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Volatility in equity markets and monetary policy rate uncertainty

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Abstract

Asset pricing models assume the risk-free rate to be a key factor for equity prices. Hence, there should be a strong link between monetary policy rate uncertainty and equity return volatility, both in theory and data. This paper uses regression-based projections for realized variance to examine the relationship between short horizon forecasts of equity variance and proxies for monetary policy rate uncertainty. By assessing various projection models for UK, US and euro-area equity indices, we show that the proxies for monetary policy rate uncertainty have a significant and positive predictive power for the equity return variance. Adding monetary policy rate uncertainty variables can significantly improve forecasting models for equity variance and volatility at weekly, monthly and even quarterly horizons. The findings imply that market views of short-term interest rate developments may indeed be embedded in equity prices and their variations.

Key words: Equity indices, monetary policy rate uncertainty, option implied volatility, realized volatility, risk-free interest rates, volatility forecasting.

JEL classification: C22, C52, G12, E52.

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1. Introduction

In this paper we show that variables capturing monetary policy rate uncertainty have an important predictive power for short-term equity return volatility forecasts.

The empirical finance literature has made considerable progress on understanding and forecasting equity return volatility. In terms of short-horizon forecasting, we know that the standard set of short-term predictive factors should contain variables capturing volatility persistence (like lagged realized volatility, e.g. Chernov, 2007, its most recent realizations from mixed data sampling, e.g. Corsi, 2009, or their jump and continuous components, e.g. Andersen, Bollerslev, and Diebold, 2007); forward-looking variables representing market views about future realized volatility, like equity implied volatility (e.g. Christensen and Prabhala, 1998); and variables capturing asymmetric nature of volatility, like negative returns (e.g. Engle and Ng, 1993). However, none of these variables can actually explain the underlying sources of changes in equity return volatility.

On the other hand, we also know that there is a link between the long-term component of equity market volatility and economic activity. As Engle, Ghysels, and Sohn (2013) show, the long-term volatility component is driven by inflation and industrial production growth. In addition, Engle and Rangel (2008) find that, along with volatility in GDP and inflation, volatility in short-term interest rates has a smaller but still significant and positive effect on low-frequency equity volatility. Market commentaries often mention monetary policy rate uncertainty as a possible factor affecting volatility in wider financial markets.

Given that the monetary policy (i.e. short-term risk-free) rate is a key factor for pricing many securities and derivatives, there should be a strong link between monetary policy rate uncertainty and equity return volatility. Moreover, this link should be observed not only in the longer term. Indeed, according to basic present value models, the variance of equity prices is directly linked to the conditional variances of future discount rates, which are, in turn, the explicit functions of expected risk-free interest rates and risk premia.

To analyse this dependence, we examine whether a variable reflecting ex-ante uncertainty about short-term interest rates has an explanatory power for the expected variance of equity returns in the short run. In particular, we use an empirical method of regression-based projections of realized variance over weekly, monthly, and quarterly horizons on the prior information set comprising a standard set of predictive variables. These include lagged realized variance components, most recent return variance realisations, negative return shocks, and lagged squared option-implied volatility. We then add forward-looking proxies of monetary policy rate uncertainty available at high (daily) frequency.

To obtain monetary policy rate uncertainty proxies, we refer to financial markets data, which is an obvious source of forward-looking high frequency data. In particular, we take the interest rate implied volatility based on options on short-term interest rate futures to be our main proxy.

We perform the forecasting analysis for the realized weekly, monthly variances and volatilities of the returns on three major international equity indices, namely the S&P 500 (US), FTSE 100 (UK) and EuroStoxx 50 (euro area). As a result, we show that the proxies for monetary policy rate uncertainty have a significant and positive predictive power for the short-term equity return variance and volatility. By including a monetary policy rate uncertainty proxy, we improve the forecasting performance of available models of conditional variances and volatilities of international equity indices' returns. The gains are obtained at weekly, monthly and even quarterly horizons.

Newspaper archives and other news sources from across the globe have become a popular alternative source for the news-based indices of uncertainty. For example, Baker, Bloom, and Davis (2016) recently developed an economic policy uncertainty (EPU) index based on newspaper coverage frequency. In this paper, as alternative proxies of monetary policy rate uncertainty, we use their Monetary Policy Uncertainty (MPU) component of the EPU index and a similar news-based monetary policy uncertainty index which is developed by Husted, Rogers, and Sun (2016). In addition, we examine monetary policy rate uncertainty measures based on ex-ante disagreement from surveys. Unfortunately, the main drawback of the alternative measures is that they are unavailable at a daily frequency. Furthermore, the news-based measures are considerably broader in scope and may not be directly comparable to the uncertainty proxies derived from surveys and financial markets, which could explain weaker results we obtain for the news-based proxies.

Our results are consistent with the findings from the vast and growing literature on equity price sensitivity to monetary policy. The relationship between asset prices and monetary policy is complicated by the endogeneity of monetary policy; on top of this, monetary policy and equity prices can react to same macroeconomic and finance variables. In our paper, we address this endogeneity by using the predictive relationship. Other approaches include heteroskedasticity-based estimation to correct for possible simultaneity bias, as in Rigobon and Sack (2004), who reported a significant response of the stock market to interest rate surprises derived from eurodollar futures. Event-study analysis is another way to tackle the simultaneity issue. For example, Bernanke and Kuttner (2005) show that equity markets tend to overreact to MPC decisions, possibly because announcement days are perceived riskier than other days (Savor and Wilson, 2013). Finally, in a general equilibrium framework, Pastor and Veronesi (2012) construct a model which features uncertainty about government policy, and show that policy changes should increase equity volatilities.

The remainder of the paper is organized as follows: Section 2 explains the link between monetary policy rate uncertainty and variance of equity returns in greater detail. We describe the volatility forecasting models and high frequency monetary policy rate uncertainty proxies in Section 3. Section 4 describes the data; Section 5 discusses the variance forecasting performance of the models and its robustness. Section 6 concludes our analysis.

2. Short-term interest rates and equity returns' volatility

While much has been learned about the dynamics and components of equity returns' volatility over last twenty years, the empirical literature is less clear about the fundamental driving forces behind it. The question "Why does equity market volatility change over time?" (Schwert, 1989) has remained largely unanswered. The main reason is the simple fact that fundamental economic variables are only available at low frequency - monthly or quarterly - while equity volatility changes even on a daily basis.

Recently, the advances in the econometric models based on mixed data sampling (MIDAS) have returned the question to the forefront of the empirical finance literature. Engle, Ghysels, and Sohn (2013) use a MIDAS based model suited to combine data sampled at different frequencies and hence to incorporate low frequency macroeconomic variables directly into the specification of volatility dynamics. They revisit the economic sources of equity returns' volatility and show that long-term equity volatility component is driven by inflation and industrial production growth. The approach builds on Engle and Rangel (2008), who introduce a Spline-GARCH model, in which daily equity volatility is a product of a mean reverting unit GARCH and a slowly moving deterministic component. In this earlier paper, Engle and Rangel (2008) find that, together with macroeconomic factors, such as GDP growth and inflation, short-term interest rate is an important explanatory variable that increases low-frequency equity volatility. Their results show that low-frequency volatility is higher in countries where short-term interest rates are more volatile.

Still, the emphasis on the long-term volatility component in these models could to a certain extent be explained by the low frequency nature of the supplied economic data. But asset pricing theory tells us that short-term interest rate volatility should also be an important driver of equity volatility at short horizons.

The basic idea of asset pricing theory is that the fundamental value of an asset equals the expected discounted future cash flows. It is common to formulate the equity present value models in terms of required rate of return, r, so that

$$P_t=E_t\sum_{s=1}^{\infty} D_{t+s}/(1+r)^s, \tag{1}$$

where P_t is the equity price at time t, D_t is the dividend in period t, and r is the required rate of return, which is equal to the sum of risk-free interest rate and a risk premium, $r=rf+rp$.

The risk-free rate is typically proxied by a monetary policy rate, or a 1-month or a 3-month T-bill rate.

Although simple models and applications assume risk-free rates to be constant, over long horizons, the risk-free rate is likely to change its value, implying that such models misprice the equity and miscalculate the variance of expected returns. Therefore Ang and Liu (2004) emphasize that the present value model for pricing equity (1) should be written in the more general form:

$$P_t = E_t \sum_{s=1}^{\infty} D_{t+s} / exp(s\mu_t(s)), \tag{2}$$

where $\mu_t(s)$ is the discount rate, so that each different expected dividend at time $t+s$ is discounted at its own time-varying discount rate. By computing and analysing a variance decomposition of time-varying required rates of returns (or, discount rates) they show that the impact of time-varying risk-free rates is important at both, short and long horizons. As Ang and Liu (2004) explain, the intuition for this result can be gained by examining the one period expected return within the conditional CAPM:

$$\begin{aligned} r_t &= rf_t + rp_t = rf_t + \beta_t \lambda_t = (rf_t + r^* - r^*) + (\beta_t + \beta^* - \beta^*)(\lambda_t + \lambda^* - \lambda^*) = \\ &= constant + (rf_t - r^*) + \lambda^*(\beta_t - \beta^*) + \beta^*(\lambda_t - \lambda^*) + (\beta_t - \beta^*)(\lambda_t - \lambda^*) \end{aligned} \tag{3}$$

where β_t is the time-varying beta measuring the asset riskiness with respect to the market, λ_t is time-varying market price of risk, and r^*, β^*, λ^* are the unconditional means of risk-free rates, beta and market price of risk, respectively. Ignoring the covariance and other higher-order terms in (3), they obtain:

$$\text{var}(r_t) \approx \text{var}(rf_t) + \lambda^2 \text{var}(\beta_t) + \beta^2 \text{var}(\lambda_t). \tag{4}$$

The variance of risk-free rate enters one for one and so has a large effect. In particular, Ang and Liu (2004) show that $var(rf_t)$ accounts for approximately 65% of $var(r_t)$ for neutral stocks and for up to 71% for value stocks. Instead, the average risk premia per unit of risk in the data is small, of the order of 5%, implying that the impact of $var(\beta_t)$ is substantially lower. Given that average $\beta \approx 1$, the impact of variance of market price of risk for one period returns is also large and at a par with that of risk-free rate variance. However, it becomes smaller for longer horizons if the shocks to market prices of risk are less persistent than shocks to interest rates. At long horizons, depending on the relative persistence of the risk-free rate versus beta, the variance decomposition of $var(r_t)$ can be dominated either by

$var(rf_t)$ or by $var(\beta_t)$. For example, the autocorrelation of beta for the value portfolio is much larger than for growth stocks, allowing for $var(\beta_t)$ to dominate the variance of required returns for the value portfolio. Hence, they conclude that it is crucial to account for time-varying risk-free rates, but especially at short horizons.

Economically speaking, equation (4) and the findings by Ang and Liu (2004) suggest that monetary policy rate uncertainty is a fundamental component of equity return volatility, and markedly so at short horizons. Indeed, increased interest rate uncertainty is commonly associated with more volatile interest rates. In particular, in finance and economics, interest rate volatility and interest rate uncertainty are often used interchangeably (e.g. Creal and Wu (2016), among many others, define interest rate uncertainty by interest rate volatility). And given that short-term interest rates are set directly by monetary policy, the uncertainty about the future course of short-term interest rate represents the uncertainty about the expected path of Federal Reserve monetary policy (e.g. Bauer (2012)). Therefore, the short-term interest rate volatility should be a sign of monetary policy rate uncertainty[1]. The direct link between interest rate volatility and monetary policy uncertainty is also documented empirically. For example, the realized interest rate volatility is significantly higher the day before and on the day of monetary policy announcement, but it tends to decrease after the announcement, when the uncertainty about monetary policy should subside (see, for example, Chang and Feunou (2014)).

In this paper, we link the short horizon forecasts of equity variance directly to the measures of the uncertainty about risk-free rates. To do this, we introduce the high frequency proxies of monetary policy rate uncertainty into state-of-the-art so-called 'HAR-RV-CJ' based models for short-term equity variance forecasts. We describe the extended HAR-RV-CJ models and high frequency monetary policy rate uncertainty proxies in the next section.

3. Modelling the variance of equity returns

As the vast empirical literature on the volatility of asset returns reveals, the variances of asset returns fluctuate over time, with large change in returns tending to cluster (known as volatility clustering), e.g. Bollerslev, Chou and Kroner (1992).

Different methods for estimating the dynamics of conditional volatilities have evolved in the literature. The main obstacle in modelling conditional volatility, however, is the fact that

[1] Potential causes for and sources of monetary policy rate uncertainty could be various. For example, markets can anticipate higher uncertainty in the future when interest rates are subject to higher inflation uncertainty. Presence of data uncertainty or increased uncertainty about a monetary policy reaction function would be alternative sources of interest rate and monetary policy uncertainty. Finally, the volatility of monetary policy itself, stemming from the volatility of structural shocks such as monetary policy, supply, and demand, represents another determinant of uncertainty.

not only the expected dynamics, but even the true volatility of returns cannot be observed directly. Therefore the actual volatility also needs to be modelled. A basic measure of the volatility of returns is the rolling standard deviation of daily returns, a method still widely employed by market practitioners. However, this measure is subject to numerous critiques, e.g. it is sensitive to the chosen length of rolling window. The financial econometric literature, starting from the ARCH model by Engle (1982) and the GARCH model by Bollerslev (1986), tried to address the critiques and to come up with superior models of volatility. Subsequently, applications and extensions of the ARCH/GARCH approach have become the norm in more sophisticated volatility modelling. Finally, the latest literature on volatility forecasting stresses the importance of model-free measures of the `realized variance' of returns.

The concept of `realized volatility', introduced by Andersen and Bollerslev (1998), is based on using high-frequency data and provides a more precise estimate of the daily volatility of asset returns. The idea is simple: the daily realized volatility of a single asset return is measured via the sample variance of high frequency data, such as 5-minute returns data. This method has been applied to equity returns in Andersen, Bollerslev, Diebold, and Ebens (2001) and has remained popular since then. The resulting realized variance V_t^{equity} is not latent, but observed, and its sample average can be used for computing the unconditional variance of returns. It has also been shown that models of the conditional variance, $E_t(V_{t+h}^{equity})$, produce more accurate forecasts when based on these realized volatility measures (see Chen and Ghysels, 2012).

3.1. Methodology

To estimate the conditional variance, we follow a method of empirical regression-based projections of realized variance on the prior information set comprising a wide set of possible predictive variables. For each of the equity indices, we base our econometric models of $E_t(V_{t+h}^{equity})$ on the latest findings of variance forecasting literature, which emphasizes:

1. Variance is persistent, so current realized variances predict next period variance realizations (e.g. Chernov, 2007), providing the 'AR-RV' model.
2. There can be information in the most recent return variances (Muller et al, 1997; Corsi, 2009), producing the heterogeneous AR model for the realized volatility, the 'HAR-RV' model.
3. There can be different predictive information in jump versus continuous variance components, setting the stage for 'HAR-RV-CJ' model (e.g. Andersen, Bollerslev, and Diebold, 2007), which includes the HAR-RV models as a special case.
4. Implied variance contains information about future realized variance, so can be used as a predictor (e.g. Christensen and Prabhala, 1998); and

5. Variance is asymmetric (e.g. Engle and Ng, 1993), so that good news and bad news have different predictability for future variance. (This is sometimes called `leverage effect', since a negative return increases leverage, making the security more risky and so increasing its volatility, e.g. Campbell and Hentschel, 1992, and Bekaert and Wu, 2000).

Therefore, in its most general form, a forecasting model for the monthly (22 working days) equity realized variance can be represented as an extension of a HAR-RV-CJ model, which incorporates implied variance and negative returns as additional predictors:

$$RV_{t+22}^{(22)} = \beta_0+\beta_{-}r_t^{(22)-}+\beta_1 IV_t^2+\beta_2 RV_t^{(22)}+\beta_3 RV_t^{(5)}+\beta_4 RV_t^{(1)}+\beta_5 C_t^{(22)}+\beta_6 J_t^{(22)}+$$

$$+\beta_7 C_t^{(5)}+\beta_8 J_t^{(5)}+\beta_9 C_t^{(1)}+\beta_{10} J_t^{(1)}+\varepsilon_{t+22}, \qquad (5)$$

where the dependent variable is the next month's monthly realized variance, $RV_{t+22}^{(22)}$, which is the sum of the daily realized variances over 22 trading days.

As independent variables, we include the most recent values of the monthly, $RV_t^{(22)}$, weekly, $RV_t^{(5)}$, and daily, $RV_t^{(1)}$, realized variances. Lagged implied variance is included as IV_t^2, which is the implied volatility expressed as monthly percentage squared. For example, for the S&P 500 we can use the VIX and $IV_t^2= VIX_t^2/12$. As in Bekaert and Hoerova (2014), we identify the jump component using the threshold bipower variation proposed by Corsi, Pirino, and Renò (2010), which significantly reduces the small-sample bias in the standard bipower variation estimates (e.g. Barndorff-Nielsen and Shephard, 2004). Using the methodology from Corsi, Pirino, and Renò (2010), we define the jump, J, in the daily realized variance, as:

$$J_t=max[RV_t-TBPV_t,0] \qquad (6)$$

where $TBPV_t$ is the threshold power variation. We then define the continuous component as

$$C_t=RV_t-J_t \qquad (7)$$

To get weekly and monthly continuous and jump components, we average the daily components and express them in monthly units: $J^h_t =(22/h)\sum_{j=1:h}J_{t-j+1}$ and $C^h_t =(22/h)\sum_{j=1:h}C_{t-j+1}$ for $h=5$ for weekly units and $h=22$ for monthly units. When using the model with jumps, one can only have two of RV, C and J as $RV=C+J$. Therefore, we omit RV in these cases. Finally, to incorporate the 'leverage' effect, we follow Corsi and Renò (2012) in adding average monthly negative returns as an independent variable. This is defined as $r_t^{(22)-}=min[r_t^{(22)},0]$, where $r_t =\sum_{j=1:22}r_{t-j+1}$, for daily returns r_t.

The model (5) for one-month variance extends straightforwardly to other horizons h, so that:

$$RV_{t+h}^{(h)} = \beta_0+\beta_{-}r_t^{(22)-}+\beta_1 IV_t^2+\beta_2 RV_t^{(22)}+\beta_3 RV_t^{(5)}+\beta_4 RV_t^{(1)}+\beta_5 C_t^{(22)}+\beta_6 J_t^{(22)}+$$

$$+\beta_7 C_t^{(5)}+\beta_8 J_t^{(5)}+\beta_9 C_t^{(1)}+\beta_{10} J_t^{(1)}+\varepsilon_{t+22}, \quad (8)$$

with h=5 for weekly, h=22 for monthly and h=65 for quarterly horizons.

Importantly, in this paper we propose to introduce in (8) a variable reflecting monetary policy rate uncertainty as a possible additional factor affecting variance. In its most general form, our variance forecasting model is therefore:

$$RV_{t+h}^{(h)} = \beta_0+\beta_- r_t^{(22)-}+\beta_{IV} IV_t^2+\beta_2 RV_t^{(22)}+\beta_3 RV_t^{(5)}+\beta_4 RV_t^{(1)}+\beta_{CM} C_t^{(22)}+\beta_{JM} J_t^{(22)}+$$

$$+\beta_{CW} C_t^{(5)}+\beta_{JW} J_t^{(5)}+\beta_{CD} C_t^{(1)}+\beta_{JD} J_t^{(1)}+ \beta_{mp} MPU_t +\varepsilon_{t+h}, \quad (9)$$

where MPU_t is a proxy for monetary policy rate uncertainty at time t.

In terms of volatilities, which are often used in practical applications rather than variances, (9) would take a form of:

$$(RV_{t+h}^{(h)})^{1/2}= \beta_0+\beta_- r_t^{(22)-}+\beta_1 IV_t+\beta_2 (RV_t^{(22)})^{1/2}+\beta_3 (RV_t^{(5)})^{1/2}+\beta_4 (RV_t^{(1)})^{1/2}+\beta_5 C_t^{(22)}+$$

$$+\beta_6 J_t^{(22)}+\beta_7 C_t^{(5)}+\beta_8 J_t^{(5)}+\beta_9 C_t^{(1)}+\beta_{10} J_t^{(1)}+ \beta_{mp} MPU_t +\varepsilon_{t+h}, \quad (10)$$

where all $C_t^{(j)}$, $J_t^{(j)}$ components are expressed in terms of volatilities rather than variances.

3.2 Monetary policy rate uncertainty as an additional factor affecting volatility

To obtain monetary policy rate uncertainty proxies, MPU_t, in (10), at high frequencies, we refer to financial markets data, which is an obvious source of readily available high frequency data. In particular, we take short-term interest rate implied volatility, based on options on short-term interest rate futures, to be our main proxy. Implied volatility as a proxy for monetary policy rate uncertainty has been used in the past (e.g., among others, Swanson, 2006 and Bauer, 2012).

We want to emphasize that realized interest rate volatility and uncertainty about monetary policy rates over short horizons are linked, but are not the same. Given that we aim to forecast equity volatility, we should be using ex-ante forward-looking rather than backward-looking measures. Market prices on options on short-term interest rate futures imbed market views (forecasts) of volatility of underlying interest rate over the life of option. Although that does not mean that they are good forecasts of how actually volatility will turn out to be, the option implied interest rate volatilities are nonetheless a good candidate for ex-ante forward-looking measure of uncertainty about future interest rates.

Newspaper archives and other news sources from across the globe have become a popular alternative source for the uncertainty indices. In this paper, we seek to apply the approach behind the new indices of monetary policy uncertainty based on newspaper coverage frequency, such as those by Baker, Bloom, and Davis (2016) and Husted, Rogers, and Sun (2016). In addition, we refer to measures of uncertainty (or disagreement) from surveys. However, there are two main issues with the available alternatives.

First, it is hard to get most of the traditional and state-of-the-art uncertainty proxies at a high frequency. For example, Husted, Rogers, and Sun (2016) and Baker, Bloom, and Davis (2016) make their news based MPU estimates available only at the monthly frequency. Their main motivation of not using the news measures at the daily frequency is that these may not be capturing the uncertainty at a given date, given that many articles can be written earlier but published at an editorial discretion on a later date, or, vice versa, many articles are planned in advance to be written and go life on a certain date, like e.g. around monetary policy decision dates. Correspondingly, as most of the surveys are conducted at the monthly frequency, disagreements from surveys are also unavailable at higher frequency.

Second, although all these uncertainty measures are related, they are not capturing exactly the same information. For example, earlier literature has documented that survey forecasts are not independent and tend to conform to the mean forecasts (eg Gallo, Granger, and Jeon, 2002); therefore the uncertainty measures extracted from the distributions of reported survey forecasts tend to underestimate the actual dispersion of the forecasters' views and their uncertainty. Relatedly, according to Lahiri and Sheng (2010), aggregate forecast uncertainty can be expressed as the disagreement among the forecasters plus the perceived variability of future aggregate shocks; therefore, in periods with large volatility of aggregate shocks, disagreement becomes a less reliable proxy. Similarly, as Husted, Rogers, and Sun (2016) discuss, there are conceptual differences between news-based measures and the market-based indicators, since the uncertainty perception is based on different sets of individuals (not all of the people that read and write newspapers participate in financial markets). Also, news-based indices of monetary policy uncertainty are not necessarily a perfect reflection of actual market uncertainty, given that monetary policy committee meetings are scheduled at regular, often monthly, intervals, and the news agencies are expected to give them certain coverage in any case.

Using off-the-shelf MPU indices requires another justifying assumption. Namely, for our analysis, we have to assume that an MPU index is a proxy for *interest rate* uncertainty. Prior to the financial crisis in 2008, when short-term interest rates were the main monetary policy tool, the assumption is easily justified. However, when monetary policy rates in the United Kingdom, the United States and the euro area became constrained by effective lower bounds, the central banks had to refer to alternative measures, such as quantitative easing and forward guidance.[2] Nonetheless, both of these measures may affect market

[2] The Bank of England, Federal Reserve and ECB have provided considerable information on their reaction functions through forward guidance, reducing uncertainty about the path of policy in the future. For example, the Bank of England's Monetary Policy Committee (MPC) introduced forward guidance in August 2013. The MPC stated that it intended, at a minimum, to maintain the exceptionally accommodative stance of monetary

uncertainty over the future path of the interest rates, which is required to price equities. Therefore, monetary policy rate uncertainty should be an important element for equity pricing also during the period of unconventional monetary policy.

4. Data

We study the forecasting performance of our models for three markets: US, UK and euro area. We obtain S&P 500, FTSE 100, Euro Stoxx 50 equity indices and corresponding implied volatility indices (VIX for S&P 500, VFTSE for FTSE 100 and VSTOXX for Euro Stoxx 50) from Bloomberg.

Following Sheppard, Liu and Patton (2013), who show that realized variance based on 5-minute data is the best estimator of the realized variance across different assets, we estimate realized variances from squared 5-minute intraday returns. We use daily realized variance of 5 minute returns data from the underlying equity indices, as published by the Oxford-Man Institute (Heber, Lunde, Shephard and Sheppard, 2009).[3] From their website,[4] data on realized variance for S&P 500 is available from 3 January 1996, for FTSE 100 - from 21 October 1997, and from 3 January 2000 for Euro Stoxx 50. Figure 1 displays the daily realized variance series, exhibiting a high degree of own serial correlation for each of the three indices. In fact, all of the series have significant autocorrelation even at 22 lags, according to the Ljung-Box Q-tests.

For our main proxy of monetary policy rate uncertainty, we use squared three3-month implied volatility from at-the-money options on 3-month interest rate futures. The data are from a relatively liquid market of exchange traded call and put options on 3-month Eurodollar and Short Sterling futures, which are calculated on LIBOR at settlement, and 3-month Euribor futures, which are relatively liquid exchange-traded instruments based on Euribor. The sources of the underlying data are Bloomberg and BarclaysLive, while the implied volatility estimates are calculated using the Black-Sholes pricing model.[5]

To get alternative proxies for monetary policy rate uncertainty, we obtain the US MPU index by Baker, Bloom, and Davis (2016) from http://www.policyuncertainty.com/categorical_epu.html, and alternative MPU indices for the UK and US from Husted, Rogers, and Sun (2016). In addition, we construct measures of uncertainty as disagreement for short term interest rates from Consensus surveys. Figure 2 brings together the implied 3-month interest rate volatility and the alternative proxies at

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policy until economic slack had been substantially reduced, provided that this did not put at risk either price stability or financial stability. See Bank of England (2013).

[3] The Oxford-Man Institute library is based on underlying high frequency data, obtained through Reuters. To get the realised variance series, some data cleaning was applied, e.g. index entries with a time stamp outside the interval when the exchange is open were deleted. The realised measures miss out on the overnight return.
[4] http://realized.oxford-man.ox.ac.uk/
[5] Short Sterling implied volatility estimates are published by the Bank of England.

the monthly frequency. As is also evident from Table 1, for each of the markets, the measures are positively correlated. We find that the two news-based measures are similarly correlated to what is reported in Husted, Rogers, and Sun (2016) (we find the correlation on our sample to be 0.57 versus their 0.55). However, the news-based MPU measures tend to be less correlated with the implied volatility measures than survey-based MPU measures. They also have less pronounced spike-ups during the crisis and stay on the relatively higher levels in the aftermath of the crisis. Notably, the survey dispersion measures, which are forward-looking, are more correlated with the implied volatility than with backward-looking realised volatility measures.

Our data are based on the longest common samples available for all variables required to estimate (9) and (10), which are 3 January 1996 to 31 April 2017 for the US, and 4 January 2000 to 31 April 2017 for the UK and euro area, excluding public holidays and other inactive trading days.

We have a total of 4981 daily observations for the case of S&P 500, 4257 for the FTSE 100, and 4024 for the Euro Stoxx 50. Tables 2 A-C show the descriptive statistics. As a starting point for data analysis, the correlation matrices reported at the bottom of the Tables 2 may be of interest. In particular, the MPU measures based on interest rate implied volatility appear to be highly correlated with equity index implied volatilities (ranging from 0.71 to 0.78) and with realised equity return volatilities (0.69-0.73) and its continuous components (0.67-0.73).

5. Results

5.1. In-sample regressions

Table 3 reports estimates for realized variance forecasting regression (9) for S&P 500, FTSE 100 and EuroStoxx 50 from a common sample of January 2000 to April 2017. The results confirm the importance of the ex-ante measure of monetary policy rate uncertainty, measured as interest rate implied variance. The coefficient on monetary policy rate uncertainty, β_{mp}, is positive and strongly statistically significant for all indices. The magnitude of the estimated β_{mp} loadings suggests that the monetary policy uncertainty measures are among the most important predictive variables. The coefficient estimates for other explanatory variables align fairly well with those from standard regressions (5), in which the monetary policy rate uncertainty variable is omitted. Moreover, the addition of this variable increases the adjusted R^2 of the already complex regressions by up to 7 percentage points.

Overall, the regression results are consistent with the volatility forecasting literature. As expected, we find that the most recent continuous components of daily and weekly realized variances are positively related to the next month realized variance, confirming the existence of highly persistent volatility dependence and importance of the HAR-RV models. We also find that negative returns (i.e. associated with bad news) play an important role in predicting the variance of EuroStoxx 50, FTSE 100, and S&P 500 equity indices. The negative sign of β_{-} is due to the fact that the variable $r_t^{(22)-}=min[r_t^{(22)},0]$ has itself a negative sign and hence the negative coefficient estimate means that variance is increased with negative returns. This confirms the well-known result that volatility is affected more by bad news than by good news, and that negative returns increase volatility more than positive returns (see, for example, Bekaert and Wu, 2000).[6]

Tables 4 A-C report variance and volatility forecasting results for the S&P 500, FTSE 100 and EuroStoxx 50 respectively, with the full data sample available in each case. For the S&P 500, this means the sample is January 1996 to August 2016. For the FTSE 100 and EuroStoxx 50, the sample is January 2000 to August 2016. In each table, results for 1 week (5 days), 1 month (22 days) and 1 quarter (65 days) forecast horizons are shown. Importantly, the results in Tables 4 a, b and c show that monetary policy rate uncertainty - measured as interest rate implied variance or volatility - is a highly statistically significant positive predictor of equity variance or volatility, for each forecast horizon and for each market. For the volatility regressions, the qualitative features of the different parameter estimates are generally the same as for the variance regressions. The biggest improvement in adjusted R^2 tends to be for 1 month horizon variance forecasts.

To ensure the robustness of our results, we also estimated the logarithmic version of the optimal variance predictive regression model, which contains monthly, weekly and daily continuous variation in addition to the last day negative returns and squared equity implied volatility as in Bekaert and Hoerova (2016):

$$log(RV_{t+22}^{(22)}) = \beta_0+\beta_{-}r_t^{(1)-}+\beta_1 \, log(IV_t^2)+ \beta_5 \, log(C_t^{(22)})+\beta_7 \, log(C_t^{(5)})+ \beta_9 \, log(C_t^{(1)})+ \varepsilon_{t+22}.$$

The results are reported in Table 5 and confirm the findings by Bekaert and Hoerova (2014). Namely, forecasting the log transformation of the variance delivers more stable performance for the VIX and negative returns. Nonetheless, our main result also holds for

[6] One of potential drawbacks in the estimation is the multi-collinearity of the regressors. To address this issue and better understand the relevance of the MPU proxy, we also reestimated the predictive model (9) by first regressing the MPU proxy on the other regressors and then including only the MPU residual in the regression. The results from this exercise confirm our findings: the MPU measures derived from interest rate implied volatility have a predictive power above and beyond the one contained in the standard regressors, Because the results are very similar to those already included in Table 3, we do not report them here.

log regressions: the monetary policy rate uncertainty measures are significant predictors of future volatility and variance.

To provide a stronger support to our findings, we try and get additional evidence based on a wider range of alternative monetary policy rate uncertainty proxies. As we explained earlier, the main issue with the available alternative measures of monetary policy rate uncertainty is that these are not available at the daily frequency. Therefore, we estimate the alternative predictive regressions on monthly data.

Table 6 reports the estimated coefficients of the regressions (9) for the alternative cases, with the EPU and B-MPU indices as news based monetary policy rate uncertainty proxies, and survey dispersions as additional monetary policy rate uncertainty proxies. As a result, the main proxy of monetary policy rate uncertainty calculated from option prices remains positive and significant for the monthly analysis. Similarly, the survey based measures are positive and significant, albeit with slightly lower t-statistics, which may be due to the inaccurate nature of the dispersion-based uncertainty measures (see Gallo, Granger, and Jeon (2002), and Lahiri and Sheng (2010)). Instead, the two news-based measures usually considered in the literature, namely the MPU indices by Baker, Bloom, and Davis (2016) and by Husted, Rogers, and Sun (2016), turn to be insignificant predictors for next month equity volatility. The results become probably less surprising, once we look at their dynamics in Figure 2 and observe that the behaviour of these two news-based indices is very different from the financial market and survey based proxies. In particular, the high uncertainty about monetary policy rates during the financial crisis in 2008-2009 is reflected in survey and implied volatility measures but not in the textual news-based measures, and the subsequent drop in monetary policy rate uncertainty after 2010 is not shown in the news-based measures, which tend to be only very weakly correlated with survey and interest rate implied volatility measures. Notably, changing the MPU measure does not substantially affect other regression coefficients, pointing to the stability of our results.

However, all the models based on the in-sample criteria selected are quite complex, containing up to nine regressors on top of the constant. The good estimation results could simply reflect a well-known fact that as more complexity is added to a model, the better the model will fit the data in-sample. Therefore, we study the out-of-sample forecasting performance of the models enriched by monetary policy rate uncertainty proxies in the next subsection.

5.2. Out-of-sample model selection

In total, there are more than a hundred different possible model specifications based on different combinations of independent variables in (9). In this subsection, we select optimal models for variance forecasting from the various combinations of regressors by analysing their relative out-of-sample forecasting performance. To perform the out-of-sample forecast evaluation, we employ a rolling scheme, which uses a fixed number of the most recent observations for estimation at each point of the forecast.

We first estimate the competing models using a rolling window equal to 20% of the sample. This means that the first estimation window involves the data starting from 1 February 1996 and going up to 7 March 2000 for the US index; from 23 January 2000 up to 1 April 2002 for the UK and up to 8 April 2002 for the euro area data. At each stage, we produce and evaluate forecasts from all models on the remaining parts of the samples and then shift the estimation window by one period. Table 7 shows the statistics and the ranking of all best performing models for each of the indices, i.e. models for which the forecasting performance is not significantly different from the model with the lowest mean squared forecasting errors (MSFE). The significance is taken to be 1% and is measured by Giacomini and White (2006) test.

For each of the three markets, all of the best out-of-sample performing models contain the variable for monetary policy rate uncertainty. On top of the 3-month interest rate implied volatility as a proxy for monetary policy rate uncertainty, the best performing models include negative returns, lagged realized variance (and their more recent realizations for FTSE100 and SP500), and lagged squared option-implied volatility (for SP500 and ES50). The results remain qualitatively the same if we use a rolling window of 30% of the sample.

As it can be seen from Table 7, the equity variance forecasting models which use the monetary policy rate uncertainty variable as an additional predictor perform significantly better than a random walk. Moreover, the selected models also perform better than industry standards such as AR, HAR, and HAR-CJ models. All these standard models represent particular cases of (9) and hence were included in the model selection procedure, but have not delivered superior performance for any of the indices. For example, the model based on lagged variance, negative returns and the monetary policy rate uncertainty proxy outperforms the AR(1) model with ratios of MSFE 0.42, 0.79, and 0.63 for US, UK and euro indices correspondingly (based on 20% sample rolling window). The differences in forecasts are significant at 1% level.

We have to acknowledge that we use simple linear models for variance forecasting, and hence the possibility of forecasts turning negative has not been ruled out. However, when evaluating ex-post forecasts from the best performing linear models, we notice that negativity is not a big concern, as there are very few outturns of negative out-of-sample volatility and variance forecasts. In fact, they are positive in more than 99% cases.

Finally, we have to observe that the differences in out-of-sample forecasts between the various model versions are quantitatively small. Nonetheless, we believe that our model provides investors and financial intermediaries with qualitatively superior forecasts of equity realised volatility. Volatility forecasting is quintessential in asset valuation and risk management. Prices of virtually all derivative securities are sensitive to shifts in volatility. Miscalculated volatility projections can expose investors to losses and leave banks and other intermediaries with inadequate levels of capital. At the same time, the standard reduced form models reflect only statistical properties of the realised returns and volatilities and so are not very helpful in providing investors with a tool that can be relied upon on the eve of fundamental economic changes. Instead, our results should be useful for practitioners in their attempts to understand underlying drivers of volatility in the financial markets and hence should help market participants to better anticipate changes in equity volatility regimes. For example, our results imply that the recent low equity volatility levels should not be surprising, as they in part reflect lower uncertainty about monetary policy rates during the period of accommodative monetary policies. But once central banks begin the process of removing policy accommodation, markets need to be vigilant to increased volatility.

6. Conclusion

Asset pricing models assume the risk-free rate to be a key factor for equity prices. Hence there should be a strong link between monetary policy rate uncertainty and equity return volatility. In this paper we show that this relationship holds ex-ante. In particular, uncertainty about the future path of interest rates helps to predict future variance of equity returns. Adding monetary policy rate uncertainty variables can significantly improve forecasting models for equity variance and volatility at weekly, monthly and even quarterly horizons. Consistently with the theory, monetary policy rate uncertainty is positively and significantly related to uncertainty in equity markets. The results suggest that investors' views on monetary policy rate developments may indeed be embedded in equity prices and their variations.

There has been a recent focus in market commentaries on monetary policy rate uncertainty as a possible factor affecting asset price volatility. Market participants have suggested that the lower volatility of financial markets implied by derivatives prices observed post-crisis reflected reduced uncertainty around the path of monetary policy (see e.g. Bank of England, 2014). Indeed our results imply that the low level of equity volatility during 2013-2014 partially reflected lower uncertainty about short-term interest rates. Such low monetary policy rate uncertainty may have resulted from unconventional monetary policies, such as forward guidance and quantitative easing.

This paper should be useful for practitioners and policy makers in their attempts to understand the drivers of near term volatility in financial markets. In addition, the results of the paper allow us to improve estimation of the variance risk premium (VRP) for various equity indices, which is estimated as a difference between the index implied variance (e.g. squared VIX) and an estimate of corresponding expected realized variance; VRP is often used as a measure of market risk aversion (see, for example, Bollerslev, Tauchen, and Zhou, 2009; Bollerslev, Gibson, and Zhou, 2011; Bollerslev, Marrone, Xu, and Zhou, 2014). By proposing a better estimated conditional variance, we should advance the empirical research on the extracting time-varying risk aversion.

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Table 1. Correlation between MPU measures

US\UK	IV_{rates}	*Surveys*	MPU_{BBD}	MPU_{HRS}	RV_{rates}
IV_{rates}	1	0.57	-	0.09	0.79
Surveys	0.54	1	-	0.07	0.42
MPU_{BBD}	0.48	0.18	1	-	-
MPU_{HRS}	0.23	0.18	0.56	1	0.04
RV_{rates}	0.69	0.35	0.50		1

Note: The table shows the pairwise correlation between various country-specific MPU measures at monthly frequency. The UK correlations are shown above the diagonal (shaded area), the US correlations are below the diagonal. The MPU_t are proxied by: IV_{rates} - the interest rate implied volatility, MPU_{HRS} - measure based on newspaper articles by Husted, Rogers, and Sun (2016), MPU_{BBD} - measure based on newspaper articles by Baker, Bloom, and Davis (2016), ***Surveys*** - dispersion of one year ahead interest rate forecasts from Consensus survey, and RV_{rates} - realised monthly volatility of 3-month interest rates (calculated from the daily data). The correlations are calculated on the longest sample available, which is January 2000- April 2017 for all pairs, apart from those based on MPU_{HRS} **,** which is available only until January 2016.

Table 2A Summary Statistics for daily SP500 variables and US MP uncertainty proxies

	IV (rates)	$r^{(22)-}$	IV	RV_22	C_22	J_22	C_5	J_5	C	J	EPU
Mean	230.94	-1.57	41.81	24.62	21.87	2.75	21.86	2.75	0.99	0.13	2078
St.Dev	329.41	3.33	42.38	38.96	34.56	9.01	37.54	17.53	1.94	1.52	1041
Min	4.54	-38.3	8.15	2.59	2.59	0.00	1.47	0.00	0.00	0.00	650
Max	5901.93	0.00	544.86	456.59	379.11	77.48	600.05	340.90	35.35	77.48	6939

Correlation Matrix

	IV (rates)	$r^{(22)-}$	IV	RV_22	C_22	J_22	C_5	J_5	C	J	EPU
IV (rates)	1.00	-0.53	0.71	0.69	0.69	0.35	0.73	0.28	0.67	0.21	0.37
$r^{(22)-}$		1.00	-0.66	-0.60	-0.54	-0.54	-0.66	-0.37	-0.61	-0.20	-0.33
IV			1.00	0.89	0.89	0.44	0.87	0.27	0.79	0.17	0.56
RV_22				1.00	0.98	0.58	0.90	0.24	0.77	0.10	0.54
C_22					1.00	0.39	0.90	0.14	0.78	0.06	0.52
J_22						1.00	0.41	0.49	0.34	0.22	0.35
C_5							1.00	0.21	0.86	0.09	0.48
J_5								1.00	0.20	0.49	0.16
C									1.00	-0.04	0.42
J										1.00	0.07
EPU											1.00

Note: Sample: 3 January 1996 to 31 August 2016. Total number of observations, N=4981. Daily economic policy uncertainty (EPU) from Baker, Bloom and Davis (2016), which can be seen as a proxy for news-based MPU is expressed in weekly terms, all other variables are expressed as one month (22 days) variance or returns. Equity return variance is expressed as percent squared, whereas interest rate implied variance is expressed as basis points squared.

Table 2B **Summary Statistics for daily FTSE100 variables and UK MP uncertainty proxies**

	IV (rates)	$r^{(22)-}$	IV	RV_22	C_22	J_22	C_5	J_5	C	J	BB-MPU	EPU
Mean	230.94	-1.57	41.81	24.62	21.87	2.75	21.86	2.75	0.99	0.13	0.60	2078
St.Dev	329.41	3.33	42.38	38.96	34.56	9.01	37.54	17.53	1.94	1.52	0.46	1041
Min	4.54	-38	8.15	2.59	2.59	0.00	1.47	0.00	0.00	0.00	0.00	650.3
Mac	5901.9	0.00	545	456.6	379	77.5	600	341	35.4	77.5	4.19	6939
	Correlation Matrix											
IV (rates)	1	-0.36	0.76	0.72	0.73	0.48	0.73	0.31	0.62	0.17	0.32	0.31
$r^{(22)-}$		1.00	-0.57	-0.47	-0.41	-0.46	-0.57	-0.44	-0.52	-0.24	-0.06	-0.10
IV			1.00	0.89	0.88	0.64	0.92	0.46	0.80	0.27	0.19	0.38
RV_22				1.00	0.96	0.80	0.91	0.39	0.77	0.18	0.17	0.37
C_22					1.00	0.59	0.92	0.26	0.78	0.11	0.20	0.40
J_22						1.00	0.62	0.54	0.52	0.25	0.05	0.21
C_5							1.00	0.34	0.86	0.16	0.18	0.36
J_5								1.00	0.30	0.49	0.03	0.11
C									1.00	-0.06	0.16	0.31
J										1.00	0.01	0.05
BB-MPU											1.00	0.22
EPU												1.00

Note: Sample: 4 January 2000 to 31 August 2016. Total number of observations, N=3997. Variables are expressed as one month (22 days) variance or returns. UK BB-MPU is expressed as a share of all Bloomberg news stories. Equity return variance is expressed as percent squared, whereas interest rate implied variance is expressed as basis points squared.

Table 2C Summary Statistics for daily ES50 variables and Euro MP Uncertainty proxies

	IV (rates)	$r^{(22)-}$	IV	RV_22	C_22	J_22	C_5	J_5	C	J	BB-MPU
Mean	159.27	-2.47	60.36	39.11	33.78	5.34	33.73	5.34	1.53	0.24	0.82
St.Dev	187.72	4.48	55.30	48.85	34.28	23.10	36.91	36.55	1.97	2.90	1.49
Min	5.61	-44.76	11.21	5.61	4.92	0.00	0.00	0.00	0.00	0.00	0.00
Mac	2680.47	0.00	638.2	505.7	210.3	325.4	281.9	664.05	22.94	108.27	10.76
	Correlation Matrix										
IV (rates)	1	-0.54	0.78	0.73	0.67	0.55	0.67	0.46	0.56	0.33	0.23
$r^{(22)-}$		1.00	-0.67	-0.63	-0.51	-0.58	-0.64	-0.49	-0.58	-0.29	-0.03
IV			1.00	0.87	0.89	0.52	0.91	0.41	0.78	0.30	0.08
RV_22				1.00	0.90	0.77	0.83	0.43	0.69	0.22	0.08
C_22					1.00	0.43	0.91	0.23	0.75	0.11	0.09
J_22						1.00	0.41	0.58	0.33	0.29	0.04
C_5							1.00	0.27	0.85	0.15	0.07
J_5								1.00	0.22	0.54	0.02
C									1.00	-0.06	0.06
J										1.00	0.01

Note: Sample: 4 January 2000 to 31 August 2016. Total number of observations, N=4024. Variables are expressed as one month (22 days) variance or returns. BB-MPU is expressed as a share of all Bloomberg news stories. Equity return variance is expressed as percent squared, whereas interest rate implied variance is expressed as basis points squared.

Table 3. Predictive power of monetary policy uncertainty for next month variance of returns

	S&P 500		FTSE 100		ES 50	
β_{mp}	**0.42*** [3.33]**	-	**0.23** [1.99]**	-	**0.23** [2.19]**	-
β_{-}	-0.08** [-2.04]	-0.10** [-2.03]	-0.16*** [-2.86]	-0.13** [-2.51]	-0.14*** [-4.00]	-0.13*** [-3.53]
β_{IV}	-0.02 [-0.20]	0.00 [0.02]	0.04 [0.28]	0.16* [1.66]	0.14 [1.35]	0.26*** [2.95]
β_{CM}	0.05 [0.31]	0.12 [0.71]	0.13 [1.00]	0.17 [1.38]	-0.02 [-0.23]	-0.01 [-0.12]
β_{CW}	0.28* [1.66]	0.42** [2.10]	0.25 [1.55]	0.29 [1.62]	0.32*** [2.90]	0.37*** [2.98]
β_{CD}	0.12* [1.71]	0.20** [2.35]	0.15*** [2.78]	0.14** [2.40]	0.10 [1.38]	0.10 [1.34]
β_{JM}	-0.01 [-0.25]	-0.02 [-0.42]	-0.08 [-1.45]	-0.08 [-1.44]	-0.14*** [-2.93]	-0.11*** [-2.79]
β_{JW}	-0.03 [-0.88]	0.02 [0.79]	0.02 [0.70]	0.03 [0.94]	-0.02 [-0.69]	-0.01 [-0.30]
β_{JD}	0.01 [0.41]	0.06*** [2.72]	0.06** [2.44]	0.06** [2.09]	0.02 [1.21]	0.03** [1.59]
β_0	0.09*** [2.71]	0.15*** [3.78]	0.05 [1.33]	0.05 [1.30]	0.10*** [3.29]	0.11*** [3.92]
DoF	4234	4235	4286	4287	4325	4326
AdjR^2	0.68	0.61	0.62	0.59	0.56	0.54

Note: The forecasting model is $RV_{t+h}^{(22)} = \beta_0+\beta_- r_t^{(22)-}+\beta_{IV}IV_t^2+\beta_{CM}C_t^{(22)}+\beta_{JM}J_t^{(22)} +\beta_{CW}C_t^{(5)}+\beta_{JW}J_t^{(5)}+\beta_{CD}C_t^{(1)}+\beta_{JD}J_t^{(1)}+ \beta_{mp}MPU_t +\varepsilon_{t+22},$ where the dependent variable is the next month monthly realised variance, $RV_{t+h}^{(22)}$, which is the sum of the daily realised variances over 22 trading days; independent variables are: implied variance, IV_t^2, which is the implied volatility expressed as monthly percentage squared; realised variance split into continuous and `jump' components at daily, weekly and monthly frequencies: C_t, J_t, $C_t^{(h)}$ $J_t^{(h)}$: $J^h_t =(22/h)\sum_{j=1:h}J_{t-j+1}$ and $C^h_t =(22/h)\sum_{j=1:h}C_{t-j+1}$ for $h=5$ for weekly units and $h=22$ for monthly units; average monthly negative returns as $r_t^{(22)-}=min[r_t^{(22)},0]$, where $r_t =\sum_{j=1:22}r_{t-j+1}$, for daily returns r_t; and monetary policy rate uncertainty, MPU_t, proxied by squared interest rate implied volatility based on options on short-term interest rate futures. The sample is January 2000 - April 2017. All regressors are standardised. Student t-statistics calculated using Newey-West standard errors with 44 lags shown in square brackets.

Table 4A **Weekly, Monthly and Quarterly S&P 500 Regressions**

	$RV_{t+h}{}^{(h)}$			$(RV_{t+h}{}^{(h)})^{0.5}$		
h	5	22	65	5	22	65
β_{mp}	0.28** [2.35]	0.37*** [2.96]	0.24*** [3.56]	0.05 [1.53]	0.12** [2.35]	0.25*** [5.12]
β_{-}	-0.19*** [-4.63]	-0.12** [-2.57]	-0.09*** [-2.37]	-0.13*** [-4.31]	-0.07** [-2.08]	-0.00 [-0.03]
β_{IV}	0.15** [2.25]	-0.08 [-0.98]	-0.05 [-0.91]	0.23*** [5.83]	0.12** [2.26]	-0.04 [-0.67]
β_{CM}	0.06 [0.47]	0.07 [0.46]	0.12*** [2.95]	0.12** [2.11]	0.17** [2.36]	0.17*** [3.40]
β_{CW}	0.12 [0.63]	0.33* [1.96]	0.05 [1.05]	0.24*** [4.25]	0.31*** [3.44]	0.17*** [2.68]
β_{CD}	0.19** [2.22]	0.12* [1.77]	0.01 [0.19]	0.20*** [6.31]	0.14*** [4.15]	0.05 [1.27]
β_{JM}	-0.05*** [-1.16]	-0.02 [-0.42]	-0.04 [-1.33]	-0.05*** [-3.53]	-0.06*** [-4.47]	-0.02 [-0.80]
β_{JW}	-0.02 [-0.41]	-0.02 [-0.68]	-0.04 [-1.43]	-0.01 [-0.85]	-0.01 [-0.95]	-0.05*** [-3.39]
β_{JD}	0.06*** [2.71]	0.02 [0.81]	-0.02 [-0.91]	0.05*** [5.53]	0.03*** [3.45]	0.01 [1.48]
β_0	-0.07* [-1.82]	0.10*** [2.82]	0.39*** [10.47]	0.03 [0.73]	0.27*** [4.17]	0.83*** [10.78]
$AdjR^2$	0.71	0.66	0.13	0.77	0.70	0.28

Note: The forecasting models are $RV_{t+h}{}^{(h)} = \beta_0+\beta_- r_t{}^{(22)-}+\beta_1 IV_t{}^2+ \beta_5 C_t{}^{(22)}+\beta_6 J_t{}^{(22)}+\beta_7 C_t{}^{(5)}+\beta_8 J_t{}^{(5)}+\beta_9 C_t{}^{(1)}+\beta_{10} J_t{}^{(1)}+ \beta_{mp} MPU_t +\varepsilon_{t+22}$, $(RV_{t+h}{}^{(h)})^{0.5}= \beta_0+\beta_- r_t{}^{(22)-}+\beta_1 IV_t+ \beta_5 C_t{}^{(22)}+\beta_6 J_t{}^{(22)}+\beta_7 C_t{}^{(5)}+\beta_8 J_t{}^{(5)}+\beta_9 C_t{}^{(1)}+\beta_{10} J_t{}^{(1)}+ \beta_{mp} MPU_t +\varepsilon_{t+22}$, where the dependent variables are realised variance, or realised volatility. Independent variables, correspondingly, are: lagged implied variance, IV^2_t, or volatility, IV_t; realised variance (or volatility) split into daily, weekly and monthly continuous and `jump' components: $C_t{}^{(h)}$, $J_t{}^{(h)}$ with h=1, 5, 22; average monthly negative returns $r_t{}^{(22)-}$; monetary policy rate uncertainty, MPU_t, proxied by lagged interest rate implied volatility (or its square) based on options on short-term interest rate futures. Sample: January 1996 - August 2016. All regressors are standardised. Student t-statistics calculated using Newey-West standard errors with 44 lags shown in square brackets.

Table 4B **Weekly, Monthly and Quarterly FTSE 100 Regressions**

	$RV_{t+h}{}^{(h)}$			$(RV_{t+h}{}^{(h)})^{0.5}$		
h	5	22	65	5	22	65
β_{mp}	0.10 [0.98]	0.24** [2.11]	0.28*** [5.46]	0.06 [1.48]	0.15*** [2.82]	0.28*** [6.43]
β_{-}	-0.16*** [-3.97]	-0.19*** [-3.26]	-0.12** [-2.39]	-0.12*** [-4.43]	-0.12*** [-2.99]	-0.06 [-1.63]
β_{IV}	0.30*** [3.14]	0.01 [0.05]	-0.45*** [-4.06]	0.42*** [8.38]	0.28*** [3.74]	-0.17* [-1.72]
β_{CM}	-0.15* [-1.72]	0.15 [1.12]	0.28*** [4.25]	0.03 [0.60]	0.20*** [2.86]	0.25*** [4.00]
β_{CW}	0.34*** [2.99]	0.21 [1.27]	0.38*** [3.63]	0.22*** [4.22]	0.12 [1.53]	0.21*** [2.68]
β_{CD}	0.20*** [2.58]	0.16*** [2.89]	0.07 [1.56]	0.14*** [3.81]	0.11*** [3.34]	0.08** [2.19]
β_{JM}	-0.08* [-1.65]	-0.07 [-1.29]	-0.15** [-2.38]	-0.01 [-0.99]	-0.04*** [-3.07]	0.04 [1.16]
β_{JW}	0.03 [0.96]	0.01 [0.35]	-0.01 [-0.24]	0.00 [0.05]	0.00 [0.04]	-0.05*** [-2.69]
β_{JD}	0.07 [1.50]	0.07*** [2.61]	0.04* [1.68]	0.03** [2.46]	0.02*** [3.43]	0.01 [1.62]
β_0	-0.08** [-2.06]	0.05 [1.09]	90.36*** [9.49]	-0.03 [-0.77]	0.17*** [3.08]	0.78*** [10.29]
AdjR^2	0.68	0.62	0.23	0.81	0.74	0.38

Note: The forecasting models are $RV_{t+h}{}^{(h)} = \beta_0+\beta_{-}r_t{}^{(22)-}+\beta_1 IV_t{}^2+ \beta_5 C_t{}^{(22)}+\beta_6 J_t{}^{(22)}+\beta_7 C_t{}^{(5)}+\beta_8 J_t{}^{(5)}+\beta_9 C_t{}^{(1)}+\beta_{10} J_t{}^{(1)}+ \beta_{mp} MPU_t +\varepsilon_{t+22}$, $(RV_{t+h}{}^{(h)})^{0.5}= \beta_0+\beta_{-}r_t{}^{(22)-}+\beta_1 IV_t+ \beta_5 C_t{}^{(22)}+\beta_6 J_t{}^{(22)}+\beta_7 C_t{}^{(5)}+\beta_8 J_t{}^{(5)}+\beta_9 C_t{}^{(1)}+\beta_{10} J_t{}^{(1)}+ \beta_{mp} MPU_t +\varepsilon_{t+22}$, where the dependent variables are realised variance, or realised volatility. Independent variables, correspondingly, are: lagged implied variance, IV^2_t, or volatility, IV_t; realised variance (or volatility) split into daily, weekly and monthly continuous and `jump' components: $C_t{}^{(h)}$, $J_t{}^{(h)}$ with h=1, 5, 22; average monthly negative returns $r_t{}^{(22)-}$; monetary policy rate uncertainty, MPU_t, proxied by lagged interest rate implied volatility (or its square) based on options on short-term interest rate futures. Sample: January 2000 - August 2016. All regressors are standardised. Student t-statistics calculated using Newey-West standard errors with 44 lags shown in square brackets.

Table 4C **Weekly, Monthly and Quarterly ES 50 Regressions**

	$RV_{t+h}^{(h)}$			$(RV_{t+h}^{(h)})^{0.5}$		
h	5	22	65	5	22	65
β_{mp}	0.29* [1.92]	0. 29** [2.46]	0.18*** [2.70]	0.04 [0.84]	0.09** [1.97]	0.17*** [3.29]
β_{-}	-0.20*** [-4.48]	-0.17*** [-4.33]	-0.34*** [-4.71]	-0.15*** [-5.76]	-0.13*** [-4.74]	-0.17*** [-3.22]
β_{IV}	0.01 [0.06]	0.03 [0.23]	-0.14 [-1.34]	0.46*** [7.48]	0.45*** [7.29]	0.26*** [2.98]
β_{CM}	-0.17** [-1.98]	-0.07 [-0.79]	0.13*** [2.61]	-0.05 [-1.04]	0.03 [0.54]	-0.05 [-0.99]
β_{CW}	0.44*** [3.59]	0.37*** [2.87]	0.11* [1.80]	0.23*** [3.93]	0.15** [2.28]	0.08 [1.23]
β_{CD}	0.17** [2.30]	0.12** [2.48]	-0.00 [-0.12]	0.13*** [2.96]	0.06* [1.82]	-0.02 [-0.67]
β_{JM}	-0.09* [-1.63]	-0.10* [-1.72]	-0.28*** [-4.84]	-0.04 [-1.08]	-0.05** [-2.28]	-0.05 [-1.53]
β_{JW}	0.00 [0.11]	-0.01 [-0.29]	-0.02 [-0.61]	-0.01 [-0.37]	-0.03 [-0.19]	-0.05*** [-3.75]
β_{JD}	0.09** [2.21]	0.03 [1.34]	-0.02 [-1.00]	0.04*** [3.20]	0.01 [1.53]	-0.01 [-1.39]
β_0	-0.05* [-1.59]	0.08** [2.33]	0.53*** [8.44]	-0.00 [-0.00]	0.22*** [3.77]	0.93*** [8.30]
$AdjR^2$	0.64	0.56	0.14	0.77	0.68	0.27

Note: The forecasting models are $RV_{t+h}^{(h)} = \beta_0+\beta_{-}r_t^{(22)-}+\beta_1 IV_t^2+ \beta_5 C_t^{(22)}+\beta_6 J_t^{(22)}+\beta_7 C_t^{(5)}+\beta_8 J_t^{(5)}+\beta_9 C_t^{(1)}+\beta_{10} J_t^{(1)}+ \beta_{mp} MPU_t +\varepsilon_{t+22}$, $(RV_{t+h}^{(h)})^{0.5}= \beta_0+\beta_{-}r_t^{(22)-}+\beta_1 IV_t+ \beta_5 C_t^{(22)}+\beta_6 J_t^{(22)}+\beta_7 C_t^{(5)}+\beta_8 J_t^{(5)}+\beta_9 C_t^{(1)}+\beta_{10} J_t^{(1)}+ \beta_{mp} MPU_t +\varepsilon_{t+22}$, where the dependent variables are realised variance, or realised volatility. Independent variables, correspondingly, are: lagged implied variance, IV^2_t, or volatility, IV_t; realised variance (or volatility) split into daily, weekly and monthly continuous and `jump' components: $C_t^{(h)}$, $J_t^{(h)}$ with h=1, 5, 22; average monthly negative returns $r_t^{(22)-}$; monetary policy rate uncertainty, MPU_t, proxied by lagged interest rate implied volatility (or its square) based on options on short-term interest rate futures. Sample: January 2000 - August 2016. All regressors are standardised. Student t-statistics calculated using Newey-West standard errors with 44 lags shown in square brackets.

Table 5. Estimates from the logarithmic regressions

	RV_{t+22}				$RV_{t+22}^{0.5}$			
	S&P 500		FTSE 100		S&P 500		FTSE 100	
$\boldsymbol{\beta_{mpu}}$		0.08** [2.07]		0.08** [2.29]		0.05*** [2.63]		0.04** [2.25]
β_{-}	-0.05*** [-4.29]	-0.05*** [-4.41]	-0.04*** [-5.05]	-0.05*** [-5.13]	-0.02*** [-4.13]	-0.02*** [-4.25]	-0.02*** [-4.61]	-0.02*** [-4.69]
β_{IV}	0.31*** [4.47]	0.30*** [4.21]	0.29*** [4.62]	0.25*** [3.70]	0.17*** [5.51]	0.16*** [5.21]	0.16*** [5.43]	0.14*** [4.50]
β_{CM}	0.13** [1.99]	0.09 [1.39]	0.22*** [4.34]	0.20*** [3.61]	0.07** [2.44]	0.05 [1.52]	0.11*** [5.13]	0.10*** [4.31]
β_{CW}	0.28*** [5.12]	0.28*** [5.16]	0.23*** [3.46]	0.23*** [3.63]	0.12*** [4.85]	0.12*** [4.84]	0.09*** [2.93]	0.09*** [3.06]
β_{CD}	0.06*** [2.96]	0.06*** [2.73]	0.06*** [3.17]	0.14** [2.40]	0.03*** [3.87]	0.03*** [3.69]	0.03*** [4.62]	0.03*** [4.63]
β_0	-3.62*** [-19.57]	-3.73*** [-18.87]	-3.21*** [-18.09]	-3.34*** [-18.11]	-2.07*** [-17.36]	-2.13*** [-16.85]	-1.92*** [-16.78]	-1.97*** [-16.56]
$AdjR^2$	0.70	0.71	0.76	0.77	0.72	0.73	0.78	0.79

Note: The forecasting models are $RV_{t+h}^{(h)} = \beta_0+\beta_- r_t^- +\beta_{IV}IV_t^2+ \beta_{CM}C_t^{(22)}+ \beta_{CW}C_t^{(5)}+ \beta_9 C_t^{(1)}+ \beta_{mp}MPU_t +\varepsilon_{t+22}$, $(RV_{t+h}^{(h)})^{0.5}= \beta_0+\beta_- r_t^{(22)-}+\beta_{IV}IV_t+ \beta_{CM}C_t^{(22)}+ \beta_{CW}C_t^{(5)}+ \beta_{CD}C_t^{(1)}+\beta_{mp}MPU_t +\varepsilon_{t+22}$, where the dependent variables are realised log variance, or realised log volatility. Independent variables, correspondingly, are logarithms of implied variance, IV^2_t, or volatility, IV_t; continuous daily, weekly and monthly components of realised variance (or volatility): $C_t^{(h)}$, with h=1, 5, 22; most recent negative returns $r_t^-=\min(0, r_t)$; monetary policy rate uncertainty, MPU_t, proxied by interest rate implied volatility (or its square) based on options on short-term interest rate futures. Sample: January 2000 - April 2017. All regressors are standardised. Student t-statistics calculated using Newey-West standard errors with 44 lags shown in square brackets.

Table 6. Estimates from the alternative monthly forecasting regressions

	S&P500				FTSE100			ES50
β_{mp} *(IV)*	0.20*** [2.60]				0.18*** [2.87]			0.19** [2.00]
β_{mp} *(HRS)*		0.01 [0.35]				-0.01 [-0.36]		
β_{mp} *(Bloom)*			0.02 [0.42]					
β_{mp} *(Surveys)*				0.08*** [2.77]			0.07** [2.29]	
β_{-}	-0.00 [-0.00]	-0.06 [-1.56]	-0.01 [-0.05]	-0.01 [-0.06]	-0.07* [-1.78]	-0.09** [-1.96]	-0.08* [-1.89]	-0.03 [-.36]
β_{IV}	-0.15 [-0.67]	-0.15 [-0.76]	-0.12 [-0.48]	-0.11 [-0.46]	-0.14 [-0.59]	-0.02 [-0.08]	0.01 [0.07]	
β_{CM}	0.57*** [2.71]	0.77*** [3.68]	0.71** [2.52]	0.68** [2.53]	0.48** [2.48]	0.51** [2.31]	0.45** [2.09]	0.34*** [2.77]
β_{CD}	0.26*** [2.81]	0.19** [2.51]	0.23*** [2.74]	0.23** [2.50]	0.34*** [3.59]	0.32*** [3.24]	0.32*** [3.43]	0.32*** [2.94]
β_0	0.34*** [3.21]	0.39** [3.31]	0.36*** [3.69]	0.24** [2.55]	0.26** [1.94]	0.29** [2.03]	0.14 [1.15]	0.27** [2.21]
Nobs	207	192	207	207	207	192	207	183
AdjR^2	0.66	0.63	0.65	0.65	0.71	0.69	0.70	0.62

Note: The forecasting models are $RV_{t+1} = \beta_0 + \beta_{mp}MPU_t + \beta_{-}r_t^{(22)-} + \beta_{IV}IV_t + \beta_5 C_t^{(22)} + \beta_9 C_t^{(1)} + \varepsilon_{t+22}$, where the dependent variable is next month realised volatility. Independent variables, correspondingly, are: monetary policy rate uncertainty, MPU_t, proxied by either the average interest rate implied volatility *IV*, or by measures based on newspaper articles by Husted, Rogers, and Sun (2016) and Baker, Bloom, and Davis (2016), or dispersion of one year ahead US interest rate forecasts from Consensus survey average realised monthly and latest daily volatility: $C_t^{(h)}$, h=1, 22; monthly negative returns $r_t^{(22)-}$. Sample: January 2000 – April 2017. All regressors are standardised. Student t-statistics calculated using Newey-West standard errors with 5 lags shown in square brackets.

Table 7. Best performing variance forecasting models for equity indices out of sample.

	Rolling window=20%			Rolling window=30%		
Model regressors	S&P500	FTSE100	ES50	S&P500	FTSE100	ES50
$MPU_t, RV_t^{(22)}, r_t^{(22)-}$	0.92***		0.79***	0.83***	0.87***	0.77***
$MPU_t, RV_t^{(22)}, RV_t^{(5)}, RV_t^{(1)}, r_t^{(22)-}$		0.90***		0.84***	0.85***	
$MPU_t, RV_t^{(22)}, RV_t^{(5)}, RV_t^{(1)}$	0.89***	0.90***		0.83***	0.85***	
$MPU_t, RV_t^{(22)}, RV_t^{(5)}$	0.90**	0.92**		0.83***	0.86***	
MPU_t, IV_t^2	0.95			0.83***		
$MPU_t, IV_t^2, r_t^{(22)-}$			0.80***	0.85***		0.77***
$MPU_t, RV_t^{(22)}, RV_t^{(5)}, r_t^{(22)-}$				0.85***	0.86***	
$MPU_t, RV_t^{(22)}, IV_t^2, r_t^{(22)-}$						0.80***
$MPU_t, RV_t^{(22)}$	0.92***					
$MPU_t, IV_t^2, r_t^{(22)-}$				0.84***		

Note: The general model is $RV_{t+h}^{(h)} =$
$\beta_0+\beta_- r_t^{(22)-}+\beta_{IV}IV_t^2+\beta_2 RV_t^{(22)}+\beta_3 RV_t^{(5)}+\beta_4 RV_t^{(1)}+\beta_{CM}C_t^{(22)}+\beta_{JM}J_t^{(22)}+\beta_{CW}C_t^{(5)}+\beta_{JW}J_t^{(5)}+\beta_{CD}C_t^{(1)}+\beta_{JD}J_t^{(1)}+\beta_{mp}MPU_t+\varepsilon_{t+h}$. All particular cases of the model based on various combinations of regressors have been considered; as a result, the table shows the mean squared forecasting errors (MSFE) relative to Random Walk over the out-of-sample periods for individual forecasting models insignificantly different from the models with the lowest MSFE (shown in bold). A value lower than one means the model outperforms the benchmark. *** or ** mark significant difference in performance at 5% or 1% significance level by Giacomini-White test. Only model regressors from best performing models are shown, all other models perform significantly worse and hence are omitted. MPU_t is measured by squared 3-month rate implied volatility.

Figure 1. Daily realized variances

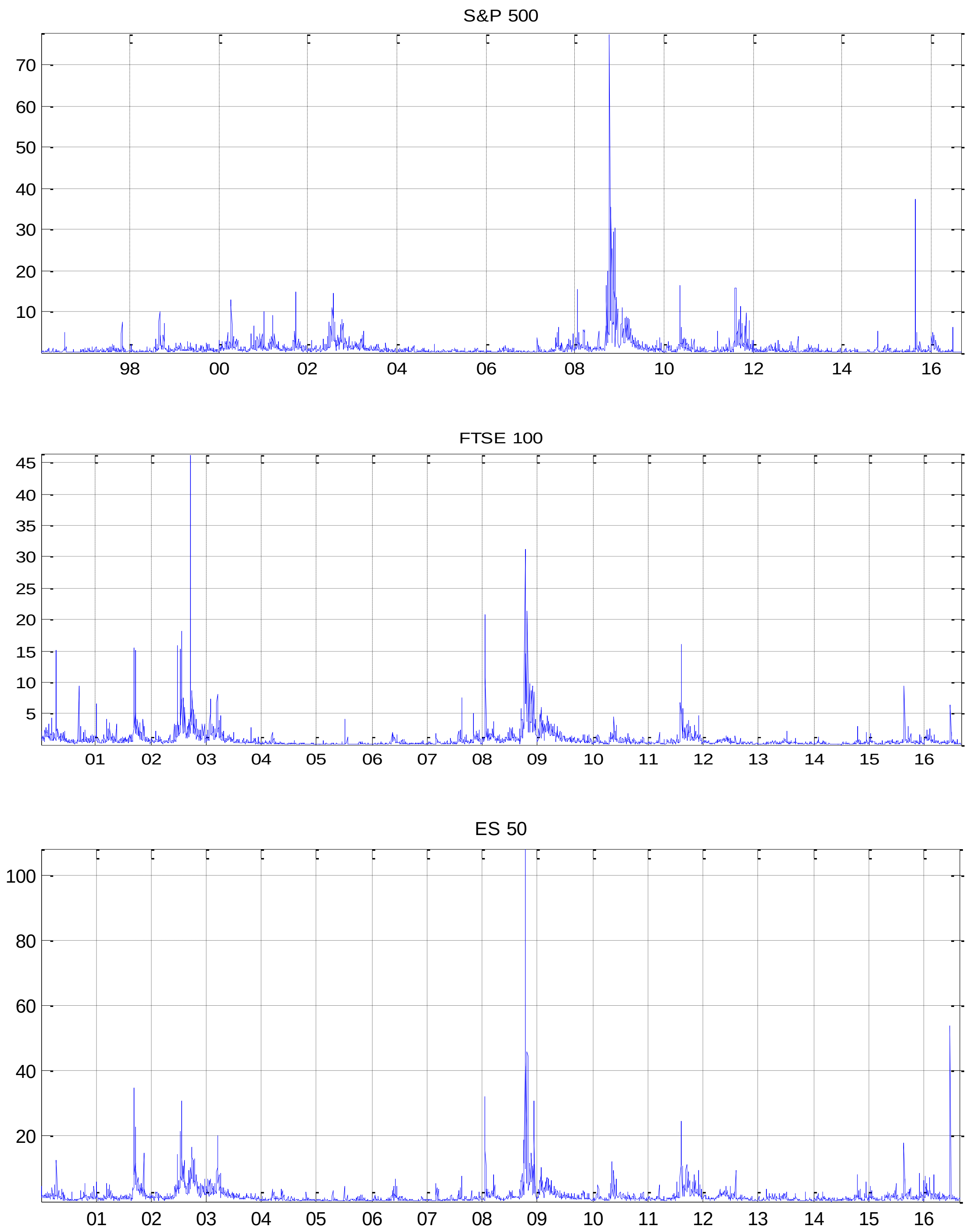
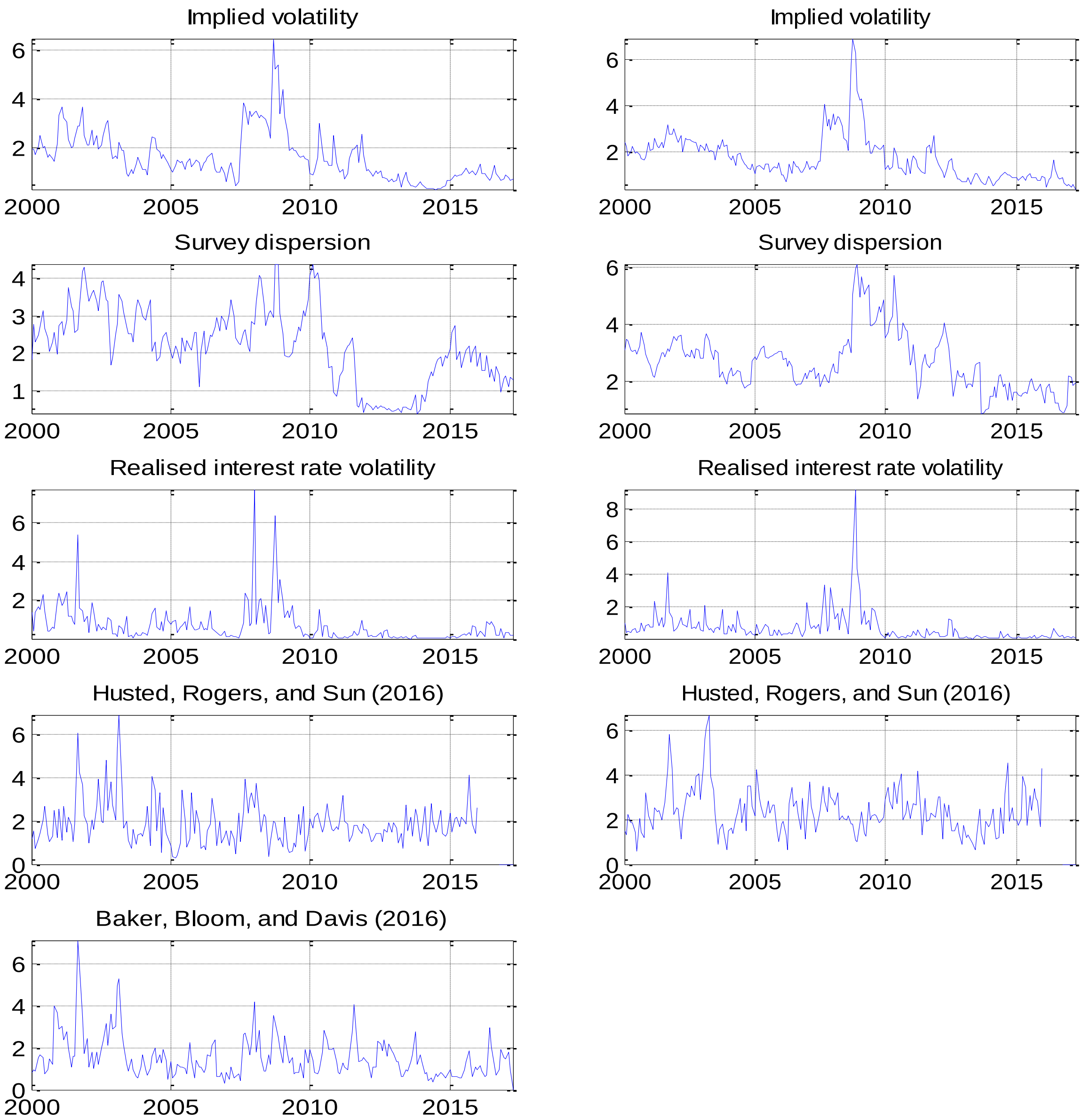


Figure 2. Monetary policy rate uncertainty measures

US | UK



Note: The charts plot normalised monetary policy rate uncertainty proxies for US and UK. Implied volatility, IV_{rates}, is proxied by interest rate implied volatility based on options on short-term interest rate futures, survey dispersion is constructed from next year ahead Consensus surveys for short term interest rates. The news-based measures of uncertainty are given by MPU_{BBD}, Baker, Bloom, and Davis (2016), and MPU_{HRS}, Husted, Rogers, and Sun (2016), indices based on newspaper articles. Sample: January 2000 – April 2017. (MPU_{HRS} is available only until January 2016). All variables shown are standardised.