05)
% adj. R^2		65.5	52.6	47.4	45.8	45.9	49.6

Table B11. Predicting RV using multiple regression model, during the pre-crisis period

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (SP500RV). The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 to December 2006. The estimated multiple predictive regression model is given below:

$$LN(RV_t) = b_0 + b_1 LN(RV_{t-h}) + b_3 SLOPE_{t-h} + b_4 LN(SLOPERV)_{t-h} + b_5 LN(EPU)_{t-h} + b_6 LN(MPU)_{t-h} + b_7 Defspr_{t-h} + b_8 IPG_{t-h} + \varepsilon_t$$

Sample		***1m***	***2m***	***3m***	***6m***	***9m***	***12m***
Const	Coef.	-2.771**	-2.543	-2.368	-1.917	-1.163	2.030
	t-stat	(-2.32)	(-1.58)	(-1.29)	(-1.32)	(-0.74)	(1.25)
RV	Coef.	0.708***	0.589***	0.507***	0.494***	0.522***	0.463***
	t-stat	(11.47)	(7.04)	(5.44)	(6.75)	(6.91)	(5.60)
SLOPE	Coef.	-8.389**	-9.493*	-11.91*	-15.08**	-17.34***	-20.48***
	t-stat	(-2.13)	(-1.73)	(-1.84)	(-2.22)	(-3.02)	(-3.67)
SLOPERV	Coef.	-0.0701	-0.100*	-0.0800	-0.0777	-0.0794	0.0333
	t-stat	(-1.32)	(-1.84)	(-1.63)	(-1.36)	(-1.61)	(0.67)
EPU	Coef.	0.0246	-0.278	-0.360	-0.576	-0.495	-1.310***
	t-stat	(0.08)	(-0.64)	(-0.72)	(-1.42)	(-1.17)	(-3.62)
MPU	Coef.	-0.101	-0.136	-0.203	-0.0786	-0.189	0.0573
	t-stat	(-0.89)	(-1.02)	(-1.34)	(-0.62)	(-1.45)	(0.52)
Defspr	Coef.	32.38***	45.34***	52.89***	49.15***	31.30	30.75
	t-stat	(3.23)	(3.17)	(3.07)	(2.72)	(1.59)	(1.40)
IPG	Coef.	3.199	-1.399	-2.767	10.95	-12.26	-1.785
	t-stat	(0.37)	(-0.18)	(-0.27)	(1.31)	(-1.64)	(-0.20)
% adj. R^2		65.5	52.9	47.6	46	45.3	49.3

Table B12. Predicting RV using multiple regression model, during the pre-crisis period

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (SP500RV). The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 to December 2006. The estimated multiple predictive regression model is given below:

$$LN(RV_t) = b_0 + b_1 INF_{t-h} + b_2 VIX_{t-h} + b_3 SLOPE_{t-h} + b_4 LN(SLOPERV)_{t-h} + b_5 LN(EPU)_{t-h} + b_6 LN(MPU)_{t-h} + b_7 Defspr_{t-h} + b_8 IPG_{t-h} + b_9 LN(OILRV_{t-k}) + \varepsilon_t$$

Sample		***1m***	***2m***	***3m***	***6m***	***9m***	***12m***
Const	Coef.	-6.312***	-5.158***	-4.282**	-4.562***	-4.173***	-0.653
	t-stat	(-5.29)	(-3.10)	(-2.32)	(-2.91)	(-2.84)	(-0.40)
INF	Coef.	29.94**	19.39	13.52	7.252	-21.55	-20.79
	t-stat	(2.35)	(1.09)	(0.65)	(0.36)	(-0.83)	(-0.82)
VIX	Coef.	10.08***	8.746***	7.571***	8.146***	8.379***	7.067***
	t-stat	(9.73)	(6.54)	(5.03)	(5.62)	(5.93)	(5.50)
SLOPE	Coef.	-6.039	-6.010	-7.861	-12.27*	-15.50**	-19.47***
	t-stat	(-1.26)	(-0.95)	(-1.07)	(-1.67)	(-2.53)	(-3.28)
SLOPERV	Coef.	-0.0352	-0.0782	-0.0667	-0.0531	-0.0455	0.0652
	t-stat	(-0.67)	(-1.48)	(-1.34)	(-0.95)	(-0.99)	(1.28)
EPU	Coef.	-0.692**	-0.900**	-0.903*	-1.123***	-1.009**	-1.740***
	t-stat	(-2.43)	(-2.07)	(-1.80)	(-2.65)	(-2.58)	(-4.52)
MPU	Coef.	-0.0452	-0.0901	-0.162	-0.0459	-0.150	0.0950
	t-stat	(-0.44)	(-0.69)	(-1.12)	(-0.36)	(-1.22)	(0.88)
Defspr	Coef.	39.37***	47.47***	53.23***	46.02**	26.97	29.07
	t-stat	(3.05)	(2.94)	(2.78)	(2.08)	(1.35)	(1.40)
IPG	Coef.	2.819	-1.400	-1.440	6.056	-18.80**	-6.635
	t-stat	(0.34)	(-0.17)	(-0.13)	(0.59)	(-2.20)	(-0.61)
OILRV	Coef.	0.0163	0.0530	0.0940	-0.0440	-0.0640	-0.0476
	t-stat	(0.32)	(0.81)	(1.31)	(-0.55)	(-0.70)	(-0.64)
% adj. R^2		64.7	53.8	48.8	49	48.1	50.2

Table B13. Predicting RV using multiple regression model, during the post-crisis period

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (SP500RV). The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 2007 to December 2017. The estimated multiple predictive regression model is given below:

$$LN(RV_t) = b_0 + b_1 INF_{t-h} + b_2 LN(RV_{t-h}) + b_3 SLOPE_{t-h} + b_4 LN(SLOPERV)_{t-h} + b_5 LN(EPU)_{t-h} + b_6 LN(MPU)_{t-h} + b_7 Defspr_{t-h} + b_8 IPG_{t-h} + b_9 LN(OILRV_{t-k}) + \varepsilon_t$$

Sample		***1m***	***2m***	***3m***	***6m***	***9m***	***12m***
Const	Coef.	-0.317	-1.397	-0.296	2.020	-0.527	-1.353
	t-stat	(-0.29)	(-1.00)	(-0.15)	(0.82)	(-0.22)	(-0.57)
INF	Coef.	-0.0288	17.89	46.89*	60.86*	66.60*	48.87
	t-stat	(-0.00)	(1.18)	(1.77)	(1.74)	(1.96)	(1.60)
RV	Coef.	0.648***	0.538***	0.562***	0.498***	0.517***	0.549***
	t-stat	(6.34)	(4.73)	(4.46)	(3.43)	(2.94)	(3.07)
SLOPE	Coef.	12.72*	17.46*	27.19**	23.24	1.080	-1.896
	t-stat	(1.91)	(1.91)	(2.17)	(1.42)	(0.11)	(-0.19)
SLOPERV	Coef.	0.108*	0.109	0.0719	0.240**	0.228**	0.141
	t-stat	(1.71)	(1.46)	(0.90)	(2.45)	(2.14)	(1.16)
EPU	Coef.	-0.373	-0.459	-0.881**	-0.818	-0.396	-0.875*
	t-stat	(-1.41)	(-1.34)	(-2.04)	(-1.23)	(-0.68)	(-1.73)
MPU	Coef.	-0.00193	0.0535	0.263	-0.0575	-0.0820	0.341
	t-stat	(-0.01)	(0.30)	(1.46)	(-0.21)	(-0.30)	(1.34)
Defspr	Coef.	6.681	4.945	-2.388	-19.11	-15.41	-19.85
	t-stat	(0.47)	(0.35)	(-0.15)	(-1.12)	(-0.90)	(-1.01)
IPG	Coef.	-16.01	-29.18***	-29.78***	-30.95***	-17.43	-17.73
	t-stat	(-1.17)	(-2.99)	(-4.14)	(-3.14)	(-1.35)	(-1.11)
OILRV	Coef.	-0.0447	-0.133	-0.102	-0.155	-0.337**	-0.527***
	t-stat	(-0.50)	(-1.31)	(-0.73)	(-0.94)	(-2.06)	(-2.86)
% adj. R^2		60	46.4	43.4	36.3	29.9	37.4

Table B14. Predicting RV using multiple regression model, during the post-crisis period

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (SP500RV). The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 2007 to December 2017. The estimated multiple predictive regression model is given below:

$$LN(RV_t) = b_0 + b_1 LN(RV_{t-h}) + b_3 SLOPE_{t-h} + b_4 LN(SLOPERV)_{t-h} + b_5 LN(EPU)_{t-h} + b_6 LN(MPU)_{t-h} + b_7 Defspr_{t-h} + b_8 IPG_{t-h} + \varepsilon_t$$

Sample		***1m***	***2m***	***3m***	***6m***	***9m***	***12m***
Const	Coef.	-0.00185	-0.466	0.380	3.034	1.658	1.908
	t-stat	(-0.00)	(-0.32)	(0.19)	(1.15)	(0.58)	(0.82)
RV	Coef.	0.635***	0.489***	0.503***	0.409***	0.352*	0.313
	t-stat	(6.89)	(4.27)	(3.88)	(2.83)	(1.96)	(1.61)
SLOPE	Coef.	13.33*	19.15**	27.99**	24.54	4.065	3.546
	t-stat	(1.95)	(2.01)	(2.24)	(1.45)	(0.37)	(0.31)
SLOPERV	Coef.	0.115**	0.136*	0.104	0.289***	0.314**	0.256**
	t-stat	(2.08)	(1.83)	(1.40)	(3.03)	(2.57)	(2.00)
EPU	Coef.	-0.401	-0.525	-0.897**	-0.853	-0.522	-1.107**
	t-stat	(-1.48)	(-1.56)	(-2.14)	(-1.24)	(-0.84)	(-2.13)
MPU	Coef.	0.0100	0.0906	0.293*	-0.0109	0.00593	0.487*
	t-stat	(0.07)	(0.51)	(1.70)	(-0.04)	(0.02)	(1.79)
Defspr	Coef.	5.456	-1.128	-11.20	-30.91**	-32.38**	-40.00*
	t-stat	(0.40)	(-0.08)	(-0.80)	(-2.02)	(-2.15)	(-1.96)
IPG	Coef.	-15.47	-27.90***	-28.96***	-29.51***	-13.87	-12.30
	t-stat	(-1.15)	(-2.84)	(-3.80)	(-3.09)	(-1.17)	(-0.83)
% adj. R^2		62.2	47.4	40.8	32.7	29.5	31.2

Table B15. Predicting RV using multiple regression model, during the post-crisis period

This table shows the results of multiple predictive regressions of the U.S. stock market volatility (SP500RV). The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 2007 to December 2017. The estimated multiple predictive regression model is given below:

$$LN(RV_t) = b_0 + b_1 INF_{t-h} + b_2 VIX_{t-h} + b_3 SLOPE_{t-h} + b_4 LN(SLOPERV)_{t-h} + b_5 LN(EPU)_{t-h} + b_6 LN(MPU)_{t-h} + b_7 Defspr_{t-h} + b_8 IPG_{t-h} + b_9 LN(OILRV_{t-k}) + \varepsilon_t$$

Sample		***1m***	***2m***	***3m***	***6m***	***9m***	***12m***
Const	Coef.	-4.425***	-4.922***	-3.898*	-1.076	-3.833	-5.134*
	t-stat	(-3.17)	(-2.92)	(-1.91)	(-0.39)	(-1.54)	(-1.92)
INF	Coef.	18.88	35.55**	63.40**	73.82**	81.02**	66.62**
	t-stat	(1.12)	(2.05)	(2.33)	(2.11)	(2.39)	(2.02)
VIX	Coef.	7.374***	6.620***	6.587***	5.353***	6.058***	7.081***
	t-stat	(5.73)	(4.37)	(3.89)	(2.65)	(3.27)	(2.86)
SLOPE	Coef.	15.44*	19.53*	28.92**	23.79	1.309	-1.360
	t-stat	(1.92)	(1.97)	(2.18)	(1.45)	(0.14)	(-0.13)
SLOPERV	Coef.	0.149**	0.130*	0.0999	0.281***	0.256**	0.145
	t-stat	(2.40)	(1.89)	(1.30)	(2.96)	(2.01)	(1.15)
EPU	Coef.	-0.442	-0.502	-0.932**	-0.826	-0.383	-0.837
	t-stat	(-1.42)	(-1.34)	(-2.01)	(-1.19)	(-0.63)	(-1.56)
MPU	Coef.	0.0986	0.122	0.340*	-0.00881	-0.0493	0.380
	t-stat	(0.57)	(0.58)	(1.67)	(-0.03)	(-0.17)	(1.45)
Defspr	Coef.	-18.91	-20.32	-26.05	-37.14	-38.76*	-51.94*
	t-stat	(-1.14)	(-1.16)	(-1.30)	(-1.57)	(-1.79)	(-1.83)
IPG	Coef.	-21.70	-34.68***	-33.93***	-34.51***	-22.09**	-25.21*
	t-stat	(-1.35)	(-3.09)	(-3.84)	(-3.75)	(-1.99)	(-1.67)
OILRV	Coef.	0.0958	-0.0178	0.0221	-0.0429	-0.220	-0.399**
	t-stat	(0.91)	(-0.17)	(0.16)	(-0.27)	(-1.47)	(-2.50)
% adj. R^2		57.5	45.9	42.2	34.6	29.4	38.8

Table B16. Average out-of-sample R^2 values (percentage values) per sector and industry for the bivariate regression models on the Realized Variance of S&P500 constituents, for 1-month forecast horizon.

Average R^2 values per Factor h=1 (h= forecast horizon)	EPU	MPU	LEVEL RV	SLOPE RV
Basic Materials	**-12.9**	**-2.6**	**7.15**	**8.71**
Chemicals	-12.3	-3.0	6.66	8.46
Forestry & Paper	-25.8	-10.4	5.44	-1.73
Industrial Metals & Mining	-10.0	3.2	10.94	15.41
Consumer Goods	**-5.6**	**-3.1**	**6.03**	**11.12**
Automobiles & Parts	-8.0	0.1	12.92	16.43
Beverages	-3.9	2.1	4.03	8.55
Food Producers	-8.9	-5.7	4.72	13.38
Household Goods & Home Construction	-0.7	-0.8	2.36	9.42
Leisure Goods	0.5	-0.8	8.96	11.77
Personal Goods	-4.8	-1.0	-24.63	-34.40
Tobacco	-43.9	-68.9	7.02	10.74
Consumer Services	**-8.3**	**-3.4**	**5.89**	**5.26**
Food & Drug Retailers	-17.8	-5.0	11.03	12.08
General Retailers	-8.4	-1.3	2.25	9.51
Media	-5.0	-4.6	4.49	10.96
Travel & Leisure	-7.5	-5.2	6.01	11.99
Financials	**-7.4**	**-3.6**	**-0.82**	**6.47**
Banks	-10.0	-9.8	9.37	11.34
Financial Services (Sector)	-9.8	-2.0	4.27	14.87
Life Insurance	-2.0	-2.3	6.89	12.54
Nonlife Insurance	-4.3	-0.3	23.26	24.90
Real Estate Investment & Services	-9.4	3.5	6.75	14.74
Real Estate Investment Trusts	-6.8	-3.6	3.11	5.87
Health Care	**-11.0**	**-6.5**	**4.97**	**7.73**
Health Care Equipment & Services	-9.8	-5.1	0.47	3.22
Pharmaceuticals & Biotechnology	-12.8	-8.5	7.05	10.36
Industrials	**-8.1**	**-3.3**	**5.22**	**12.39**
Aerospace & Defense	-1.9	-0.5	2.47	7.88
Construction & Materials	-7.9	-7.3	-0.53	8.67
Electronic & Electrical Equipment	-4.6	-5.8	8.47	14.77
General Industrials	-6.3	-0.5	8.88	5.85
Industrial Engineering	-20.4	-8.5	5.94	6.89
Industrial Transportation	-7.5	-3.3	12.34	12.51
Support Services	-8.2	-0.8	6.08	8.59
Oil & Gas	**-8.0**	**-3.6**	**6.03**	**8.24**
Oil & Gas Producers	-8.8	-4.0	6.18	9.42
Oil Equipment & Services	-6.0	-2.6	4.65	5.37
Technology	**-15.6**	**-8.3**	**2.37**	**3.39**
Software & Computer Services	-16.1	-9.6	7.03	7.44
Technology Hardware & Equipment	-15.0	-7.1	23.62	19.92
Telecommunications	**-17.4**	**1.9**	**23.62**	**19.92**
Fixed Line Telecommunications	-17.4	1.9	5.82	10.05
Utilities	**-7.0**	**-3.8**	**3.96**	**7.79**
Electricity	-8.1	-6.3	9.99	15.12
Gas, Water & Multiutilities	-4.5	1.8	5.97	9.59
Grand Total	**-9.0**	**-4.2**	**7.15**	**8.71**

Table B17. Average out-of-sample R^2 values (percentage values) per sector and industry for the bivariate regression models on the Realized Variance of S&P500 constituents, for 6-month forecast horizon.

Average t-statistic values per Factor h=6 (h= forecast horizon)	EPU	MPU	LEVELRV	SLOPERV
Basic Materials	**-25.0**	**-16.9**	**2.28**	**-2.82**
Chemicals	-25.8	-17.0	1.08	-2.64
Forestry & Paper	-24.4	-19.0	3.73	-9.62
Industrial Metals & Mining	-20.6	-15.6	8.76	-0.51
Consumer Goods	**-24.5**	**-18.3**	**1.30**	**-0.53**
Automobiles & Parts	-19.1	-14.8	5.43	5.03
Beverages	-18.4	-11.7	-0.95	-3.90
Food Producers	-29.2	-20.8	-1.98	2.29
Household Goods & Home Construction	-23.2	-16.5	-7.69	-4.70
Leisure Goods	-22.9	-15.6	-0.50	0.74
Personal Goods	-22.2	-16.6	-55.20	-80.44
Tobacco	-71.2	-90.0	-0.48	-2.00
Consumer Services	**-25.2**	**-18.5**	**3.75**	**-1.68**
Food & Drug Retailers	-26.6	-15.3	2.92	-1.07
General Retailers	-23.1	-16.3	-6.57	-3.29
Media	-24.8	-20.7	-2.79	-2.63
Travel & Leisure	-28.0	-21.0	-0.08	-0.43
Financials	**-26.8**	**-18.9**	**-6.46**	**-4.34**
Banks	-33.6	-26.3	1.74	-1.89
Financial Services (Sector)	-24.1	-16.5	-0.38	3.01
Life Insurance	-23.5	-17.8	2.04	1.26
Nonlife Insurance	-23.8	-15.4	19.70	8.65
Real Estate Investment & Services	-22.2	-15.9	0.57	1.27
Real Estate Investment Trusts	-28.3	-18.9	-2.10	-4.84
Health Care	**-25.2**	**-19.4**	**-1.09**	**-3.41**
Health Care Equipment & Services	-22.7	-18.4	-3.52	-6.88
Pharmaceuticals & Biotechnology	-28.9	-20.9	0.36	-1.96
Industrials	**-25.6**	**-19.1**	**-3.09**	**1.29**
Aerospace & Defense	-20.2	-15.0	-9.49	-9.06
Construction & Materials	-33.3	-27.8	-6.50	-1.87
Electronic & Electrical Equipment	-24.3	-20.2	2.29	2.08
General Industrials	-25.8	-17.9	3.78	-6.27
Industrial Engineering	-35.9	-23.9	-4.53	-6.92
Industrial Transportation	-25.7	-18.3	8.74	1.26
Support Services	-20.9	-15.7	-3.17	-4.97
Oil & Gas	**-25.4**	**-18.3**	**-4.20**	**-6.05**
Oil & Gas Producers	-26.4	-19.2	-0.76	-2.46
Oil Equipment & Services	-23.2	-16.2	0.31	-6.50
Technology	**-28.8**	**-20.9**	**-1.88**	**-7.97**
Software & Computer Services	-29.7	-23.7	2.59	-4.97
Technology Hardware & Equipment	-27.9	-18.0	20.66	8.49
Telecommunications	**-25.4**	**-13.4**	**20.66**	**8.49**
Fixed Line Telecommunications	-25.4	-13.4	-3.37	-4.05
Utilities	**-23.6**	**-18.4**	**-6.44**	**-6.32**
Electricity	-26.7	-21.2	3.52	1.05
Gas, Water & Multiutilities	-16.6	-12.3	-0.63	-2.76
Grand Total	**-25.8**	**-18.9**	**2.28**	**-2.82**

Table B18. Average out-of-sample R^2 values (percentage values) per sector and industry for the bivariate regression models on the Realized Variance of S&P500 constituents, for 12-month forecast horizon.

Average t-statistic values per Factor h=12 (h= forecast horizon)	EPU	MPU	LEVEL RV	SLOPE RV
Basic Materials	**-33.3**	**-28.3**	**-17.56**	**-22.06**
Chemicals	-33.0	-26.5	-17.79	-20.28
Forestry & Paper	-27.1	-37.3	-23.50	-35.84
Industrial Metals & Mining	-38.1	-35.0	-13.18	-25.84
Consumer Goods	**-40.5**	**-30.3**	**-12.71**	**-15.96**
Automobiles & Parts	-32.5	-23.3	-15.69	-19.00
Beverages	-26.4	-23.6	-24.48	-27.42
Food Producers	-44.5	-32.0	-19.78	-17.50
Household Goods & Home Construction	-33.5	-24.0	-27.78	-21.47
Leisure Goods	-33.4	-22.4	-19.17	-23.68
Personal Goods	-35.0	-29.3	-178.94	-207.77
Tobacco	-269.9	-190.6	-21.17	-25.43
Consumer Services	**-37.0**	**-29.3**	**-12.74**	**-21.77**
Food & Drug Retailers	-35.4	-24.9	-18.22	-25.42
General Retailers	-33.0	-28.0	-27.30	-24.49
Media	-42.4	-29.6	-23.89	-26.89
Travel & Leisure	-40.0	-31.9	-21.57	-24.93
Financials	**-39.0**	**-29.9**	**-28.93**	**-29.45**
Banks	-51.9	-36.7	-21.34	-25.79
Financial Services (Sector)	-33.0	-28.5	-19.91	-20.71
Life Insurance	-39.7	-27.6	-18.49	-22.10
Nonlife Insurance	-32.8	-28.5	-10.58	-29.98
Real Estate Investment & Services	-37.1	-37.1	-19.38	-23.81
Real Estate Investment Trusts	-39.6	-27.7	-23.03	-25.40
Health Care	**-39.4**	**-31.2**	**-22.87**	**-24.51**
Health Care Equipment & Services	-36.7	-30.5	-23.27	-26.66
Pharmaceuticals & Biotechnology	-43.2	-32.1	-21.78	-25.65
Industrials	**-39.8**	**-32.1**	**-21.51**	**-18.08**
Aerospace & Defense	-28.9	-23.7	-38.49	-43.16
Construction & Materials	-56.4	-44.4	-26.40	-22.63
Electronic & Electrical Equipment	-39.0	-29.5	-20.71	-22.51
General Industrials	-43.2	-34.0	-17.95	-31.38
Industrial Engineering	-53.6	-38.4	-25.25	-27.70
Industrial Transportation	-30.3	-29.2	-14.05	-22.11
Support Services	-34.7	-30.0	-23.81	-24.70
Oil & Gas	**-30.2**	**-28.6**	**-25.28**	**-25.51**
Oil & Gas Producers	-30.3	-30.0	-20.36	-22.81
Oil Equipment & Services	-30.0	-25.2	-20.76	-29.26
Technology	**-41.8**	**-33.2**	**-22.75**	**-31.88**
Software & Computer Services	-44.6	-36.7	-18.67	-26.52
Technology Hardware & Equipment	-39.0	-29.6	-13.11	-29.13
Telecommunications	**-34.8**	**-28.2**	**-13.11**	**-29.13**
Fixed Line Telecommunications	-34.8	-28.2	-28.66	-26.49
Utilities	**-32.0**	**-28.3**	**-32.46**	**-29.45**
Electricity	-34.9	-30.5	-20.10	-19.81
Gas, Water & Multiutilities	-25.3	-23.2	-22.27	-25.72
Grand Total	**-38.1**	**-30.5**	**-17.56**	**-22.06**

C. Option-implied expectations and the (non) neutrality of money

I consider varying robustness checks in order to ensure the reliability of my empirical results. Firstly, I estimate identical SVAR models using alternative measures of monetary policy stance. Secondly, I conduct my analysis in different subsamples, in order to ensure that my empirical results are immune to changes in financial, macroeconomic or monetary conditions (like the zero lower bound period). Thirdly, I estimate a 4-variable SVAR and a 6-variable monetary VAR model, as I discussed in the subsection 2.3. In this section, I provide the results that derived from the robustness checks, which are related with the impact of monetary policy shocks on option-implied moments, while estimated results about the response of monetary policy to shocks of the option-implied moments, are included in the appendix.

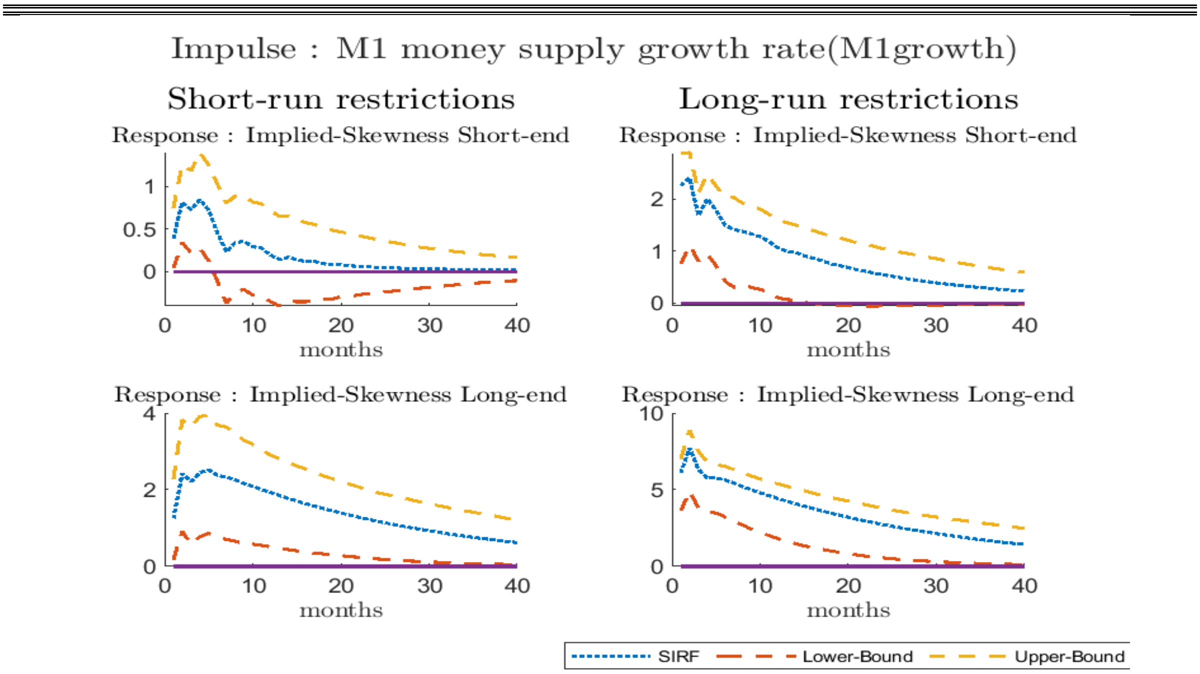
Initially, I estimate the same bivariate and multivariate SVAR and VAR models using different measures of monetary policy stance. In details, Figures C.1.9 to C.3 plot the responses of the components of IS and IK to an expansionary one standard deviation shock[49] in M1 growth rate, Taylor rule rate, and real interest rate respectively.

[49] I use the term "expansionary", instead of the term "negative", for the monetary policy shock, because, in contrast with FFR, RIR or taylor rule rate, a negative shock in M1 growth rate is a contractionary monetary policy shock. Therefore, I estimate the responses of option-implied moments to a negative one standard deviation shock in FFR, RIR and taylor rule rate, and to a positive one standard deviation shock in M1 growth rate.

Figure C.1 SIRFs of the short-end and the long-end IS-IK to positive M1growth shocks (expansionary MP shocks), for the bivariate SVAR model

In this figure I plot the SIRFs of the short-end and the long-end components of option-implied moments to a positive one standard deviation shock in M1 growth rate. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B

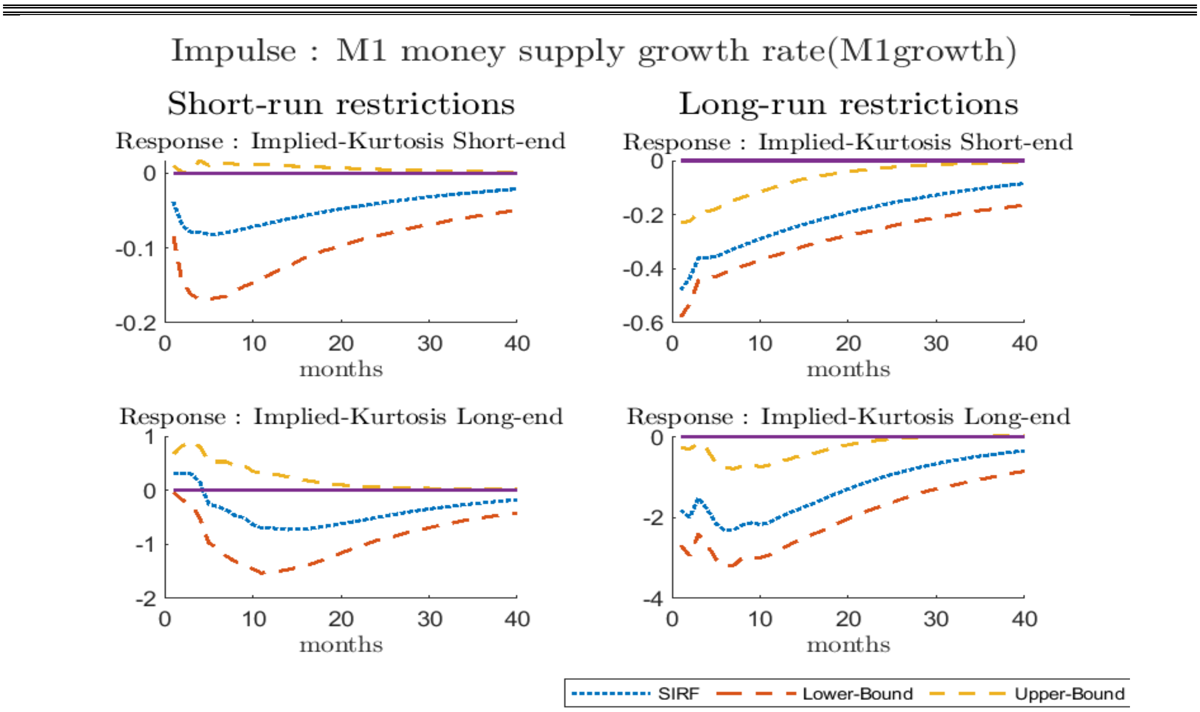
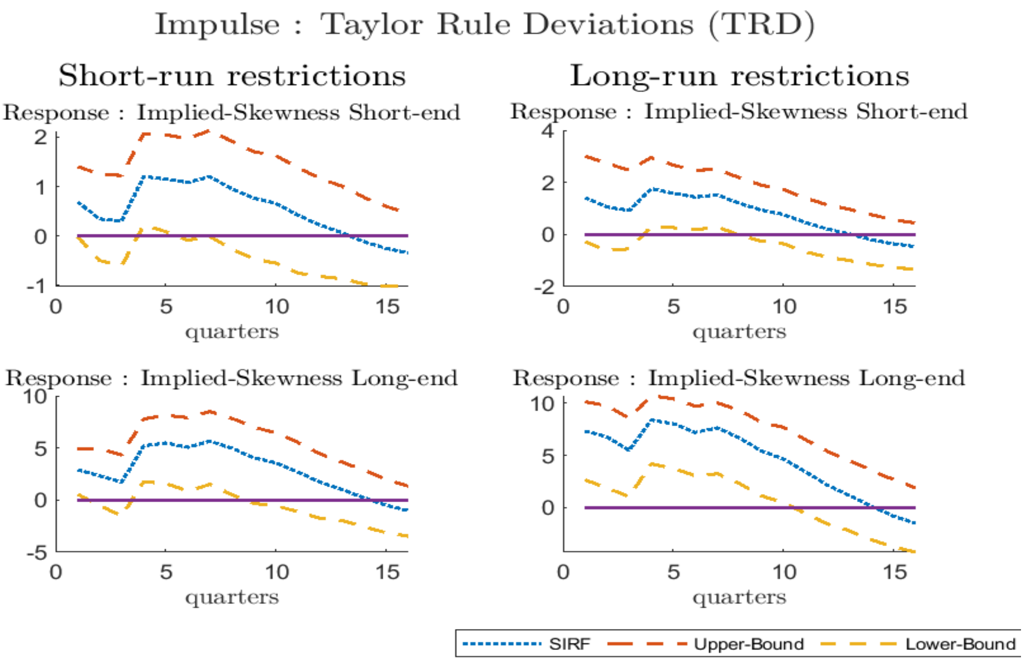


Figure C.2 SIRFs of the short-end and the long-end IS/IK to negative TRD shocks (expansionary MP shocks), for the bivariate SVAR model

In this figure I plot the SIRFs of the short-end and the long-end components of option-implied moments to a negative one standard deviation shock in Taylor rule rate. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B

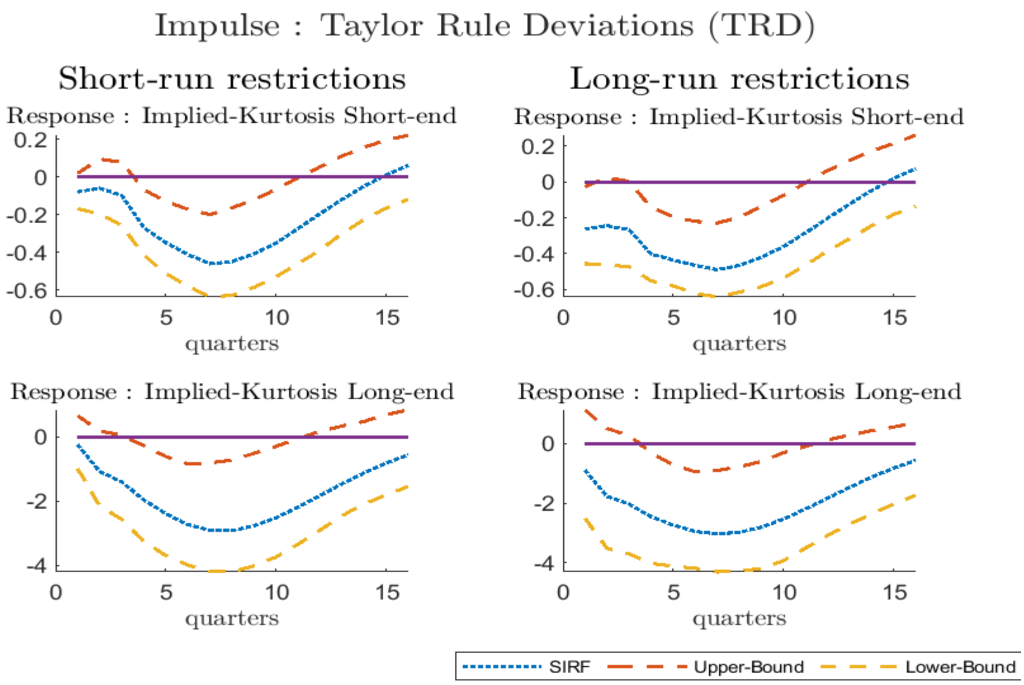
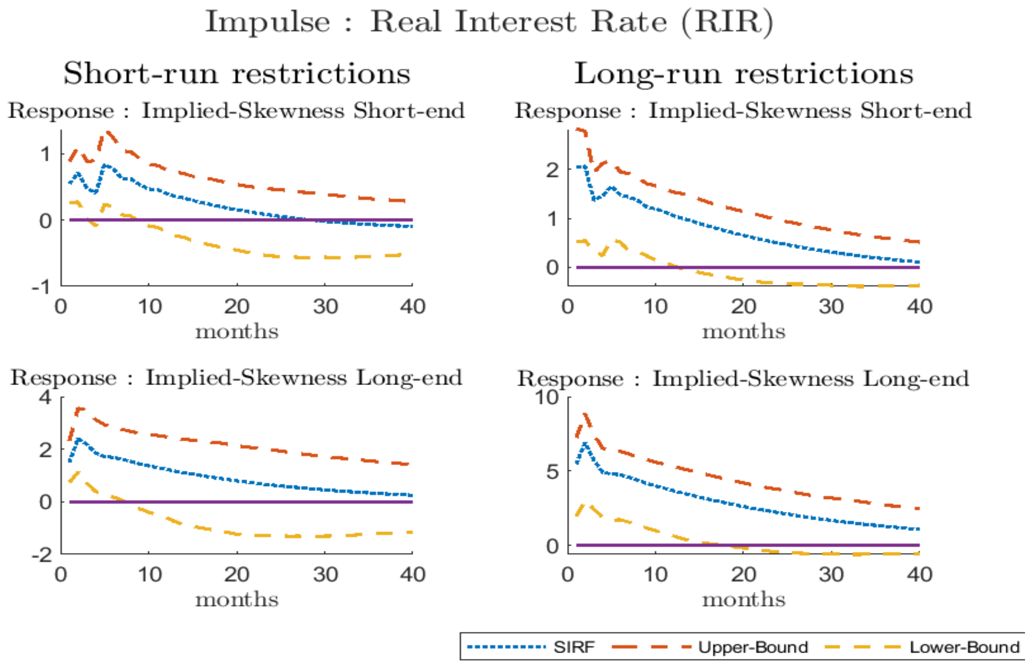


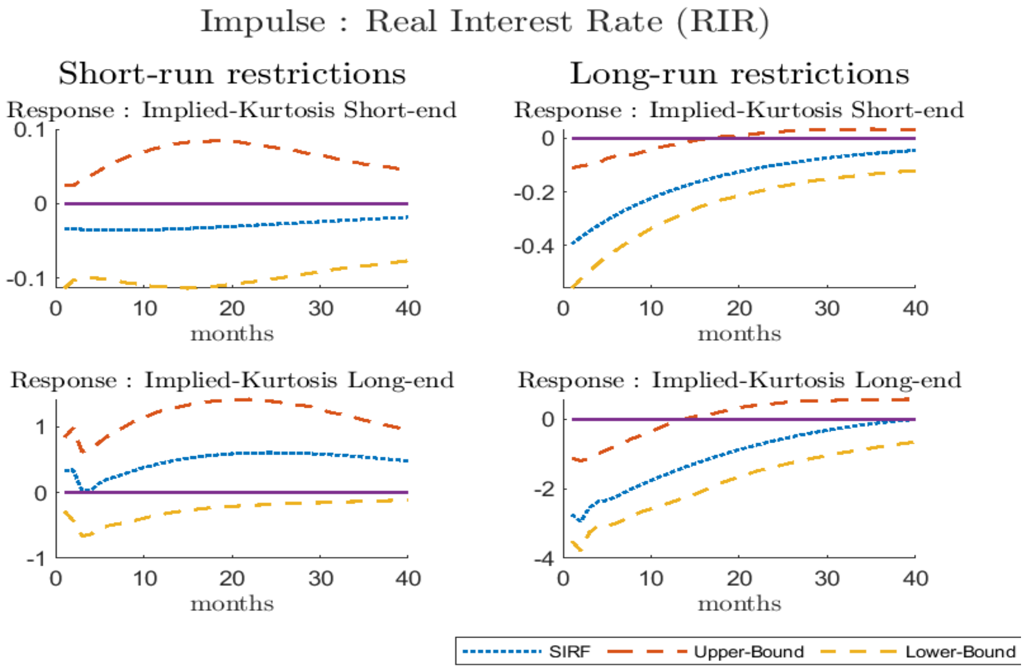
Figure C.3 SIRFs of the short-end and the long-end IS/IK to negative RIR shocks (expansionary MP shocks), for the bivariate SVAR model

In this figure I plot the SIRFs of the short-end and the long-end components of option-implied moments to a negative one standard deviation shock in RIR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B



Interestingly when I use the M1 growth rate as a proxy of monetary policy stance (**Figure C.1**), I obtain remarkable evidence about the distinct response of the long-end and short-end components of IS to monetary policy shocks. More specifically, when I apply contemporaneous restrictions in my SVAR model, I notice that an expansionary shock in M1 growth rate causes an almost 3 times greater change in long-term IS than short-term IS after 5 months. Additionally, the estimated SIRFs of long-end IS remain statistically significant for up to 40 months after the initial shock, while the SIRFs of short-end IS remain statistically significant for up to 6 months. The empirical results are similar when long-run restrictions are applied to my SVAR model. In general, my empirical results remain unaltered irrespectively of the selected measure of monetary policy stance. Namely, I find that an expansionary monetary policy shock (decrease of FFR, RIR, TRD and increase in M1growth) results an increase in IS, decrease in IK, and additionally, the long-end components of the term structure of option-implied moments are more responsive to monetary policy shocks.

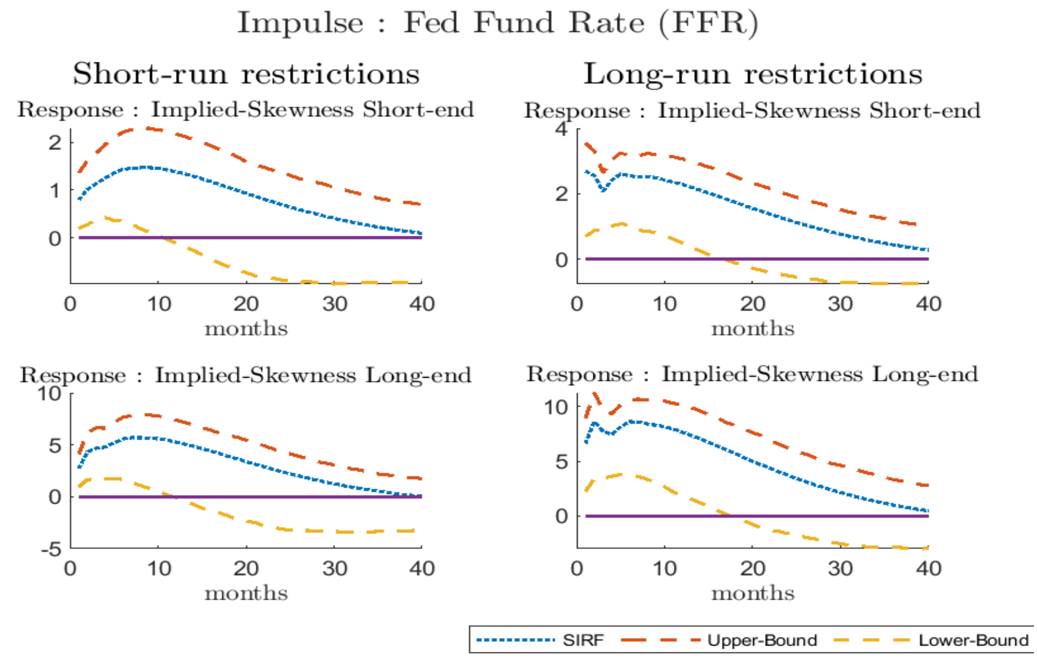
Additionally, I split my sample in two subsamples, one that corresponds to the period before the recent financial crisis of 2007 (pre-crisis period), and one that covers the period afterwards (post-crisis period). My purpose is to ensure that the response of the investors' expectations to monetary policy shocks remains statistically significant across the varying macroeconomic and monetary conditions. Specifically, during the period after the recent financial crisis of 2007, the Fed fund rate (the most common monetary policy tool during conventional periods) hits the zero-lower bound for almost 6 years, in which policy makers used unconventional monetary policy tools (like forward guidance and large asset purchases). Therefore, I estimate identical SVAR models in both subsamples in order to ensure that my results are not driven by specific macroeconomic and monetary regimes.

Figures C.4 – C.7 show the responses of option-implied moments to an expansionary monetary policy shock of the corresponding monetary policy stance measure, during the pre-crisis period. The panel A and B show the responses of the short-term and long-term IS and IK to monetary policy shocks, respectively.

Figure C.4 SIRFs of the short-end and the long-end of IS/IK to negative FFR shocks (expansionary MP shocks), for the bivariate SVAR model during the pre-crisis period

In this figure I plot the SIRFs of the short-end and long-end of option-implied moments to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B

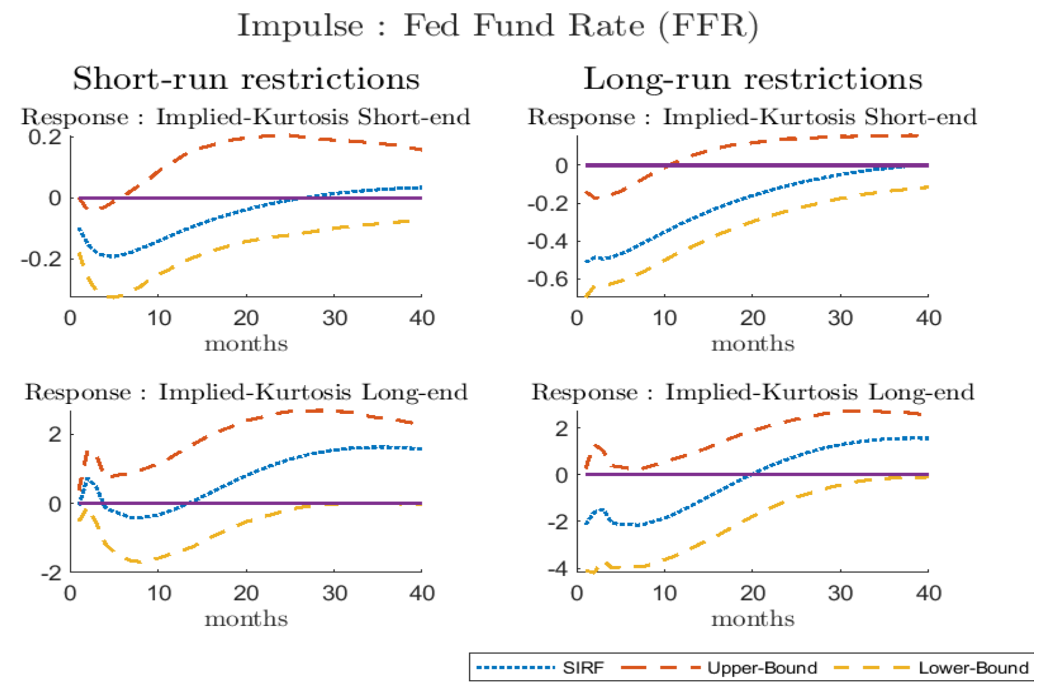
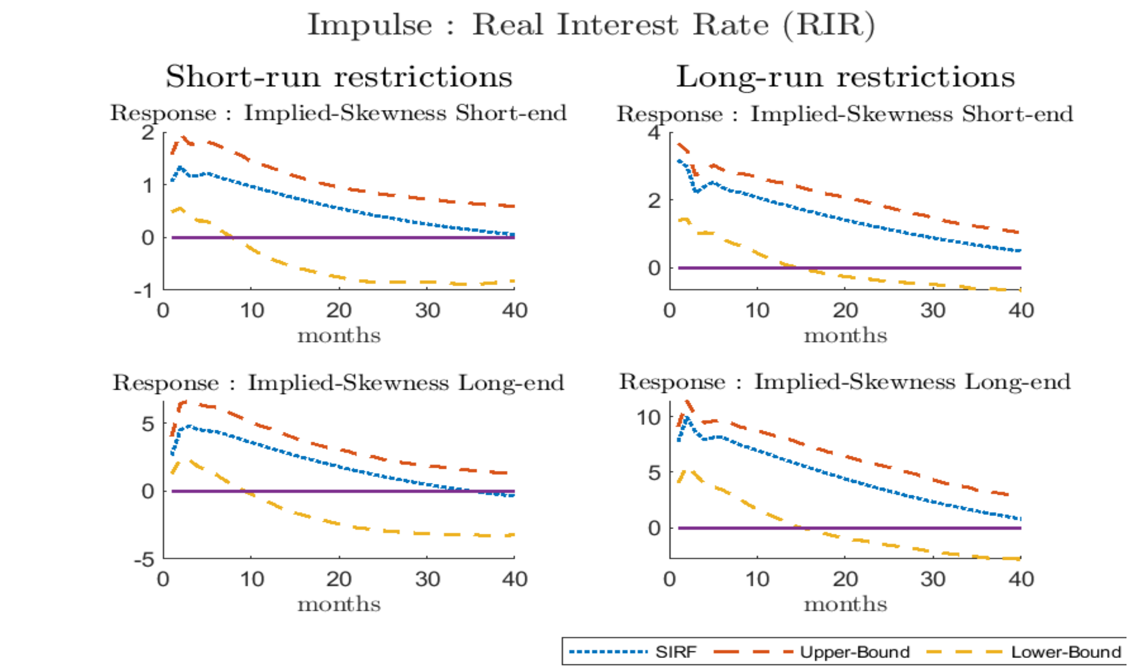


Figure C.5 SIRFs of the short-end and the long-end of IS/IK to negative RIR shocks (expansionary MP shocks), for the bivariate SVAR model during the pre-crisis period

In this figure I plot the SIRFs of the term spread and the level of option-implied moments to a negative one standard deviation shock in RIR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B

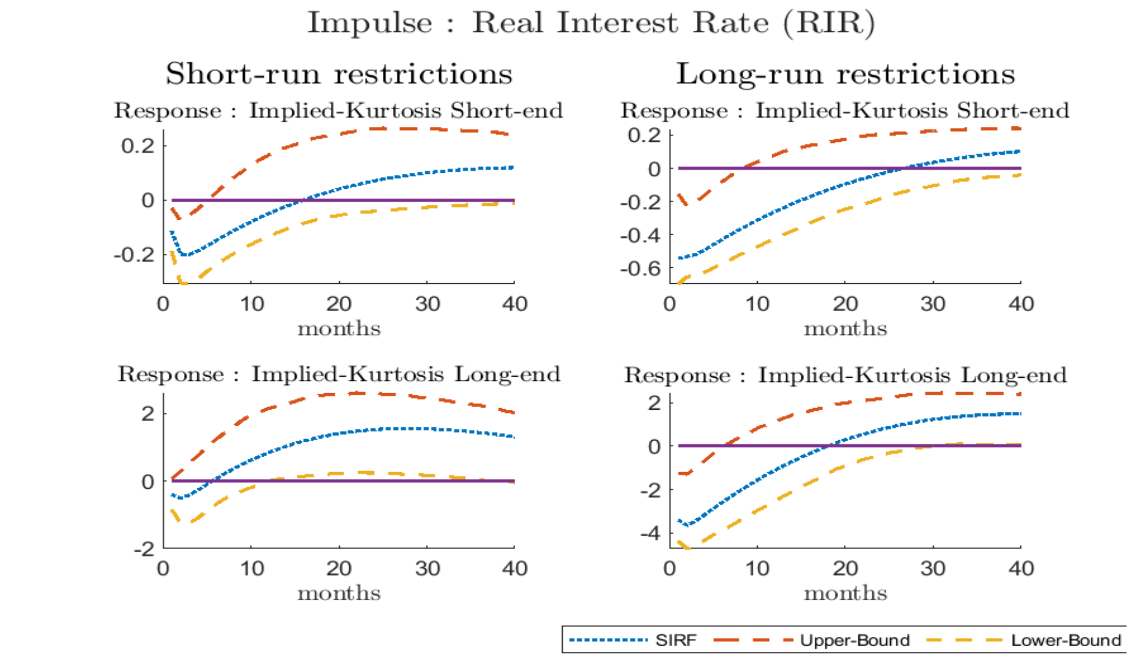
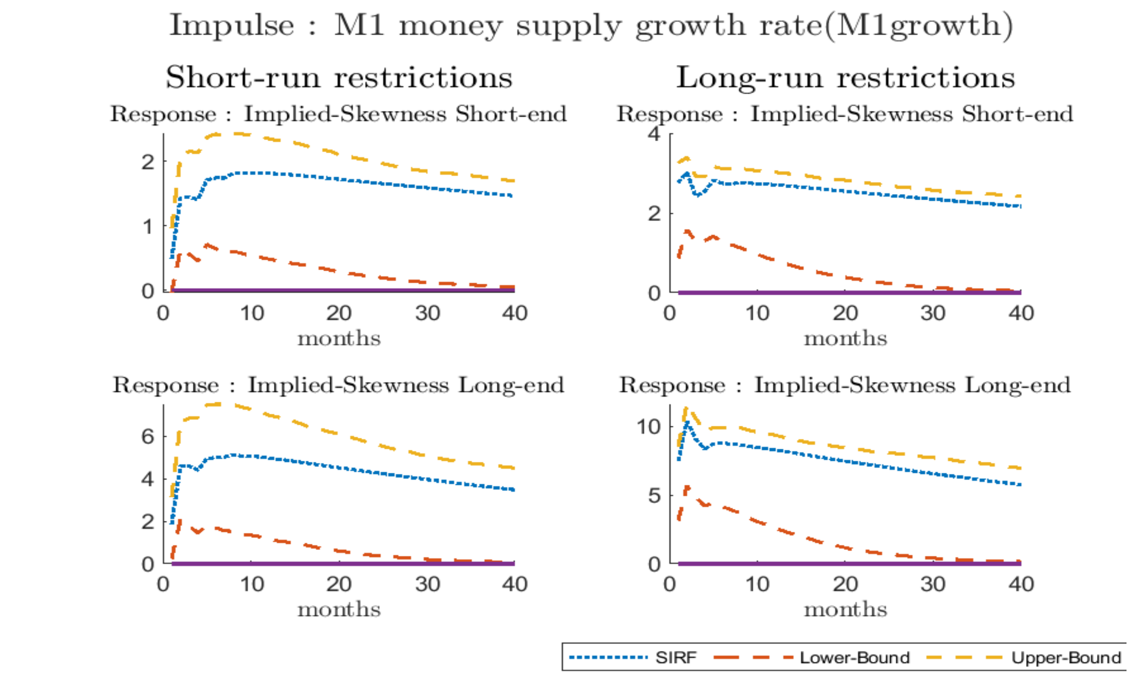


Figure C.6 SIRFs of the short-end and the long-end of IS/IK to positive M1growth shocks (expansionary MP shocks), for the bivariate SVAR model during the pre-crisis period

In this figure I plot the SIRFs of the term spread and the level of option-implied moments to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B

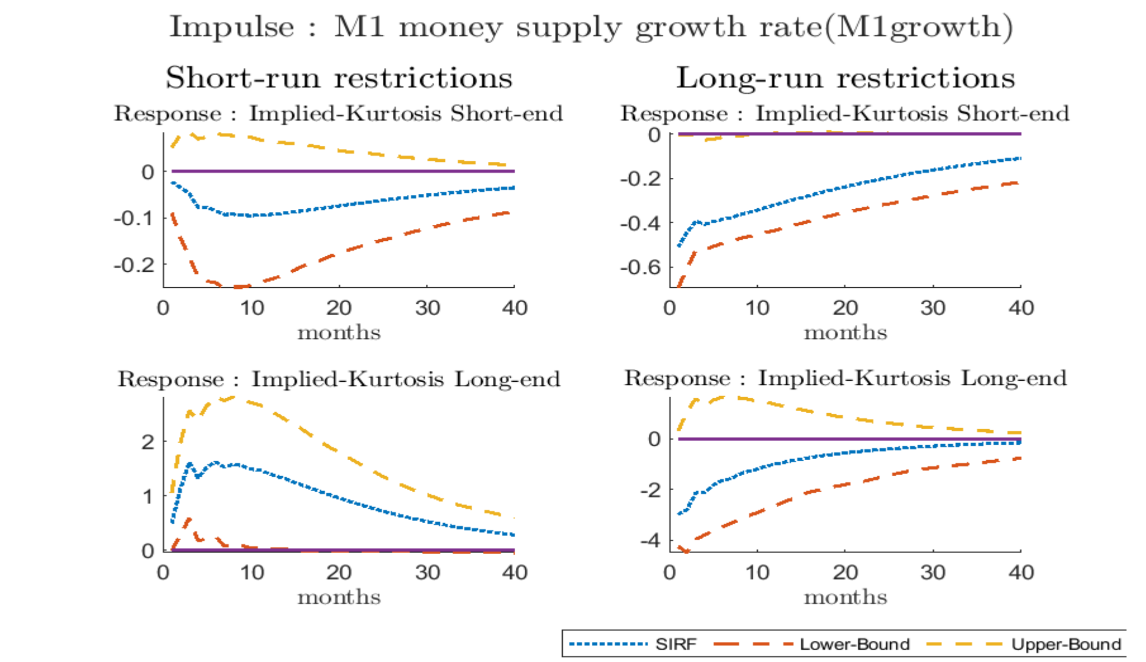
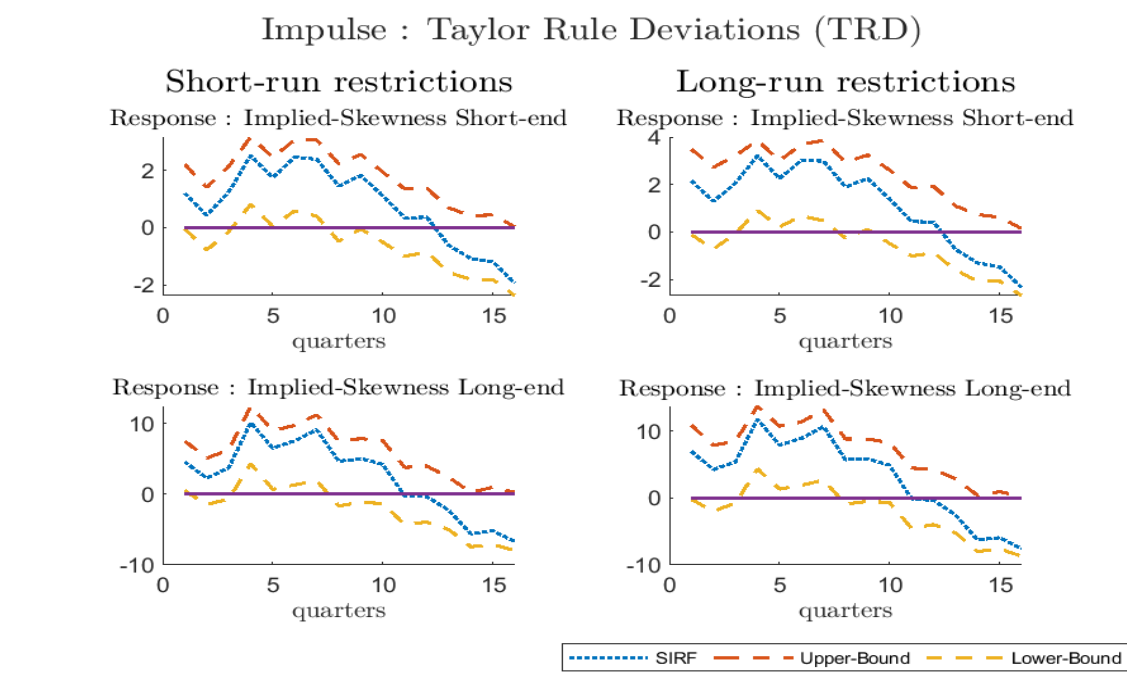


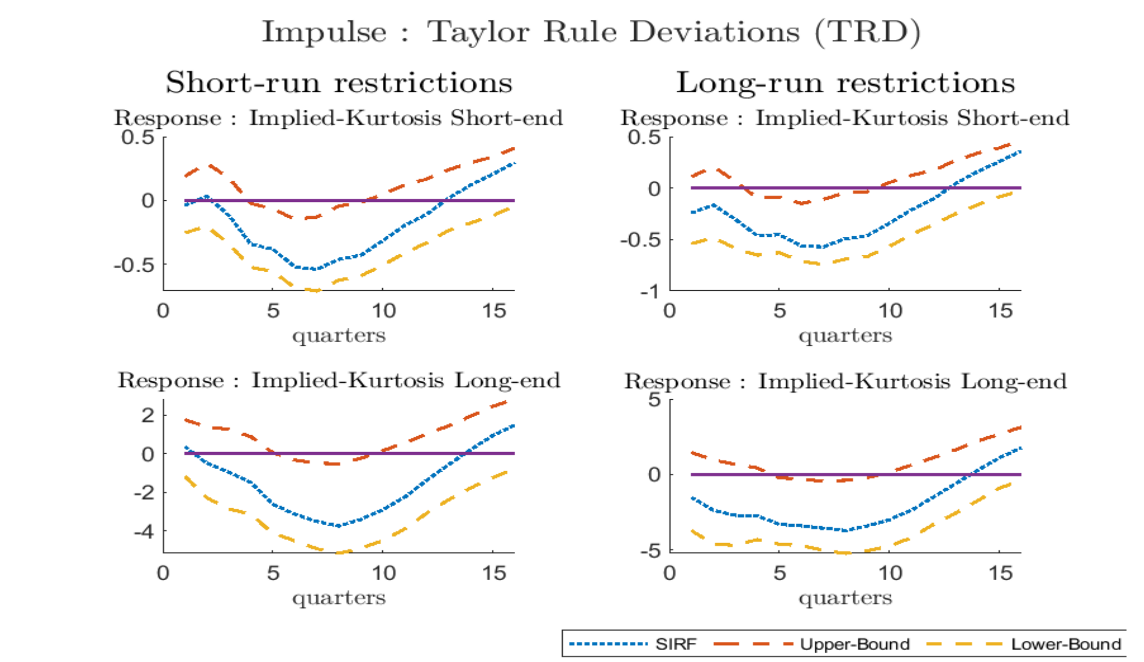
Figure C.7 SIRFs of the short-end and the long-end of IS/IK to negative TRD shocks (expansionary MP shocks), for the bivariate SVAR model during the pre-crisis period

In this figure I plot the SIRFs of the term spread and the level of option-implied moments to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B

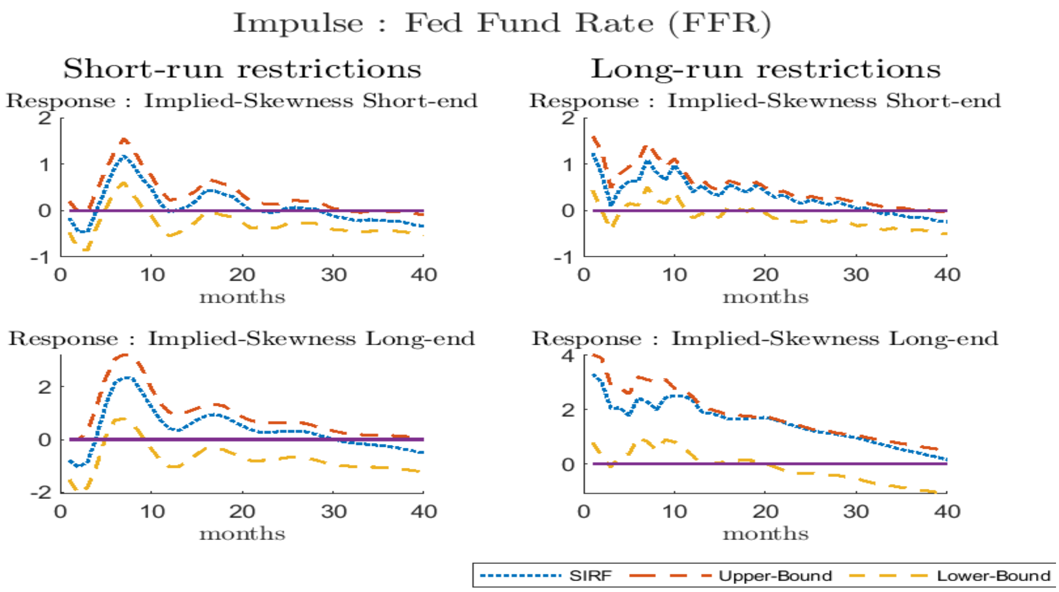


Additionally, **Tables C.8-C.11** show the responses of option-implied moments to an expansionary monetary policy, during the post-crisis period.

Figure C.8 SIRFs of the short-end and the long-end of IS/IK to negative FFR shocks (expansionary MP shocks), for the bivariate SVAR model during the post-crisis period

In this figure I plot the SIRFs of the short-end and long-end of option-implied moments to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B

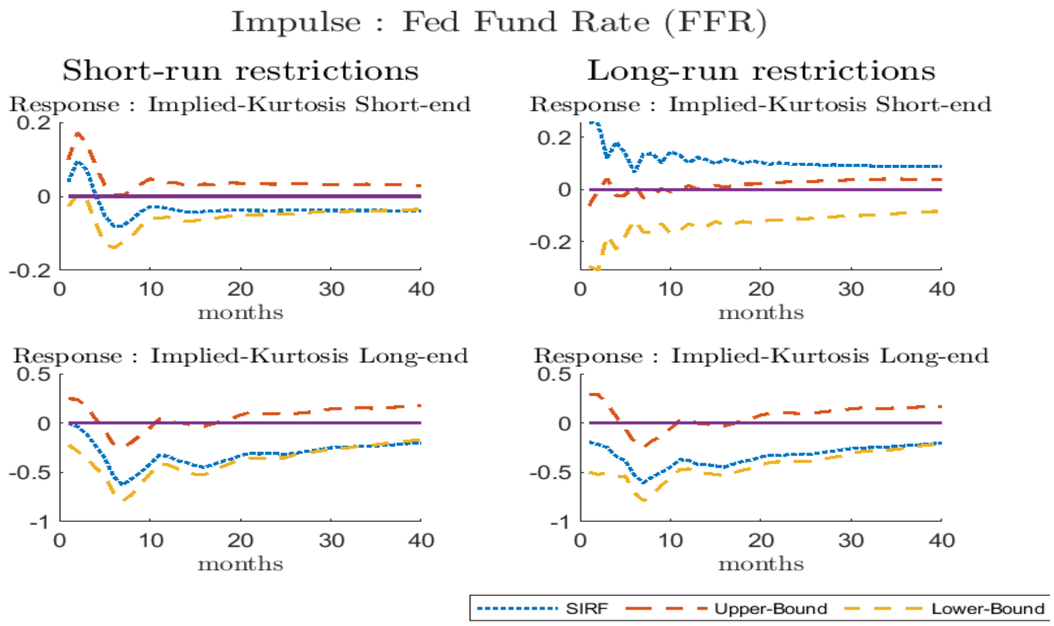
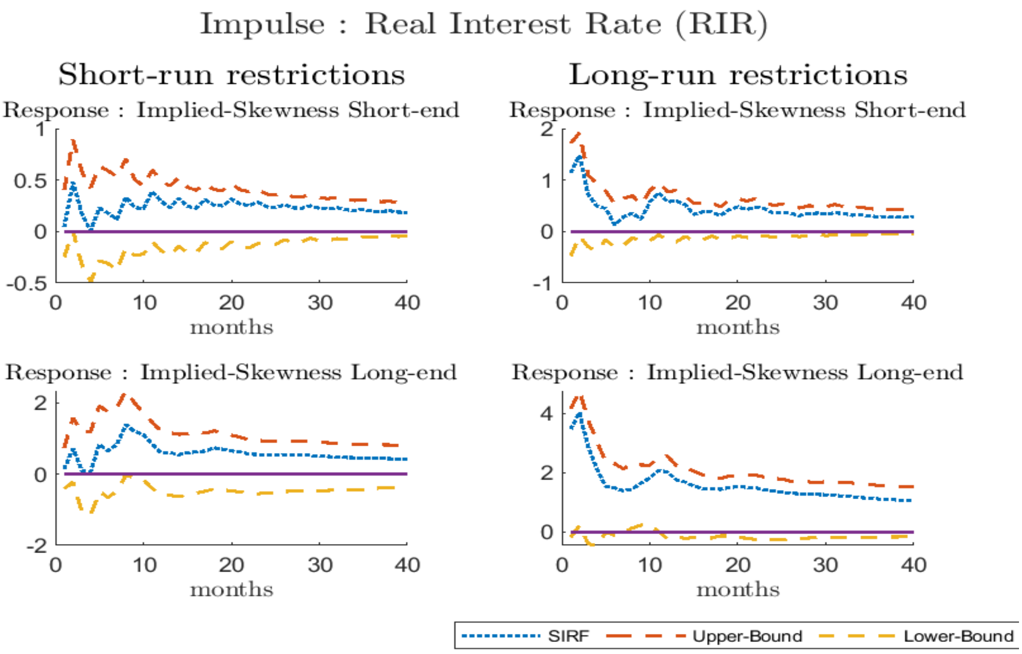


Figure C.9 SIRFs of the short-end and the long-end of IS/IK to negative RIR shocks (expansionary MP shocks), for the bivariate SVAR model during the post-crisis period

In this figure I plot the SIRFs of the term spread and the level of option-implied moments to a negative one standard deviation shock in RIR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B

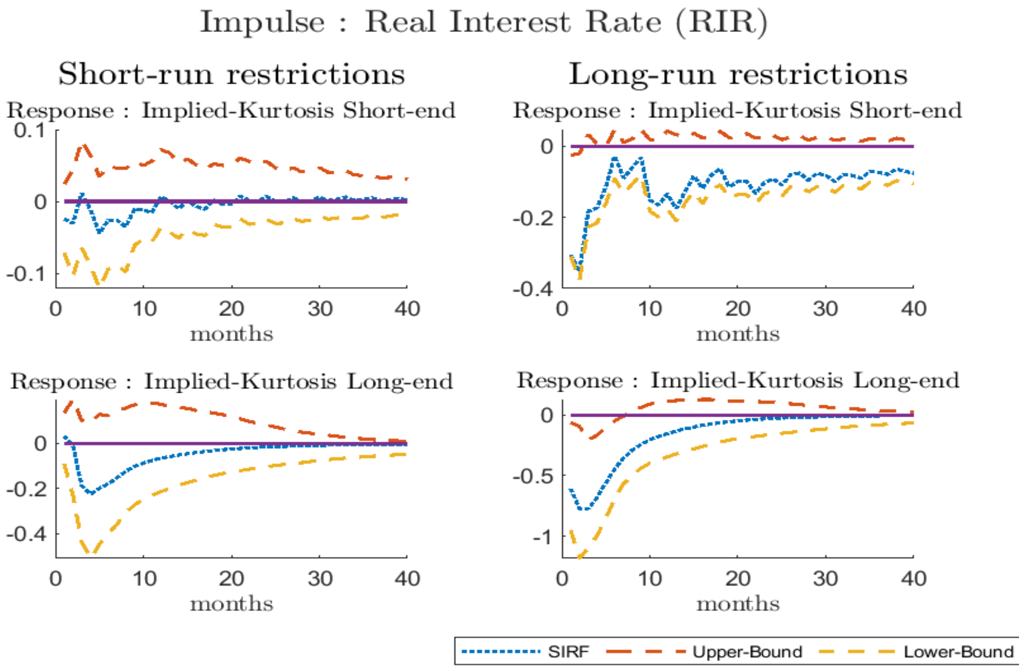
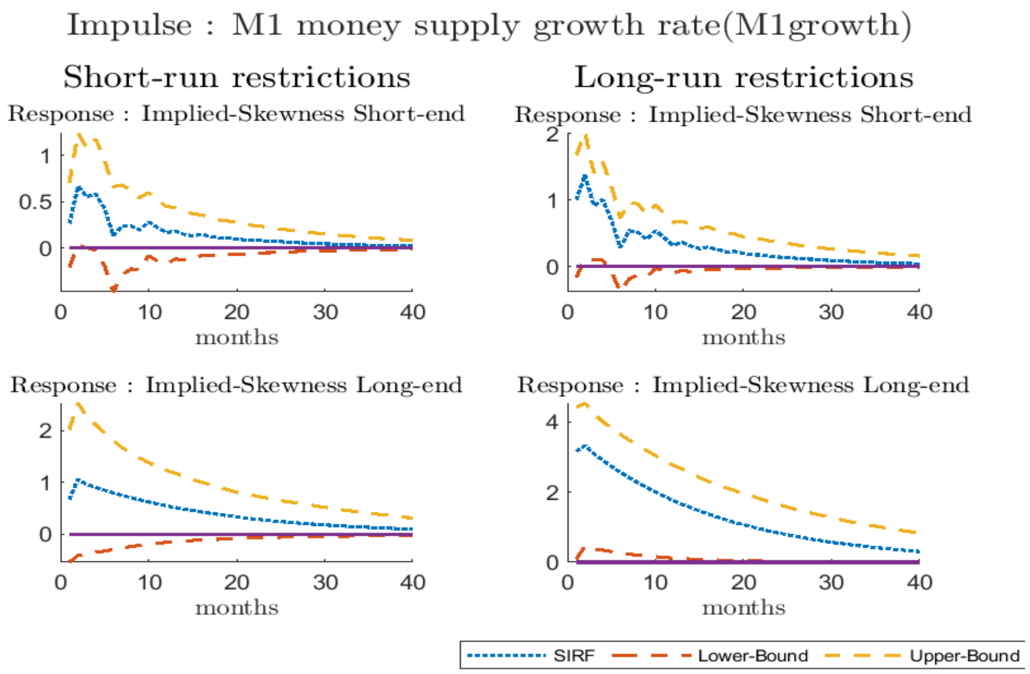


Figure C.10 SIRFs of the short-end and the long-end of IS/IK to positive M1growth shocks (expansionary MP shocks), for the bivariate SVAR model during the post-crisis period

In this figure I plot the SIRFs of the term spread and the level of option-implied moments to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B

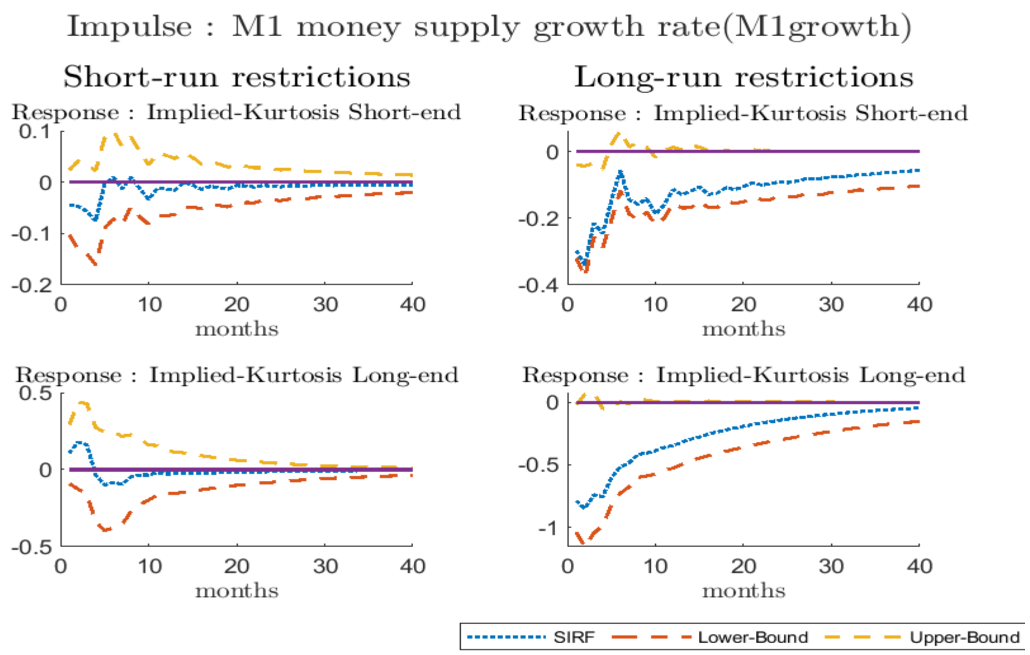
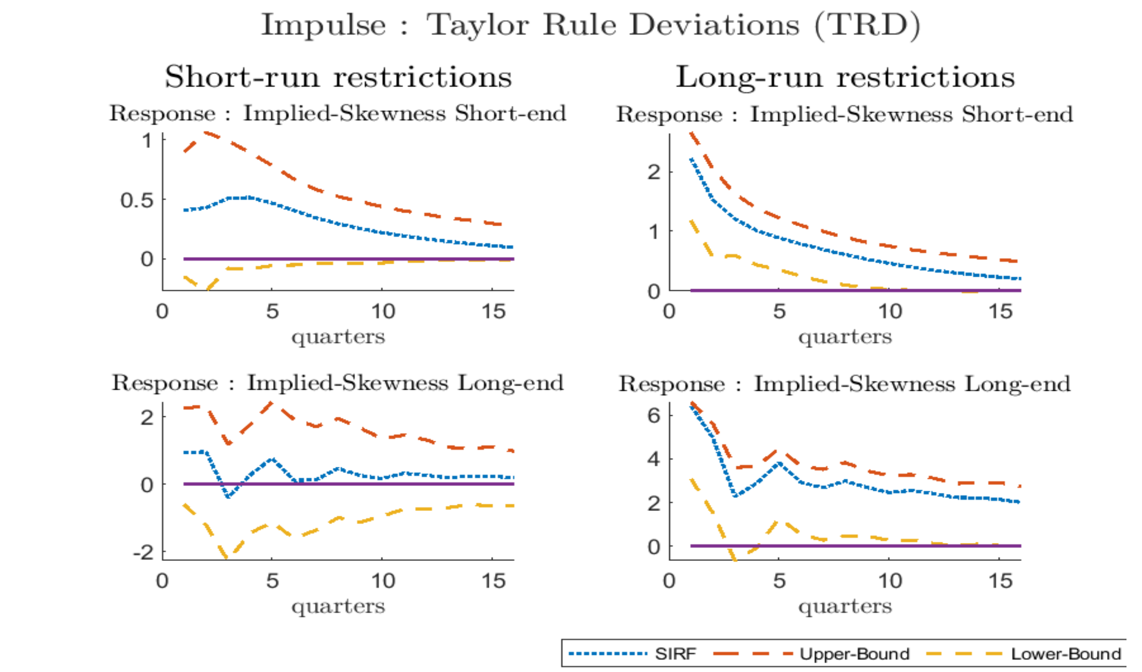


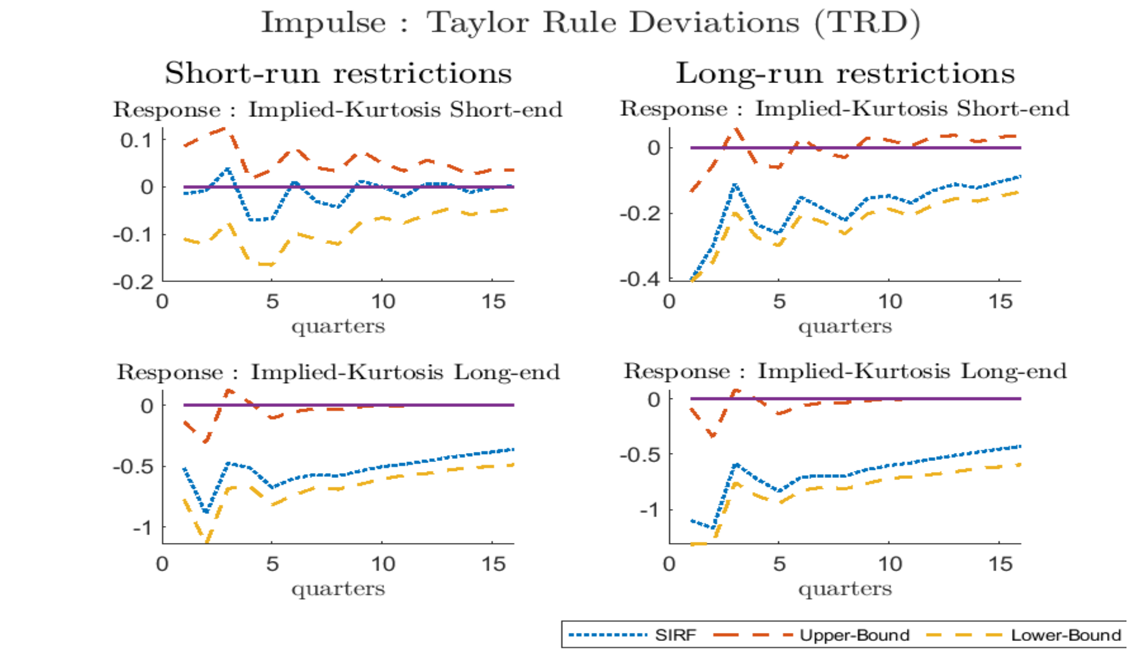
Figure C.11 SIRFs of the short-end and the long-end of IS/IK to negative TRD shocks (expansionary MP shocks), for the bivariate SVAR model during the post-crisis period

In this figure I plot the SIRFs of the term spread and the level of option-implied moments to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the components of option-implied skewness and kurtosis respectively.

Panel A



Panel B



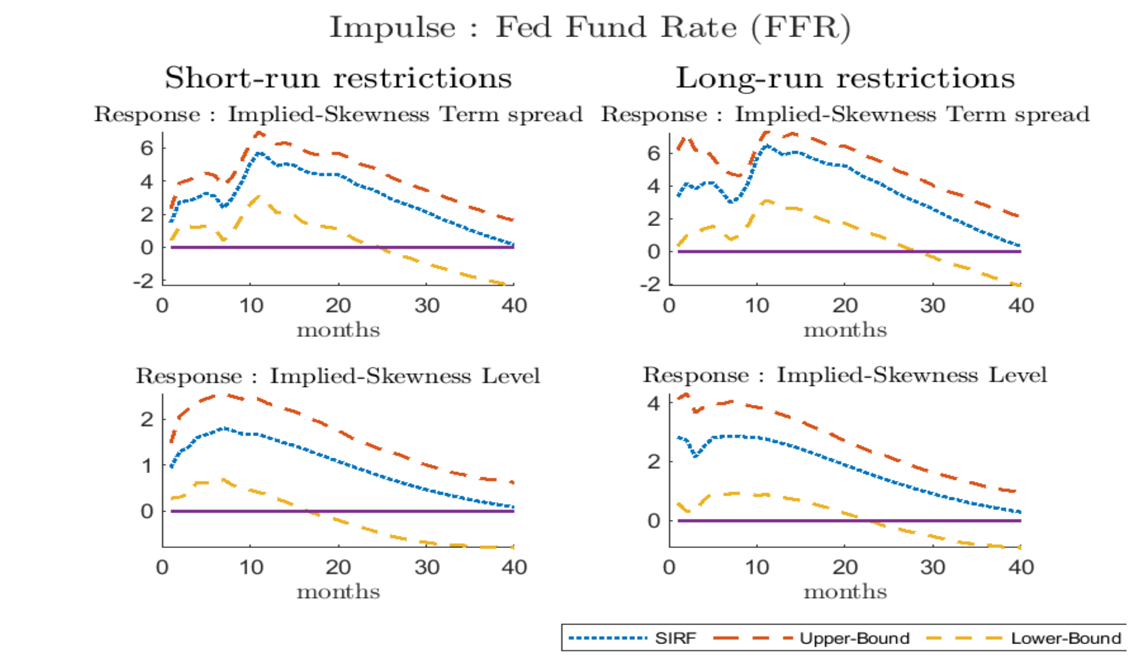
Generally, I find that the main conclusions that emerge from the estimated SVAR models using all the available sample, are not distinct when I choose other subsample. In details, during the pre-crisis period I find a stronger in magnitude and a more long-lasting impact of monetary policy shocks on investors' expectations, even though monetary policy shocks increase/decrease the components of IS/IK, during both periods..

In order to ensure that my empirical results remain robust in the inclusion of other macroeconomic variables, I estimate a 4-variable SVAR and a 6-variable VAR model as I discussed in previous subsection 2.4. Initially I estimate a 4-variable SVAR model as I described in equations (5.2) and (5.3). The **figure C.12** presents the results of the estimated SIRFs of the components of the IS to an accommodative monetary policy shock when I run the model in equation (5.2). Similarly, the **figure C.13** shows the corresponding results for the components of IK when I run the model in equation (3).

Figure C.12. SIRFs of the components of the term structure of IS to negative FFR shocks (expansionary MP shocks), for the multivariate SVAR model

In this figure I plot the SIRFs of the components of IS to a negative one standard deviation shock in FFR when I estimate the multivariate SVAR model (equation (?)). In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A includes the responses of the term spread and the level of IS to monetary policy shocks, while the panel B show the SIRFs of the short-end and long-end component of IS to a negative one standard deviation shock in FFR

Panel A



Panel B

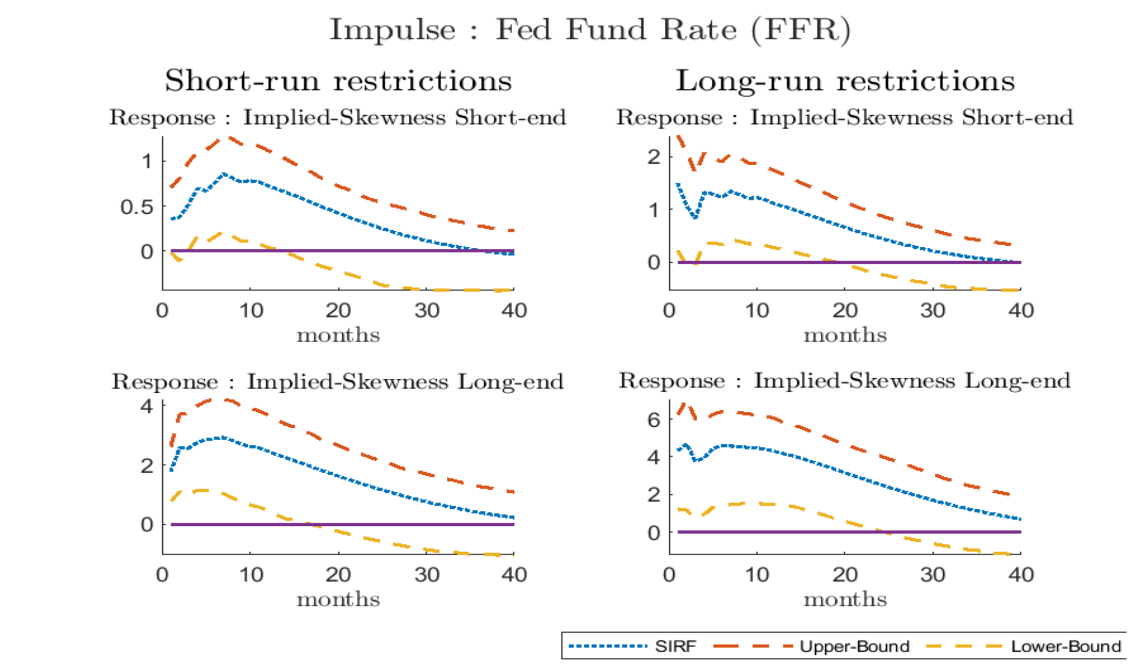
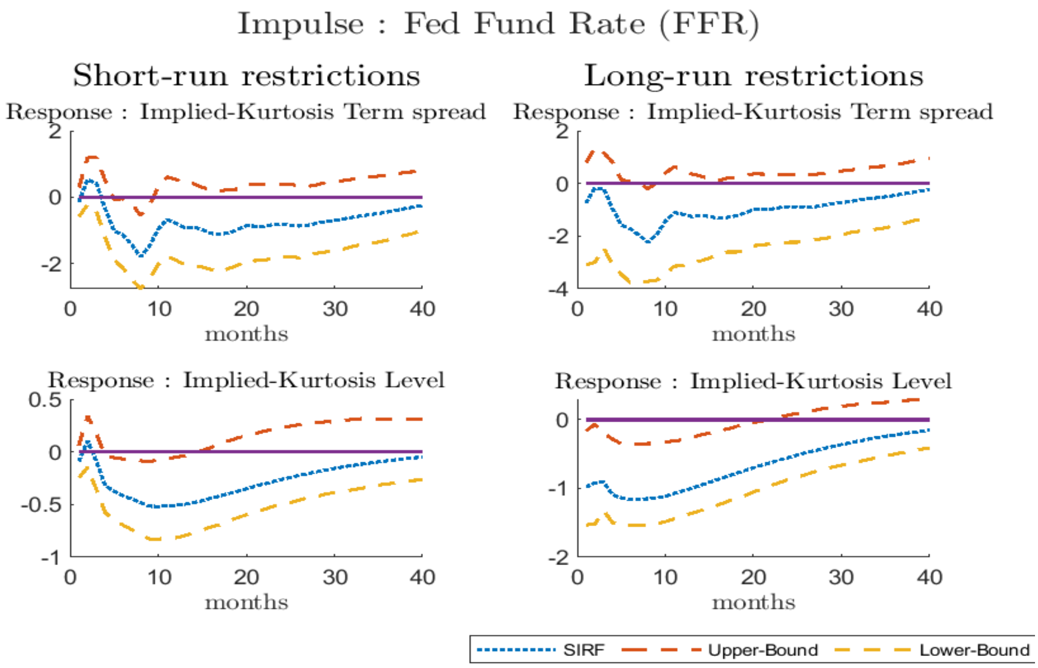


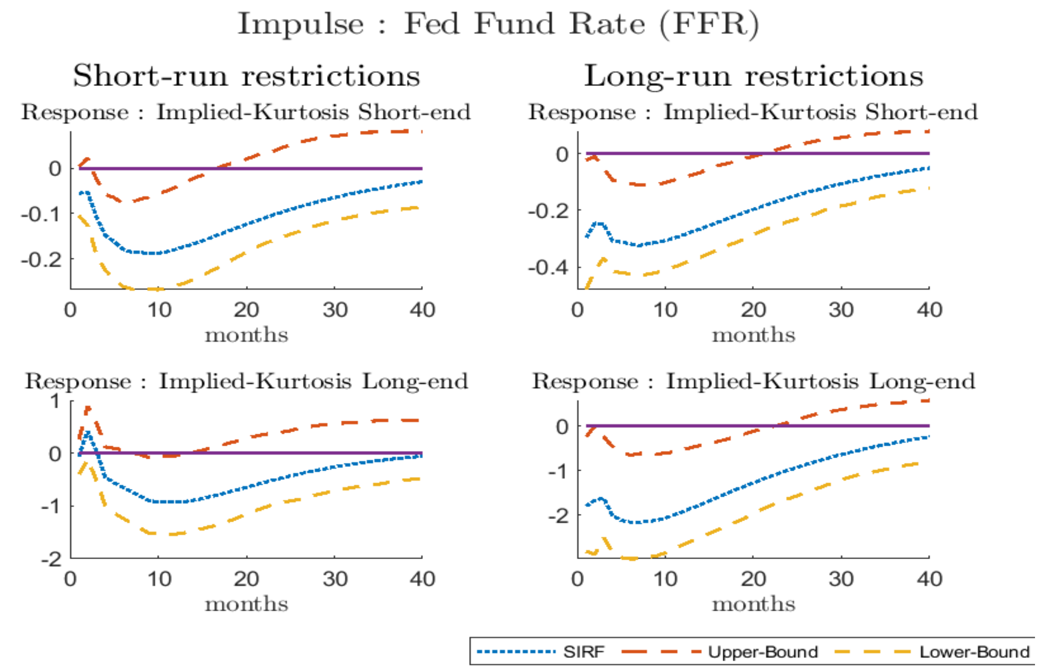
Figure C.13. SIRFs of the components of the term structure of IK to negative FFR shocks (expansionary MP shocks), for the multivariate SVAR model

In this figure I plot the SIRFs of the components of IK to a negative one standard deviation shock in FFR when I estimate the multivariate SVAR model (equation (?)). In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A includes the responses of the term spread and the level of IK to monetary policy shocks, while the panel B show the SIRFs of the short-end and long-end component of IK to a negative one standard deviation shock in FFR

Panel A



Panel B



The **figures C.12** and **C.13** demonstrate that my empirical results in section 3 are robust. Interestingly, the estimated results of the multivariate SVAR models, provide more convincing evidence about the higher sensitivity of the long-term IK to monetary policy shocks. Specifically, while I observe similar results about the response of IS to monetary policy shocks, the estimated responses of long-term and short-term IK to monetary policy in the multivariate SVAR models, are more "persistent" compare to the corresponding results of the bivariate model. In the multivariate setting, lax monetary policy results a negative statistically significant change to long-end IK, regardless of the applied-restrictions on the 4-variable SVAR model, while in the bivariate setting, I find a positive statistically significant response of long-end IK to a negative shock in FFR, when short-run restrictions are applied. Additionally, I observe that the difference between the impact of FFR shocks on long-end and short-end IK is greater when I estimate the 4-variable SVAR model.

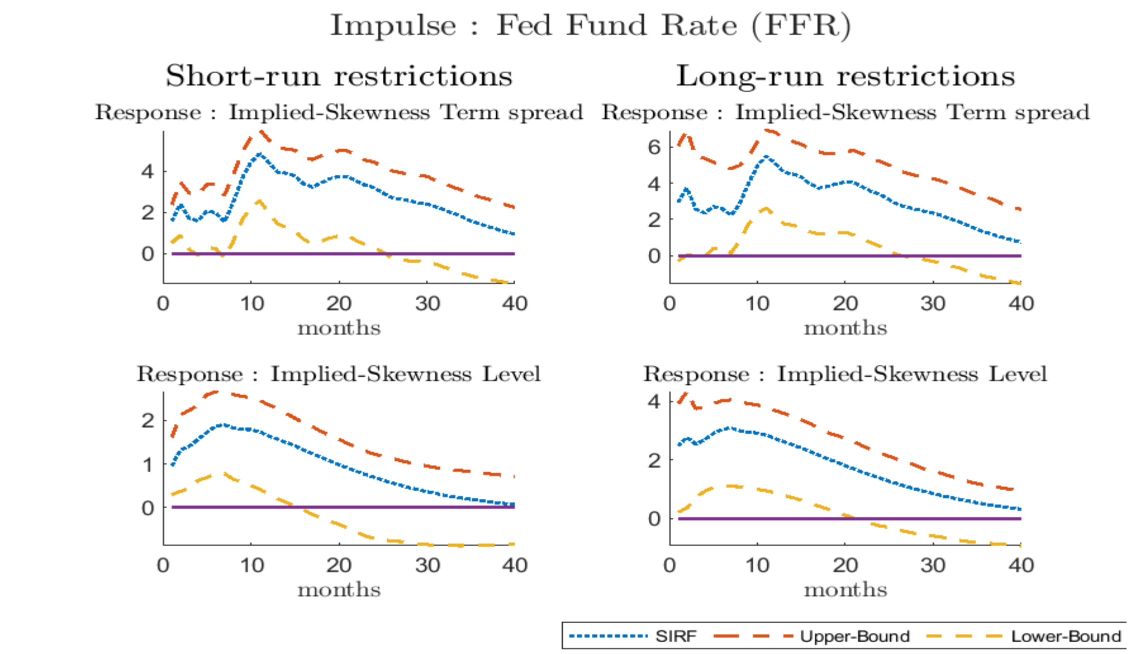
Finally, for brevity, I include in the appendix, a few other estimated multivariate models and specifications. I estimate a few modifications of the 4-variable SVAR model (equation (5.2)) and 6-variable monetary VAR models (equation 5.4 and 5.5), and the estimated results can be found in the appendix. The additional modifications that I apply in multivariate SVAR model are the following: 1) I estimate a multivariate model of the form $Y_t = [IPG_t \; MP_t \; IS_t \; IK_t]$ (5.13); 2) I change the ordering of the variables, specifically I use the ordering that Triantafyllou and Dotsis (2017) used in their empirical analysis. Specifically, the form of the SVAR models with different ordering are $Y_t = [MP_t \; IPG_t \; IV_t \; IS_t]$ (5.14) and $Y_t = [MP_t \; IPG_t \; IV_t \; IK_t]$ (5.15).

Furthermore, **Figures C.14-C.15** show the responses of the components of the IS and IK to negative shocks of FFR, when I estimate the SVAR model of equation 5.13. Additionally, **Figures C.16-C.17** show the responses of the components of the IS and IK to negative shocks of FFR, When I estimate the SVAR model of equations 5.14 and 5.15 respectively. Finally, the responses of IS and IK of the VAR multivariate model of equation 5.4 and 5.5, are showed in **Figures C.18** panel A and B, respectively**.** The **figures C.14-C118** verify that the conclusions that emerges from the main analysis are robust, since I find that the responses of IS and IK to monetary policy shocks are unaltered for other multivariate settings.

Figure C.14 SIRFs of the components of IS to negative FFR shocks (expansionary MP shocks), for the multivariate SVAR model with form: $Y_t = [IPG_t\ MP_t\ IS_t\ IK_t]$

In this figure I plot the SIRFs of the components of option-implied skewness to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the term-spread, the level and the short-end, long end components of option-implied skewness respectively.

Panel A



Panel B

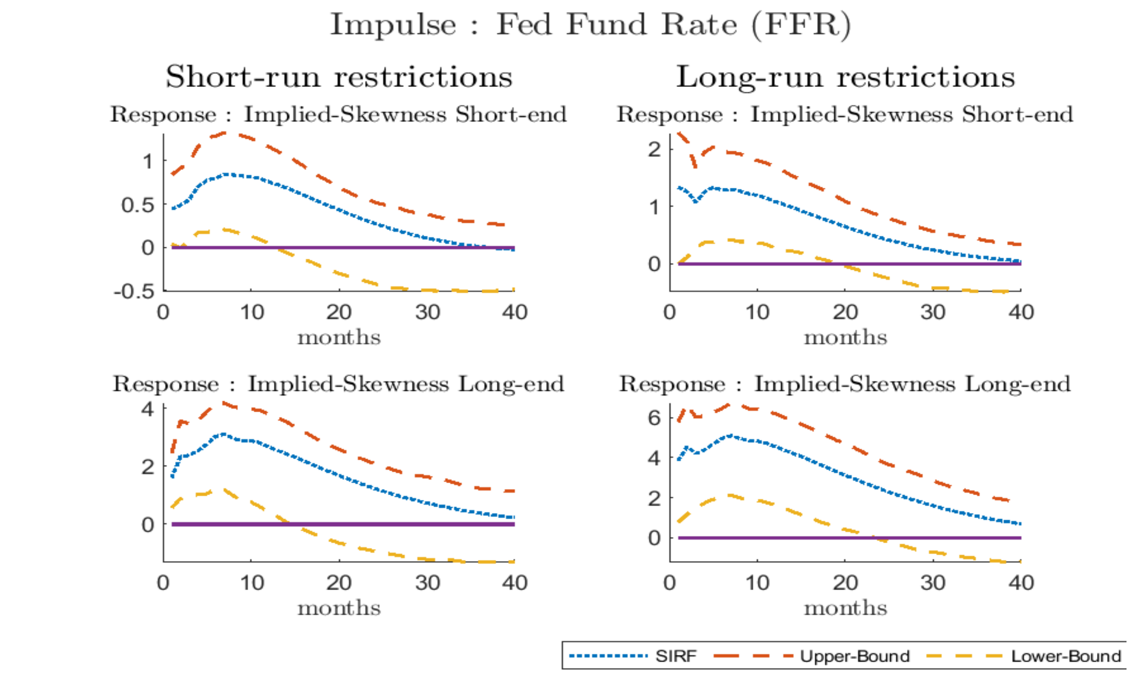
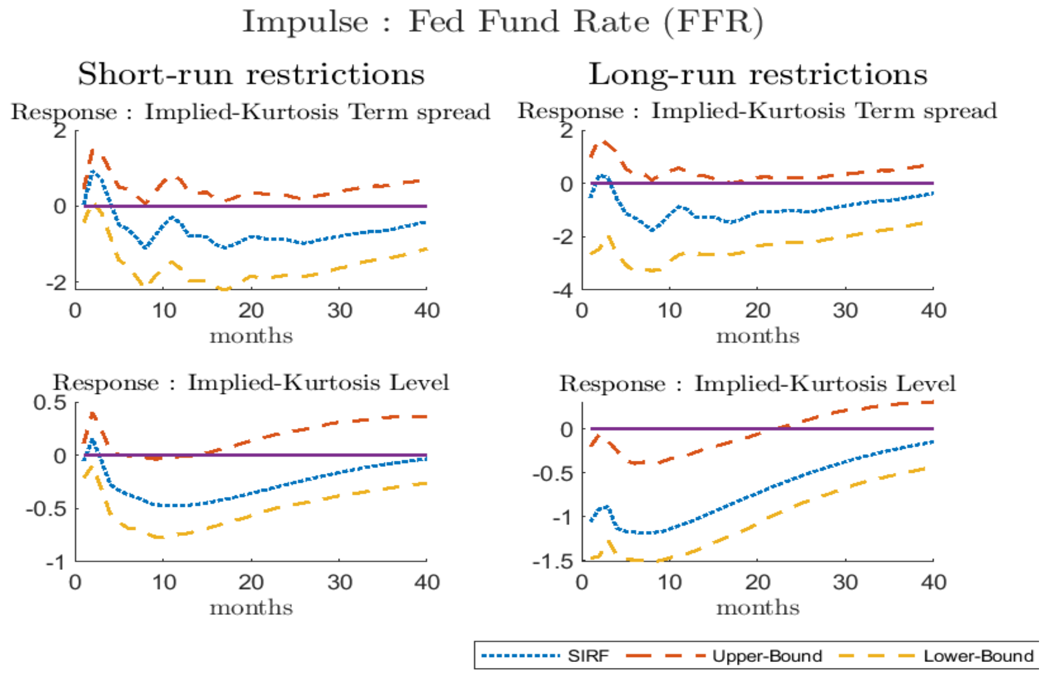


Figure C.15 SIRFs of the components IK to negative FFR shocks (expansionary MP shocks), for the multivariate SVAR model with form: $\boldsymbol{Y_t = [IPG_t\ MP_t\ IS_t\ IK_t]}$

In this figure I plot the SIRFs of the components of option-implied kurtosis to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the term-spread, the level and the short-end, long end components of option-implied kurtosis respectively.

Panel A



Panel B

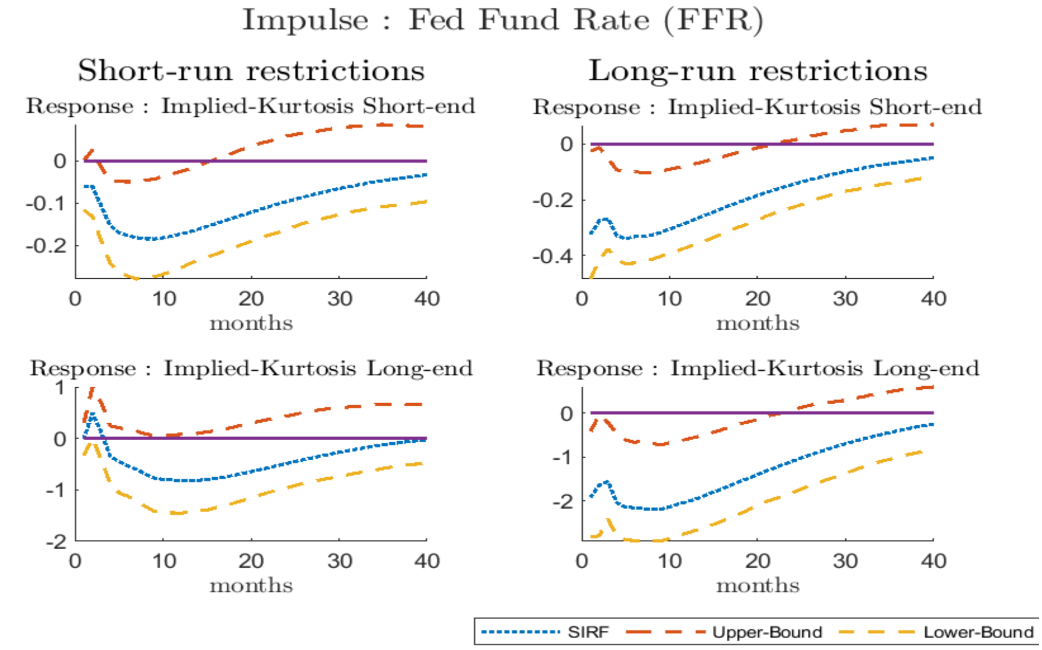
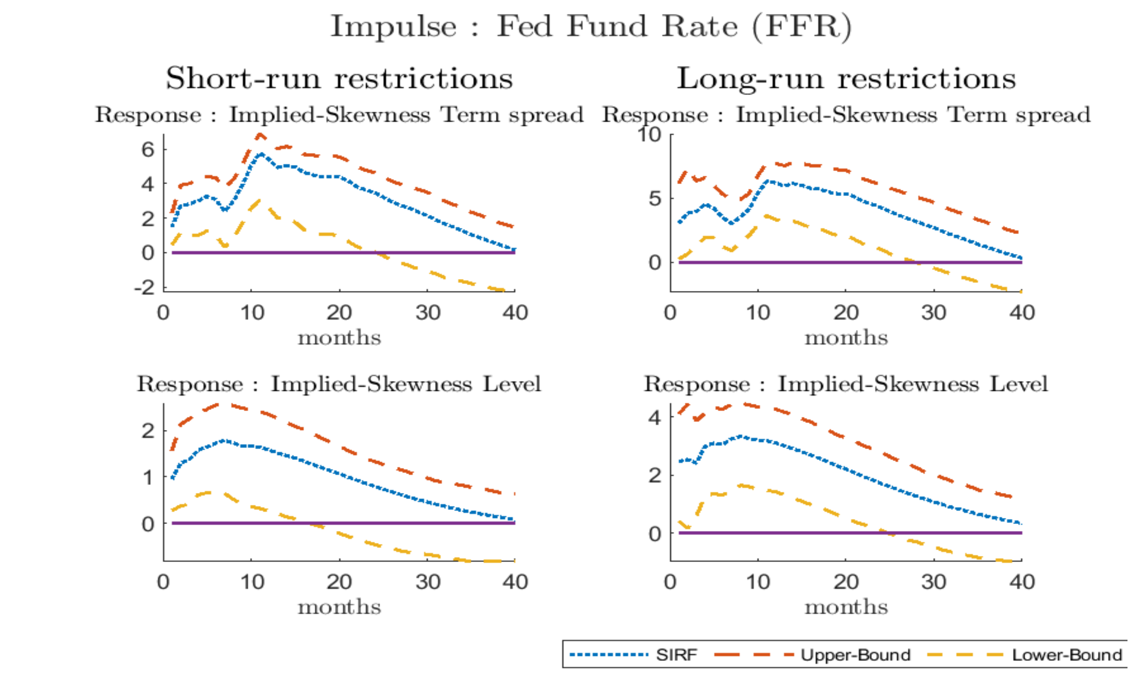


Figure C.16 SIRFs of the components of IS to negative FFR shocks (expansionary MP shocks), for the multivariate SVAR model with form: $Y_t = [MP_t \; IPG_t \; IV_t \; IS_t]$

In this figure I plot the SIRFs of the components of option-implied skewness to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the term-spread, the level and the short-end, long end components of option-implied skewness respectively.

Panel A



Panel B

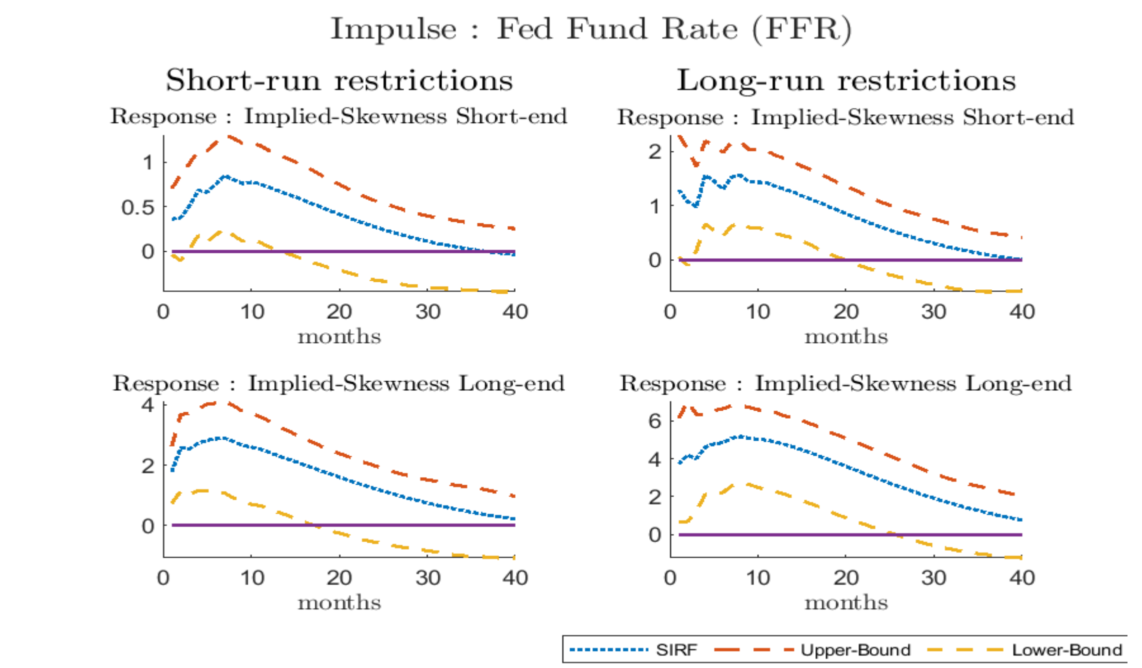
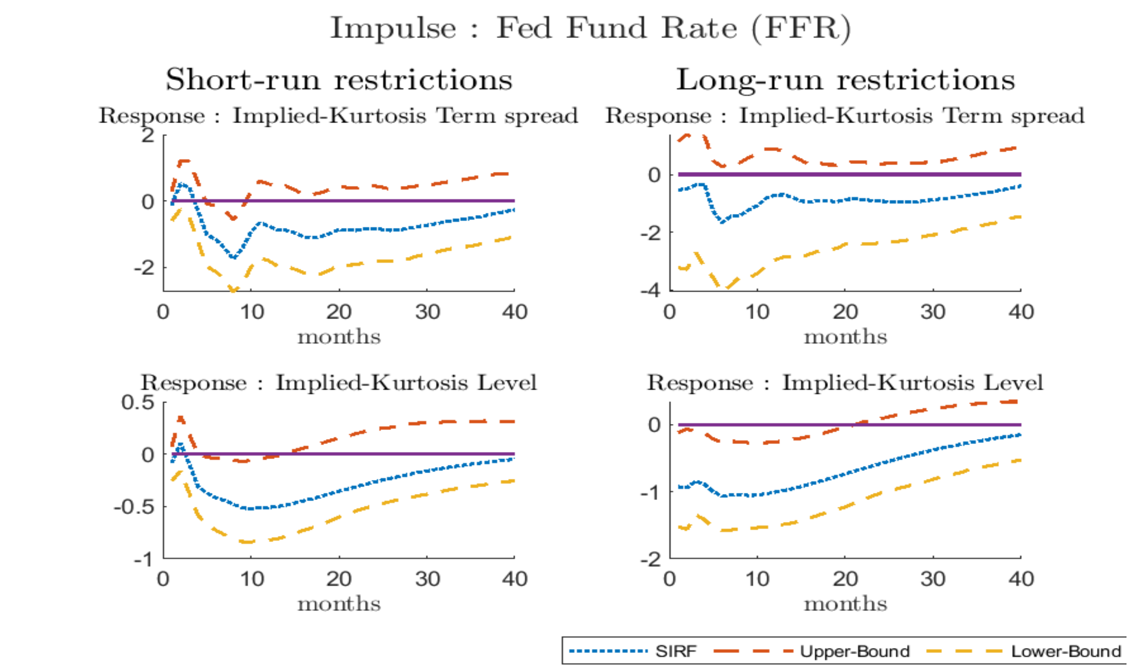


Figure C.17 SIRFs of the components of IK to negative FFR shocks (expansionary MP shocks), for the multivariate SVAR model with form: $\boldsymbol{Y_t = [MP_t\ IPG_t\ IV_t\ IK_t]}$

In this figure I plot the SIRFs of the components of option-implied kurtosis to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the term-spread, the level and the short-end, long end components of option-implied kurtosis respectively.

Panel A



Panel B

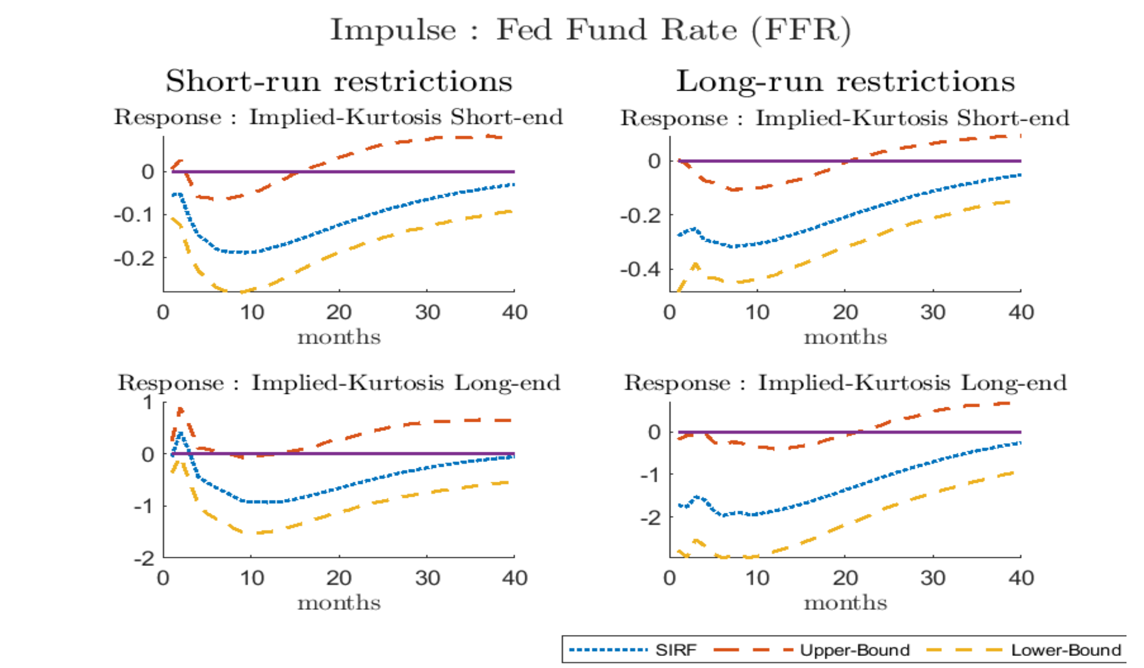
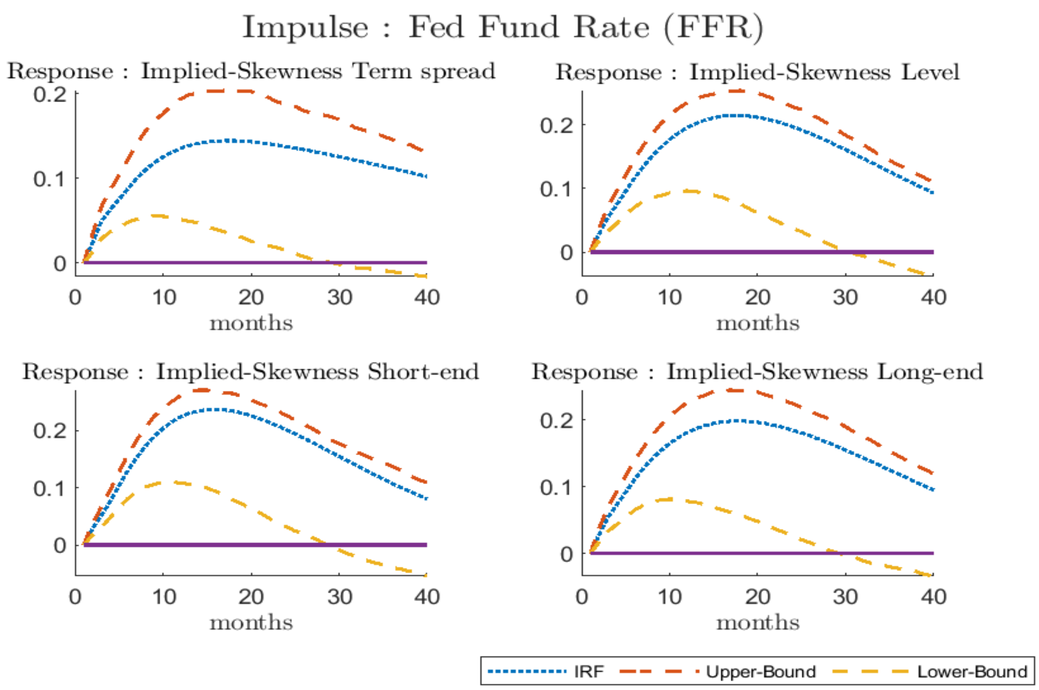


Figure C.18 IRFs of the components of IS to negative FFR shocks (expansionary MP shocks), for the multivariate VAR model with form: $Y_t = [CPI_t\ IPL_t\ FFR_t\ PPI_t\ IS_t\ IV_t]$ and $Y_t = [CPI_t\ IPL_t\ FFR_t\ PPI_t\ IK_t\ IV_t]$

In this figure I plot the IRFs of the components of option-implied skewness to a negative one standard deviation shock in FFR. In details, the left (right) column graphs include the estimated SIRFs from the SVAR models when I apply contemporaneous (long-run) restrictions. Additionally, the red and the yellow dotted lines are the upper and lower bounds of the 90% confidence interval respectively. Finally, panel A and B include the term-spread, the level and the short-end, long end components of option-implied skewness respectively.

Panel A



Panel B