Essex Finance Centre
Working Paper Series

Working Paper No 57: 04-2020

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Volatility Forecasting in European Government Bond Markets

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Abstract

In this paper we examine the predictive power of the Heterogeneous Autoregressive (HAR) model on Treasury bond return volatility of major European government bond markets. The HAR-type volatility forecasting models show that short term and medium term volatility is a robust and statistically significant predictor of the term structure of intraday-volatility of bonds with maturities ranging from 1-year up to 30-years. When decomposing volatility into its continuous and discontinuous (jump) component, we find that the jump tail risk component is a significant predictor of bond market volatility. We lastly show that approximately half of the monetary policy announcement dates coincide with the presence of jumps in bond returns, and the pre-announcement drift is present in the bond market. Hence, the monetary policy announcements are important determinant of European bond market volatility.

Keywords: Treasury Bonds, Jumps, Realized Volatility, Macroeconomic Announcements, Volatility Forecasting

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Preprint submitted to International Journal of Forecasting *April 19, 2020*

1. Introduction

Financial market participants, banks, firms and policymakers pay close attention to interest rate volatility since it plays a key role in a variety of settings, ranging from risk management (Faulkender (2005); Markellos & Psychoyios (2018)) and asset pricing (Flannery et al. (1997)) to firms' investment decisions (Bo & Sterken (2002)) and the transmission mechanism of monetary policy (Landier et al. (2013); Hoffmann et al. (2018)). The market for government bonds is essential for the analysis of interest rate volatility since sovereign yields provide the basis for the pricing of other securities, derivatives and loans. Moreover, this market has been the object of significant interventions by central banks (CBs) during Quantitative Easing programs, whereby the CB purchases assets from banks and other financial companies, in both the US and Europe. Hence, it is important to develop models that generate good forecasts of bond market volatility in order to enhance the information set of various economic agents. Surprisingly, despite the importance of this exercise, only a few previous studies attempted to forecast bond market volatility, mainly in the context of the US market for Treasuries (Remolona & Fleming (1999); Balduzzi et al. (2001); Andersen et al. (2007b)). At the same time, the literature on the forecasting of stock and commodity market volatility is richer (Bollerslev et al. (2018); Dueker (1997); Bollerslev et al. (2016); Bollerslev & Mikkelsen (1996); Luo et al. (2019)).

In this paper we attempt to fill this gap in the bond market volatility forecasting literature by analysing the predictive power of the Heterogeneous Autoregressive model of Realized Volatility (HAR-RV), developed by Corsi (2009), for the volatility term structure of European bond markets. HAR-type volatility forecasting models utilize the continuous and the discontinuous (jump) component of volatility and are popular in studies of stock and commodity markets (Degiannakis et al. (Forthcoming); Luo et al. (2019)) [1]. Our primary motivation to focus on the European bond markets is the increased turbulence in European economies, especially in the post-2007 crisis period. During the 2007-2008 global financial crisis and the subsequent European sovereign debt crisis, the volatility of government bond markets was raised to the unprecedented levels and therefore became a major concern for fixed income investors, banks, firms and European policy makers. We use government bond data for two major euro-area markets (France and Germany) and two important non-euro-area members (Switzerland and the UK) between 2005 and 2019.

We collect intraday bond market data for these four economies over the period January 2005 to October 2019. Specifically, we use data between 10:00 am and 16:00 pm in 10-minute intervals to estimate the realized volatility of bond returns. In order to compute the zero-coupon prices for 1-year, 2-year, 5-year, 10-year, 20-year and 30-year maturity securities, we employ the Nelson & Siegel (1987) (NS) model in the intraday basis. We then estimate HAR-type volatility forecasting models for daily, weekly and monthly forecasting horizon.

Our results reveal that the HAR components of realized volatility are robust and statistically significant predictors of European bond return volatility across different maturities at the 1-day, 5-day and 22-day horizon. The in-sample R^2 values range from 40% up to 80%. Out-of-sample forecasts show that HAR models can be used for real time forecasting since the respective out-of-sample R2s remain high, ranging from 20% to 70%, especially for bonds with short-term maturities. Our results provide the evidence long-

[1] The relevant literature on HAR modeling and volatility forecasting in bond markets has been extensively focused on US Treasury bond market. Andersen et al. (2007a) and Corsi et al. (2010) depend on US T-bond future data for fixed income market. Also, Andersen & Benzoni (2010) employ HAR-type model to show the unspanned stochastic volatility phenomenon using US bond data.

memory property of government bond volatility, since regardless of forecasting horizon 1-day to 22-day components of HAR models are found to be effective on future volatility. Moreover, including price jumps as an additional predictor in the HAR model, the jump tail risk component is found to be a significant predictor of bond return volatility.

We proceed by examining the role of monetary policy announcements within HAR-models of bond return volatility. We show that large jumps in realised bond market volatility tend to coincide with monetary policy announcements. More specifically, 80% of all policy announcement dates for the case of Switzerland, 40% in Germany and the UK, and 34% in France overlap with at least one statistically significant bond price jump in the respective bond market. In addition, using HAR-model framework, we identify the impact of monetary policy announcements on the volatility forecasts. Our findings indicate that there is a positive and significant monetary policy pre-announcement impact on future bond market volatility. This analysis is motivated by Lucca & Moench (2015), which document larger excess returns on US stock markets one day ahead of the FOMC meetings. Although, Lucca & Moench (2015) show the presence of pre-FOMC drift on equity market, the drift is found be not present for fixed income securities. On the contrary, our findings verify the monetary policy pre-announcement drift on the European bond market volatility. In addition, we report that the pre-announcement drift is effective through the continuous part of the volatility, integrated variation, not the jump variation.

Our work is related, and contributes, to several strands of the literature. This is the first study to demonstrate the in-sample and out-of-sample forecasting power of HAR-type models on the term structure of European bond volatility. Thus, it extends the literature that developed following the seminal work by Corsi (2009) and identified the successful forecasting performance of HAR-type for the stock and commodity market volatility (Bollerslev et al. (2018); Dueker (1997); Bollerslev et al. (2016); Bollerslev & Mikkelsen (1996); Degiannakis et al. (Forthcoming); Gong & Lin (2018); Luo et al. (2019); Franses

& Van Dijk (1996); Tian et al. (2017); Wen et al. (2016)). Furthermore, our findings on the importance of jumps for bond market volatility forecasting reveal differences between European markets and the US. While the bond volatility literature (see for example Andersen et al. (2007a)) identifies a negative and insignificant jump effect on future US bond volatility, we show that bond price jumps have a positive impact on European bond return volatility. Our results are in line with those of Corsi et al. (2010) who find that US bond price jumps have a positive and significant impact on US bond return volatility. We also show that the monetary policy announcements are important determinant of bond market volatility and the pre-announcement drift is present in the European bond market using HAR-model structure.

Our analysis is also related to the extant literature that considers the effect of macroeconomic and monetary policy announcements on stock and commodity market volatility forecasting and shows that such announcements, and the associated jumps, are key drivers of volatility releases (Bomfim (2003); Engle & Siriwardane (2018); Evans (2011); Lahaye et al. (2011); Miao et al. (2014); Papadamou & Sogiakas (2018); Rangel (2011); Andersen et al. (2003b); Andersen et al. (2007a); Andersen et al. (2007b); Corsi et al. (2010), Huang (2018); Lee (2012); Prokopczuk et al. (2016); Schmitz et al. (2014))[2]. It is also linked to previous work on the impact of such announcements for US treasuries (Remolona & Fleming (1999); Balduzzi et al. (2001); Andersen et al. (2007b); Corsi et al. (2010); Andersen & Benzoni (2010); Arnold & Vrugt (2010); de Goeij & Marquering

[2]For example, Huang (2018) finds that large stock-price jump variations are more frequently observed during macroeconomic announcement days. Lahaye et al. (2011) show that the US stock market co-jumping behavior is positively affected by macroeconomic news and monetary policy announcements, while Miao et al. (2014) show that macroeconomic news announcements coincide with approximately three-fourths of the intra-day US stock-market index price jumps.

(2006); Ederington & Lee (1993); Jones et al. (1998); Perignon & Smith (2007)) and FX markets (Andersen et al. (2003b); Andersen et al. (2007b)). The empirical studies on the determinants of European bond return volatility tend to focus on the effects of the ECB's QE programme (Zhang & Dufour (2019); Ghysels et al. (2016)) and the link between volatility and liquidity (Beber et al. (2009); O'Sullivan & Papavassiliou (2020)).

The rest of the paper is structured as follows. In Section 2, we provide the information regarding data and methodology. In Section 3 we present the results of our econometric analysis. In Section 4 we report our robustness checks and in Section 5 we provide a brief conclusion along with some policy recommendation and suggestions for further research.

2. Data and Methodology

2.1. Data

In our analysis we include the European sovereign bond markets (UK, Germany, France and Switzerland) using intraday data in the January 2005 – October 2019 period by relying on Thomson Reuters Tick History (TRTH) database. We use 1-, 2-, 5-, 10-, 20- and 30-year maturity bonds in our analysis. The dataset relies on quotes for "on-the-run", generic, instruments which are more liquid in terms off-the-run securities.

There is a wide strand of the literature on optimal intraday sampling frequency using high frequency data in computation of RV (for example Barndorff-Nielsen & Shephard (2004) and Aït-Sahalia et al. (2005)). Zhang et al. (2005) provide a comprehensive review on the causes and effects of sampling bias in the high frequency data dependent volatility estimators. Although, it is inevitable to remove all the microstructure noise from the high frequency data, the problems resulting from sampling frequency are limited when the sampling frequency is 5 minute to 10 minute periods (Zhang et al. (2005)). Andersen et al. (2011) give a detailed framework on robust volatility estimation and how to cope with possible ramifications resulted by microstructure noise. In this paper, we prefer to take into account not only the sampling effect of microstructure noise, but also the liquidity component of noise. While a large part of the RV literature on equity market volatility utilizes 5-minute intervals for the estimation of realized volatility, in the case of European bond markets, we decide to use 10-minute time intervals due to liquidity considerations. The ten-minute sampling frequency for European government bond markets is consistent with the bias-variance tradeoff and large part of the bias is assumed to be vanish at this frequency (Hansen & Lunde (2006)). We additionally control for remaining microstructure noise by employing realized kernel estimators for volatility and provide results using alternative volatility estimators that are more jump robust (see Section 4).

The bonds used in the analysis bear coupon payments and they are subject to changes in terms of underlying notes. Thus, we convert the instruments to zero-coupon securities using the underlying bonds. In zero-coupon estimation, we take into account the changes in the underlying instruments in the daily basis for all securities. When there is a change in the underlying bond of the generic security, we assume the change takes place at the beginning of the trading day. Then, we aggregate the tick data bond returns using 10-minute intraday time intervals between 10:00 am and 4:00 pm to compute daily variations, since the liquidity in the fixed income markets may not be representative during the market opening and closing hours. Also, when defining the volatility indicators as a sum of squared intraday daily logarithmic bond returns, we include the price change between 10:00 am of the next day (t+1) and 4:00 pm of today (t) for the estimation of daily (t) realized volatility.

2.2. The Nelson-Siegel Model

In this paper, we use the Nelson & Siegel (1987) model to obtain zero coupon government bond returns. This model estimates the relationship between interest rates with various maturities by fitting a discount function to bond price data. It assumes the following functional form for the instantaneous forward rates (BIS (2005)).

$$f_{t,m} = \beta_{t,0} + \beta_{t,1} \exp(\frac{-m}{\tau_{t,1}}) + \beta_{t,2} \frac{m}{\tau_{t,1}} \exp(\frac{-m}{\tau_{t,1}}) \tag{1}$$

where, the forward rates $f_{t,m}$ are defined as the instantaneous rates and m is maturity. The parameters, $\beta_{t,0}$, $\beta_{t,1}$, $\beta_{t,2}$ and $\tau_{t,1}$ are estimated by minimizing the squared deviations of theoretical rates of equation (1) and observed rates.

The zero-coupon spot interest rates $s_{t,m}$, are then related to the NS procedure by defining forward rates as instantaneous rates and continuously compounding the forward rate up to given time to maturity as shown below:

$$s_{t,m} = -\frac{1}{m} \int_0^m f(u)du \tag{2}$$

Thus, the NS function for zero coupon interest rates could easily be obtained by combining equations (1) and (2):

$$s_{t,m} = \beta_{t,0} + (\beta_{t,1} + \beta_{t,2})\frac{\tau_{t,1}}{m}\left(1 - \exp(\frac{-m}{\tau_{t,1}})\right) - \beta_{t,2} \exp(\frac{-m}{\tau_{t,1}}) \tag{3}$$

For each 10-minute time interval, the zero-coupon curves of European government bonds are fitted using equation (2). The zero-coupon rates and bond prices of corresponding maturities which are obtained using the NS model, are then used for the estimation of the realized volatility. In this study, we use bond prices (not yields) to estimate bond return volatility.

Since $P(t,T) = \exp(-\tau s_{t,m})$, the return series using prices are scaled to τ,

$$r(t+h,h,\tau) = p(t+h,\tau) - p(t,\tau) \tag{4}$$

where $p(t,\tau) = log(P(t,\tau))$. Then, the intraday return of zero-coupon bond is computed according to equation 5 below:

$$r_\tau\left(t+\frac{ih}{n},\frac{h}{n}\right) = -\tau\left(s_\tau\left(t+\frac{ih}{n}\right) - s_\tau\left(t+\frac{(i-1)h}{n}\right)\right) \tag{5}$$

2.3. Realized Volatility Measurement and Jump Detection

We follow the methodology of Andersen & Bollerslev (1998) for the estimation of realized volatility and jumps in the European sovereign bond markets. As the intraday sampling frequency increases sufficiently, the cumulative sum of intraday returns converges to genuine unobserved volatility, which is the so-called realized volatility (RV) (Andersen & Bollerslev (1998); Andersen et al. (2003a); Barndorff-Nielsen & Shephard (2002, 2004)). Since, the returns are scaled to τ, the volatility series also become proportional to τ^2 as follows:

$$vol^2_{r_\tau}(t+h,h) = \frac{1}{h}\sum_{i=1}^{n}\tau^2\left(s_\tau\left(t+\frac{ih}{n}\right) - s_\tau\left(t+\frac{(i-1)h}{n}\right)\right)^2 \tag{6}$$

Therefore, intraday bond volatility increases by the square of time to maturity. We then re-scale the volatility series, $vol^2_{r_\tau}(t+h,h)$, by τ^2 to obtain comparable realized volatility.

$$RV_\tau(t+h,h) = \frac{1}{\tau^2}\left(vol^2_{r_\tau}(t+h,h)\right) \tag{7}$$

The scaled estimator of volatility as shown in equation (7), ensures that realized bond return volatility satisfies the asymptotic properties of quadratic variation.

In addition to intraday volatility we also focus on the importance of jumps in the intraday basis. In order to decompose realized volatility into its continuous and discontinuous components, we follow the procedure suggested by Barndorff-Nielsen & Shephard (2004). This provides a partial generalization of latent volatility, namely bipower variation (BV), which approaches the continuous part of volatility in continuous sample paths and equally spaced discrete data. In estimating realized BV, we also need to re-scale the return series by the factor of τ. Therefore, the modified BV process is measured as:

$$BV_{\tau}(t+h,h) = (\frac{1}{\tau^2})\mu_1^{-2}(\frac{n}{n-1})\sum_{i=2}^{n}|\Delta_{i-1}p(t+\frac{(i-1)h}{n})||\Delta_i p(t+\frac{(i)h}{n})| \tag{8}$$

where $\mu_1 = \sqrt{2}/\sqrt{\pi}$.

The first term in equation (8), $1/\tau^2$, modifies the BV parameter proposed by Barndorff-Nielsen & Shephard (2004) as an extension for bond returns which have different time to maturity. In this article, we follow the jump separation process of Barndorff-Nielsen & Shephard (2004), where the realized volatility is assumed to have a continuous, quadratic variation, and a discontinuous, jump, component. The logarithmic price of government bond is assumed to follow a semi martingale process, which can be formalized as a drift term plus a local martingale. Thus, a general class of arbitrage free return process is given below:

$$dp(t) = \mu(t)dt + \sigma(t)dw(t) + \kappa(t)dq(t), 0 \leqslant t \leqslant T. \tag{9}$$

where $\mu(t)$ is a drift term having a locally finite variation process and the rest constitutes local martingale. $\sigma(t)$ is a strictly positive continuous volatility process with discrete jumps $\kappa(t)$. Barndorff-Nielsen & Shephard (2004) show that the quadratic variation equals to the integrated variance of instantaneous returns as given in Equation 10 below:

$$vol^2 \rightarrow QV \equiv \int_{t-1}^{t} \sigma^2(s)ds + \sum_{t-1<s\leqslant t} \kappa^2(s) \tag{10}$$

Therefore, equation (10) ensures that the realized volatility estimator does not converge to integrated volatility due to presence of the discrete jump process even under observing no noise in the prices. Barndorff-Nielsen & Shephard (2004) extend the analysis on volatility and indicate that BV is an unbiased estimator of integrated variance (IV), asymptotically. Then BV is approximated as shown below:

$$BV \rightarrow IV \equiv \int_{t-1}^{t} \sigma^2(s)ds, for\ n \rightarrow \infty \tag{11}$$

Thus, using equations (10) and (11), it is trivial to obtain an approximation of jump variation[3].

$$RV - BV \rightarrow \sum_{t-1<s\leqslant t} \kappa^2(s), for\ n \rightarrow \infty \tag{12}$$

Under the assumption of absence of jumps:

$$\sqrt{n}(RV - BV) \longrightarrow MN(0,\ 2IQ), \tag{13}$$

where IQ is integrated quarticity.

In addition, integrated variation (IQ) could be represented by a generalized realized power quarticity measure, namely tripower quarticity (TQ), which is a robust and consistent estimator of IV even in the presence of jumps (Barndorff-Nielsen & Shephard (2002)

[3]Barndorff-Nielsen & Shephard (2004) give the definitions of realized volatility (RV) and bipower variation (BV) for a general asset class, which does not have any time to maturity. Since our estimations are based on bond data, in order to have a comparable estimates, we scaled the return series by $1/\tau$ and thus RV and BV series by $1/\tau^2$.

and Andersen et al. (2007a)). We compute TQ as follows[4]:

$$TQ \equiv n\mu_{4/3}^{-3} \sum_{i=3}^{n} |\Delta_{i-2} p(t + \frac{(i-2)h}{n})|^{4/3} |\Delta_{i-1} p(t + \frac{(i-1)h}{n})|^{4/3}$$
$$|\Delta_i p(t + \frac{(i)h}{n})|^{4/3}, \tag{14}$$
$$where\ TQ \rightarrow \int_{t-1}^{t} \sigma^4(s) ds\ for\ n \rightarrow \infty$$

Since, we assume that there exists a discrete jump variation process in the asset returns, we follow the jump detection methodology, according to which a jump occurs when the ratio statistic is significant. In the literature, there are plenty of jump detection techniques, which are compared in Huang & Tauchen (2005). They find that the usage of ratio-statistics gives more powerful results than the test-statistics provided by Barndorff-Nielsen & Shephard (2004). We use the following ratio statistic to identify statistically significant bond price jumps following Huang & Tauchen (2005):

$$z = n^{-1/2} \frac{[RV - BV] RV^{-1}}{\sqrt{(\mu_1^{-4} + 2\mu_1^{-2} - 5) \max\{1, \frac{TQ}{BV^2}\}}} \sim N(0,1) \tag{15}$$

We use z-test statistics in order to identify the statistically significant bond price jumps in our sample. This test has powerful properties and is quite accurate at detecting asset price jumps (Huang & Tauchen (2005); Andersen et al. (2007a); Wright & Zhou (2009); and Tauchen & Zhou (2011)).

2.4. Realized Semivariance

The dynamic dependencies between volatility and underlying returns is also the research focus in the empirical volatility literature. In this study, we look for the relevance

[4]Similar to RV and BV estimations, TQ measure also requires scaling with respect to time to maturity. Hence $TQ' = TQ/\tau^4$.

of feedback effect, which is defined as the relationship between contemporaneous returns and volatility by Bollerslev & Zhou (2006), in the government bond markets [5].

To observe the feedback effect we follow the seminal procedure of Barndorff-Nielsen et al. (2010) by estimating realized semivariance, which is then extended by Patton & Sheppard (2015) to incorporate the impact of signed jumps.

Realized semivariances (RSV) for positive and negative intraday returns are computed as follows:

$$RSV_{\tau}^{+} = \frac{1}{\tau^2}\sum_{i=1}^{n}|\Delta_i p(t+\frac{(i)h}{n})|^2 I\Big(\Delta_i p(t+\frac{(i)h}{n}) > 0\Big), \quad (16)$$

$$RSV_{\tau}^{-} = \frac{1}{\tau^2}\sum_{i=1}^{n}|\Delta_i p(t+\frac{(i)h}{n})|^2 I\Big(\Delta_i p(t+\frac{(i)h}{n}) < 0\Big), \quad (17)$$

where $RV_{\tau} = RSV_{\tau}^{+} + RSV_{\tau}^{-}$

In the equation (16) and (17), $I(.)$ corresponds to indicator function. RSV series are calculated in the intraday basis in line with RV.

2.5. Heterogeneous Auto-Regression Model

In the HAR model of Corsi (2009), it is assumed that the heterogeneous markets hypothesis (HMH), which depends on market participants' non-homogeneity in terms of expectations and behaviors, is valid. Therefore, the general pattern of volatility structure can be generated from three different frequencies. The high frequency component for short-term traders is reflected by daily volatility, for medium-term traders by weekly volatility

[5]The asymmetric response of current volatility to the lagged returns with respect to the sign of returns was firstly introduced by Black (1976). Although the empirical findings of the literature indicate that such an asymmetry exists, its power is found to be weak and insignificant (Nelson (1991) and Bekaert & Wu (2000)). In addition, Bollerslev & Zhou (2006) provide empirical evidence that there is no significant relationship between contemporaneous returns and volatility, therefore they reject the presence of feedback effect.

and for investors focusing on long term trends by monthly volatility. Although the HAR structure does not externally impose long memory in the volatility process, the cascade type model generates slow decaying memory for the forecast horizons.

To represent weekly and monthly trends, we use simple averages as below.

$$RV_{t_1:t_2} = \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} RV_t, \ where\ t_1 \leqslant t_2. \tag{18}$$

Then, weekly and monthly averages[6] are given in the (19) below:

$$RV_{t-5:t-2} = \frac{1}{4} \sum_{t=t-5}^{t-2} RV_t. \tag{19}$$

$$RV_{t-22:t-6} = \frac{1}{17} \sum_{t=t-22}^{t-6} RV_t. \tag{20}$$

Then, HAR-RV model [7] is given in (21):

$$RV_{t+h-1:t} = \beta_0 + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t, \tag{21}$$

h corresponds to forecast horizon.

We decompose the continuous and discontinuous part of RV by following Barndorff-Nielsen & Shephard (2004). Using the discontinious jump variations, we can employ extended HAR models such as HAR-RVJ model and HAR-CJ model of Andersen et al. (2007a). The inclusion of jump parameters in the volatility forecasting regressions enable us to measure the possible magnitude of daily jumps on the future volatility and its

[6] We prefer to use non-coinciding periods in the HAR variables to avoid double counting lagged observations.

[7] For simplicity, we report the general form of HAR model, while the estimations are conducted using realized volatility, $RV^{1/2}$, in exchange for realized variance, RV.

significant life span in the investment horizon.

We identify the significant jump series using jump ratio test of Huang & Tauchen (2005):

$$\hat{J}_t = I_{z_t > \psi_\alpha}(RV_t - BV_t)^+, \tag{22}$$

where ψ_α is the cumulative distribution function at α confidence level. In this paper we choose $\alpha = 0.999$, which corresponds to a critical value of 3.0902. In addition $(RV_t - BV_t)^+$ stands for $\max(0, RV_t - BV_t)$ and $I_{z_t > \psi_\alpha}$ is the indicator function that takes values of unity when there is a significant jump.

Then, the continuous part quadratic variation accounting for the significant jumps given in (23).

$$\hat{C}_t = RV_t - \hat{J}_t \tag{23}$$

We also compute weekly, $\hat{C}_{tt-5:t-2}$, and monthly, $\hat{C}_{tt-22:t-6}$, continuous variation series, $\hat{C}_t$ similar to (19) and (20).

$$\hat{C}_{tt-5:t-2} = \frac{1}{4} \sum_{t=t-5}^{t-2} \hat{C}_{tt}. \tag{24}$$

$$\hat{C}_{tt-22:t-6} = \frac{1}{17} \sum_{t=t-22}^{t-6} \hat{C}_{tt}. \tag{25}$$

Therefore, it becomes natural to extend the HAR-RV model to include the effect of continuous and jump variation separately.

HAR-RVJ model:

$$RV_{t+h-1:t} = \beta_0 + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t \tag{26}$$

HAR-CJ model:

$$RV_{t+h-1:t} = \beta_0 + \beta_d \hat{C}_{t-1} + \beta_w \hat{C}_{t-5:t-2} + \beta_m \hat{C}_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t \tag{27}$$

3. Empirical Findings

3.1. Descriptive Statistics

In this section we present the descriptive statistics of our time series sample. Table 1 and 2 below shows the descriptive statistics for our explanatory time series variables.

[Table 1 about here.]

[Table 2 about here.]

We report summary statistics of realized volatility, $\sqrt{RV}$, and significant realized jumps, $\sqrt{\hat{J}}$, for European treasury bond markets. Our descriptive statistics reveal that the volatility term structure of European government bond markets indicates U-shaped pattern in the intraday basis since the mean of RVs for short and long term maturities is higher than the mean of medium term maturities. The same pattern is followed for the volatility-of-volatility term structure (standard deviation of RVs) of European treasury bonds. On the other hand, there is no clear evidence of similar behavior for the realized jump series in Table 2.

Figure 1 shows the boxplots of intraday volatility across European T-bond markets across the maturity span.

[Figure 1 about here.]

In all of the markets except France the volatility shows a U-shaped path for all the maturities. Moreover, the 1-year and 30-year maturities are more volatile compared to the other maturities. Also, the volatility of the volatility can be inferred from the spread between 1st and 3rd quartile of the plots. It is obvious that volatility of volatility is higher for short-term maturities, while some upward outliers are observed for the longer-term maturities.

Figure 2 and 3 show the boxplots of the realized semivariances (RSV).

[Figure 2 about here.]

[Figure 3 about here.]

Similar to the realized volatility in Figure 1, RSV series indicate a U-shaped pattern in the volatility yield curve with respect to 2^{nd} and 3^{rd} quartiles. In addition, the interquartile range for 1-year and 30-year securities is higher than the other maturities. In any quartile of the boxplot figures, we do not observe any fraction between negative and positive semi-variances so any feedback effect. Therefore, in line with the literature (Nelson (1991); Bekaert & Wu (2000); and Bollerslev & Zhou (2006)) we reject asymmetry hypothesis between contemporaneous bond returns and volatility.

The most straightforward comparison is likely to be made between France and Germany sovereign bond markets due to euro-denomination. Except for 1-year T-bill, French markets are found to be reflecting higher level of volatility in median and other quartiles.

Figures 4 to 7 gives the realized volatility series for the major European bond markets between January 2005 to October 2019.

[Figure 4 about here.]

[Figure 5 about here.]

[Figure 6 about here.]

[Figure 7 about here.]

These figures reveal a high degree of volatility co-movement across the maturity and market spectrum. We observe that government bond volatility peaks in the GFC period and also the sovereign debt markets are faced with another common high volatility period during the European debt crisis of 2010. These periods constitutes the most important disruption periods in the sample period.

In addition to the crisis impact on the bond yields and volatility, another key driver of heightened European bond volatility is the 2016 United States presidential elections. In addition to the surprising result of the election, the promises of expansionary fiscal policies in tax-cuts and infrastructure expenditures resulted in euphoria mood in the stock markets and at the same time triggered a sell-off in the bond markets in the November 2016 due to heightened risk in the US budget balance. Andersson et al. (2009) study the causes that moves bond markets in the Euro area and shows that bond markets are more sensitive to the US related news due to investor perceptions on US as a main global factor. In this perspective, our findings validate Andersson et al. (2009) since we show that the uncertainty generated by the elections at the end of 2016 is transmitted to the major European bond markets.

Moreover, from Figures 4 to 7 we can easily see that Brexit referendum on June 2016 has a positive impact on the volatility term structure of the UK government bond market. On the contrary, the low reaction of 1-year UK T-bond volatility shows that the effect of UK's decision to leave EU had an effect in medium to long-run UK bond market expectations. Also, before and after the Brexit vote, financial market participants tried to hedge their positions by increasing their allocations of safe haven securities, specifically Japanese yen and Swiss franc denominated assets. This created a gradual rise in the volatility of Swiss bond market.

In terms of idiosyncratic volatility periods, our analysis shows that the most significant country-specific event was the removal of Swiss franc peg to euro, which resulted an immense volatility clustering in Swiss financial markets. On 15th January 2015, the Swiss National Bank unexpectedly removed the peg of franc to euro, which was effective since 2011. This decision led to massive impact on Swiss FX and bond markets and resulted to increase Swiss bond return volatility during this period. In addition, our analysis shows that German bond volatility increased during May-June 2015, which is known as ”bund tantrum”. The tantrum in the bond markets is mainly attributed to the ECB’s Public Sector Purchase Program (PSPP) that is introduced in early 2015. While, low interest rate and quantitative easing policies tame the market volatility in the bond markets, its impact on liquidity makes the government bond markets more fragile and open to sudden volatility spikesBIS (September 2015)[8]. During this period the large price swings in the intraday basis lead to volatile bond markets due to deterioration of liquidity especially in the medium to long run securities (see Figure 7). These initial descriptive results are some preliminary evidence showing the significant effect of major macroeconomic events (e.g Brexit) on the volatility term structure of European bond markets.

3.2. HAR Results

In this section we present the volatility forecasting results of our HAR-type models. The econometric results for the Swiss, German, French and UK realized bond return

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[8]In BIS (September 2015), it is stated that the ECB purchased 46.3 billion of German bonds by June 30, 2015 since the start of PSPP.

volatility term structure are given in Tables 3 to 10 [9] [10].

[Table 3 about here.]

[Table 4 about here.]

[Table 5 about here.]

[Table 6 about here.]

[Table 7 about here.]

[Table 8 about here.]

[Table 9 about here.]

[Table 10 about here.]

In order to compare the results of the volatility forecasting models we follow the procedure proposed by Patton (2011) according to which the $QLIKE$ loss function gives the most robust estimator in assessing volatility forecasts using imperfect volatility proxies.

[9] We exclude the Swiss Treasury bond with 2-year maturity from our analysis due to some non-convergences in the estimations.

[10] We report in-sample and out-of-sample forecast results for 1-day and 22-day forecast horizons. The results regarding 5-day forecast horizon are given in the Online Appendix.

Additionally, we use Mincer-Zarnowitz (MZ) R^2 of forecasting regressions' for evaluating performance.

$$QLIKE = \frac{1}{T}\sum_{t=1}^{T}(\frac{RV_t}{\hat{RV}_t} - log(\frac{RV_t}{\hat{RV}_t}) - 1), \tag{28}$$

where RV_t is estimated using equation 21, 26 and 27.

We also report the $QLIKE$ and MZ R^2 when there is a jump at time "t-1", which is denoted with J, and when the path is continuous for RV_{t-1}, denoted with C. These HAR-type models are similar to those of Corsi et al. (2010) for US financial markets.

The results presented in Tables 3 to 10, indicate that daily, weekly and monthly trends of volatility are robust determinants of future bond market volatility, regardless of forecasting horizon and time to maturity of the securities. More specifically, the estimated coefficients of daily, weekly and monthly realized variance are positive and statistically significant when forecasting European government bond volatility term structure in the short (1-day) and medium term (weekly and monthly) horizons. In the HAR-type models of Corsi (2009), we aggregate realized volatilises over diverse set of horizons, which is assumed to reflect the MDH and therefore relative contributions (weights) of non-homogeneous investors in the market volatility. As a result, short-term traders are found to have a largest impact on the volatility for one day forecasting horizon, while the impact of longer term traders seem to increase as the forecasting horizon extends.

When the realized volatility is decomposed into its continuous and jump components, the jump variations have a high and positive effect on future volatility. The jump tail risk measure have a significantly positive effect on the volatility forecasts and its impact on volatility is found to be persistent for 1-day to 22-day horizons. Although, the contribution of jump variation is present, its magnitude and effectiveness are relatively reduced as the forecasting horizon increases. Our contribution in the relevant literature, is that we show for the first time in the volatility literature that jump tail risk is a significant determinant of volatility in European Treasury bond markets. While the relevant literature so far has shown that the jump coefficient in the HAR-CJ model on equity (Forsberg & Ghysels (2006); Giot & Laurent (2007); Busch et al. (2011)) and bond market volatility (Corsi et al. (2010);Andersen et al. (2007a)) is negative and/or insignificant, we show that jumps play a significant role when forecasting European bond market volatility.

Moreover, our analysis is the first to show the superior forecasting power of HAR-type when used for European bond volatility forecasting, when compared to those of the literature focusing on US bond volatility forecasting. For example, we report in sample R^2 values ranging from 40% to 80%, while Andersen & Benzoni (2010), when testing the HAR regression model for US treasury bond market their R^2 values ranging from 15% to 20%. Hence, our analysis is the first to show that HAR-type volatility models explain a much larger part of time varying volatility in European bond markets as opposed to US bond markets.

We additionally examine the out-of-sample forecasting performance of the HAR-type volatility models using a rolling window. Tables 11 and 12 below report the out-of-sample forecasting results.

[Table 11 about here.]

[Table 12 about here.]

Our results are in-line with those of the literature (see Andersen et al. (2007a); Corsi et al. (2010); Bollerslev et al. (2016); and Bollerslev et al. (2018)), as we find that the inclusion of jump variation as an explanatory variable helps to reduce forecast errors. According to Diebold-Mariano forecast comparison test results, extending HAR model as

HAR-RVJ and HAR-CJ improves the QLIKE loss functions significantly for most of the government bonds.

In addition, we report average out-of-sample forecast regression R^2s. Our out-of-sample forecasting exercise show that the HAR-type models produce significant out-of-sample forecasts with out-of-sample R^2s ranging from 20% to 70%. As expected, the out-of-sample forecasting power is higher when forecasting the volatility of treasury bonds with short-term maturity[11].

3.3. Monetary Policy and Bond Market Volatility

Through risk taking and uncertainty channels monetary policy is the determinant of market volatility. In the literature, US stock and bond market volatility is largely attributed to monetary policy shocks and to the news regarding monetary policy(see Bekaert et al. (2013); David & Veronesi (2014); Bruno & Shin (2015); Triantafyllou & Dotsis (2017); and Mallick et al. (2017)). Motivated by these findings, we examine the impact of monetary policy meetings on realized volatility of European government bonds in the intraday basis. Figure 8 shows the response of financial markets to the monetary policy announcements among major European central banks. Firstly, the announcement calendar of Swiss National Bank (SNB) is irregular in the estimation period. SNB announces the policy decision on 8:30 (GMT), 12:00 (GMT) and 13:00 (GMT), while the most frequent time is 8:30 (GMT). As we observe, on the top left of Figure 8, the volatility of Swiss bonds during these announcement dates is higher at the focused interval and its impact persists for one day long. Secondly, European Central Bank (ECB) always announces the decision

[11]For brevity, we do not include the forecasting regression results for weekly (5-day) forecasting horizon. These additional results can be found in the Online Appendix. These estimations also verify that the inclusion of the jump variation into HAR-type models improves out-of-sample volatility forecasts for European government bond markets.

on 12:45 (GMT). It is obvious that for France (bottom left of Figure 8), and Germany (top right of Figure 8), bond markets exhibit a gradual rise in the volatility especially after the ECB announcement and during the governor's press conference. Lastly, the Bank of England (BoE) monetary policy meeting announcements are released on 12:00 (GMT), that is when UK gilt volatility (bottom right of Figure 8), shows a sudden spike[12].

[Figure 8 about here.]

[Figure 9 about here.]

The jump variations for bond markets signal at least one jump in 80% of all central bank monetary policy announcement days for Swiss market, at least one jump in 42% for German market, at least one jump in 34% for French market and at least one jump in 40% for UK market. Therefore, our results show that monetary policy (MP) announcements are key drivers and early warning signals of increasing turbulence in European government bond markets. Figure 10 reports the average jumps and volatility of the yield curve on the announcement dates[13].

[Figure 10 about here.]

The volatility spikes and presence of jumps in the MP announcement days pave us the way for studying the timing and the dynamics of the bond market volatility. In this framework, we investigate whether there exist any impact of the meeting days on the volatility forecasting dynamics in the HAR framework. Lucca & Moench (2015) document that there is a presence of excess return in the US equity market before the FOMC meetings,

[12]The absolute returns for time of the day basis given in Figure 9.

[13]The distribution of jumps are available upon request.

which is then called as pre-FOMC drift. The excess return is justified by bearing non-diversifible risk and systemic risk around the meeting (see Lucca & Moench (2015) for more detail). In addition, Guo et al. (2020) show that pre-FOMC drift is depended on underlying economic sentiment and uncertainty. In this paper, we focus on the impact of pre-announcement and announcement day drifts on bond market volatility forecasts.

In this paper, we focus on pre-MP announcement, called as pre-announcement, impact on European bond market volatility. As to our knowledge it is the firs paper trying to explain the pre-meeting impact in the volatility forecasting framework.

In order to test the impact of MP announcement, we simply extend HAR-RV models with incorporating a pre-announcement date and announcement date dummy variables, separately. Therefore, HAR-RV model[14] becomes:

$$RV_{t+h-1:t} = \beta_0 + \beta_d^1 RV_{t-1} 1(pre - announcement) + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t, \tag{29}$$

and

$$RV_{t+h-1:t} = \beta_0 + \beta_d^1 RV_{t-1} 1(announcement) + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t. \tag{30}$$

Table 13 gives the results for extended HAR-RV model using pre-announcement day dummy variable. Firstly, the contribution of daily lagged volatility onto future volatility in the non-announcement day forecasts is only material apart from the results in the previous section, which validates the robustness of estimations. In this study, we call the relationship between forecast period and daily lag as volatility transmission. Our results

[14] Similar to the previous subsection, we conduct our analysis using realized volatility, $\sqrt{RV}$. For simplicity, we continue to give general HAR model representation.

indicate that the volatility transmission sensitivity of forecasts increases by almost 40% in pre-announcement days. Increased sensitivity to the daily volatility in terms of 1-day forward volatility corresponds to faster movement of the markets before the monetary policy announcements. This outcome can be interpreted as an evidence on the presence of pre-announcement drift in the bond market. Therefore, inclusion of day dummy variable highlights the importance of pre-announcement drift in the European bond market.

In addition, we analyze the announcement drift after the European central banks' meetings using equation 30. Table 14 shows that there is no change on the underlying dynamics of HAR forecasting relationship after the MP announcement. This result provides the idea that the after the announcement short term tension is tamed by the central banks in the European government bond markets, which can be interpreted as an evidence of "buy the speculation, sell the fact" behavior of financial market agents. After the monetary policy announcements generally the opportunity to speculate in the markets evaporates and markets tends to turn back its own fundamentals.

[Table 13 about here.]

[Table 14 about here.]

Moreover, we test the source of pre-announcemet drift in the integrated variation and jump variation framework. Therefore, we estimate the extended model of HAR-CJ as follows:

$$RV_{t+h-1:t} = \beta_0 + \beta_d^1 C_{t-1} 1(pre - meeting) + \beta_j^1 J_{t-1} 1(pre - meeting) + \beta_d \hat{C}_{t-1} + \beta_w \hat{C}_{t-5:t-2} + \beta_m \hat{C}_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t \quad (31)$$

[Table 15 about here.]

Table 15 show that the transmission effect is still significantly higher on the days before policy announcements, even though its magnitude is weaker. Our results indicate that the pre-announcement drift is mostly resulted by the continuous component of the daily lagged volatility not the jump variation.

4. Robustness

4.1. Market Microstructure Noise

In the realized volatility (RV) literature, the estimates are assumed to provide perfect estimators of quadratic variation (QV) under continuous time and without measurement error. Therefore, using the highest possible homogeneous discrete time frequency sum of squared returns is assumed to approximate true QV as the sampling frequency increases up to tick-by-tick observation.

On the other hand, in practice it is emphasized that the presence of microstructure noise causes the bias in the estimates that significantly increases the error in the high frequency based estimators (see Zhou (1996) and Hansen & Lunde (2006)). The market microstructure noise is generally documented by providing the intraday sampling frequency impact on estimates[15]. Even though, using high frequency data poses the microstructure related noise, volatility signature plots indicate that there is a trade-off between frequency and RV estimation (Hansen & Lunde (2006)). Therefore, the estimations are constructed by using moderate frequency, as 5 minutes to 20 minutes, to handle the bias (see Zhang et al. (2005)). In addition to using optimal sampling frequency, there are some filtering (Andersen et al. (2003a)), two-scales estimator (Zhang et al. (2005)) and kernel-based techniques

[15]Zhang et al. (2005) document a review on the impact of sampling bias using volatility signature plots.

(Barndorff-Nielsen et al. (2008, 2009)) used in the literature in providing remedies to the market microstructure noise.

Since the seminal work by Zhou (1996), realized kernels in the volatility estimation became popular. In this paper, we follow Barndorff-Nielsen et al. (2008, 2009) to construct realized kernels, RK, which help in controlling the noise generated by microstructure noise. The RV_{Kernel} is formed as follows:

$$RV_{Kernel} = \sum_{h=-H}^{H} k\Big(\frac{h}{H+1}\Big)\gamma_h, \tag{32}$$

where $\gamma_h = \sum_{i=1}^{n} \Delta p_{i,n} \Delta p_{i-h,n}$[16] and $k(x)$ is non-stochastic weight function.

Following 32, Hansen & Lunde (2006) propose RV_{AC_1} to correct bias in the realized volatility measure, where $k(x)$ is equal to unity, which is a restricted version of kernel-type estimators.

RV_{AC_1} is given as follows:

$$RV_{AC_1} = \sum_{i=1}^{n} \Delta p_{i,n}^2 + \sum_{i=1}^{n} \Delta p_{i,n} \Delta p_{i-1,n} + \sum_{i=1}^{n} \Delta p_{i,n} \Delta p_{i+1,n}, \tag{33}$$

This estimator provides more efficient measure and reduces the noise compared to RV estimators (Hansen & Lunde (2006)).

In this paper, we estimate RV_{AC_1} and RV_{Kernel} as alternative realized variance estimators. Unfortunately, the intraday based volatility estimator using $AC-type$ model suffers from negative values. In order to overcome the negativity problem, we employ the Parzen kernel, which guarantees the non-negative estimates of volatility[17].

[16] $\Delta p_{i,n}$ corresponds to logarithmic change in prices.

[17] In the Parzen kernel weighting function, we follow Zhou (1996), where H is equal to one (Barndorff-Nielsen et al. (2008)).

Hansen & Lunde (2006) assert that the asymptotic variance of RV_{AC_1} increases as the sampling frequency n increases. As a result of the trade-off between sampling frequency and estimation noise, intraday returns should not be sampled at the highest possible frequency. In addition to using a moderate sampling frequency, utilization of the realized kernel based estimators helps more in reducing microstructure noise in the estimations.

The robustness results indicate that there our main findings remain unaltered if we RK instead of RV in the volatility modelling. Table 16 reports the out-of-sample regression results of volatility forecasts. It verifies that inclusion of jump variation into the HAR model improves volatility forecasts for most of the European bond markets.

[Table 16 about here.]

4.2. Alternative Volatility Estimator

In addition to market microstructure noise, realized volatility models suffer from finite sample jump distortion that can result in upward bias in jump estimators. In order to achieve asymptotically more feasible results, we employ the estimators proposed by Andersen et al. (2012), which use nearest neighbor truncation. We estimate "MinRV" and "MedRV" as jump robust estimators in exchange for bipower variation (BV) and their relevant tripower variation measures, namely "MinRQ" and "MedRQ" in order to measure the significance of daily jumps.

Firstly, we compute "MinRV" as summing the square of the minimum of two sequential absolute returns as follows:

$$MinRV_{\tau} = (\frac{1}{\tau^2})\frac{\pi}{\pi - 2}(\frac{n}{n-1})\sum_{i=1}^{n-1} min\Big(|\Delta_i p(t + \frac{(i)h}{n})|, |\Delta_{i+1} p(t + \frac{(i+1)h}{n})|\Big)^2 \tag{34}$$

where, $min(.,.)$ corresponds to the minimum of the returns.

MinRV benefits from one-sided truncation in estimating jump robust volatility estimator. On the other hand, MedRV depends on two-sided truncation as taking the median value of three consecutive absolute returns in volatility estimation as follows:

$$MedRV_\tau = (\frac{1}{\tau^2})\frac{\pi}{6-4\sqrt{3}+\pi}(\frac{n}{n-2})\sum_{i=2}^{n-1} med\Big(|\Delta_{i-1}p(t+\frac{(i-1)h}{n})|, |\Delta_i p(t+\frac{(i)h}{n})|, |\Delta_{i+1}p(t+\frac{(i+1)h}{n})|\Big)^2 \quad (35)$$

where, $med(.,.,.)$ corresponds to the median of the returns.

The jump robust estimators have their unique asymptotic distribution properties for constructing jump statistics given in Andersen et al. (2012).

$$\sqrt{n}(RV - MinRV) \longrightarrow MN(0,\ 3.81IQ),$$
$$\sqrt{n}(RV - MedRV) \longrightarrow MN(0,\ 2.96IQ). \quad (36)$$

where IQ is integrated quarticity.

Also, alternative to tripower quarticity given in 14, we estimate "MinRQ" and "MedRQ".

$$MinRV_\tau = (\frac{1}{\tau^4})\frac{\pi n}{3\pi-8}(\frac{n}{n-1})\sum_{i=1}^{n-1} min\Big(|\Delta_i p(t+\frac{(i)h}{n})|, |\Delta_{i+1}p(t+\frac{(i+1)h}{n})|\Big)^4 \quad (37)$$

, and

$$MedRV_\tau = (\frac{1}{\tau^4})\frac{3\pi n}{9\pi+72-52\sqrt{3}}(\frac{n}{n-2})\sum_{i=2}^{n-1} med\Big(|\Delta_{i-1}p(t+\frac{(i-1)h}{n})|, |\Delta_i p(t+\frac{(i)h}{n})|, |\Delta_{i+1}p(t+\frac{(i+1)h}{n})|\Big)^4 \quad (38)$$

Then, we adjust the jump z-test with respect, 15 to the asymptotic distribution of truncation based estimators, given in 36.

The volatility forecasting results of European bond markets are in line with the results in Section 3. For the one-day forecasting in sample regressions indicate the jump variation is a significant predictor of fuure volatility, while the impact of jump variation is tend to die out as the forecasting horizon increases[18]. In addition out-of-sample regression results verifies that inclusion of jump variation into the HAR model improves volatility forecasts for most of the bond markets.

5. Conclusion

In this paper, we study the forecasting power of HAR-type models on the volatility term structure of European government bond markets using intraday data covering the period from January 2005 up until October 2019. Our econometric analysis shows that the daily, weekly and monthly realized variance is a robust predictor of volatility in European government bond markets. In addition inclusion of jump variation helps to improve volatilty forecasts. Overall, our HAR models exhibit extraordinary in-sample and out-of-sample forecasting power with in sample R^2s ranging from 50% to 80% and out-of-sample R^2s ranging from 20% to 75%. Moreover, our analysis shows that 83% of central bank rate decisions for Swiss market, 42% for German market, 34% for French market and 40% for UK market coincide with at least one statistically significant bond price jump. In addition, our HAR-type models identify the significant predictive power of jumps on Treasury bond volatility. Hence our analysis implicitly reveals that monetary policy announcements are early warning signals of rising volatility in European bond markets. Our results also indicate the presence of pre-monetary policy meeting drift in the bond markets.

To the best of our knowledge, this is the first study that forecasts European bond volatility in the intraday basis using HAR-type cascade model. Secondly, our findings indicate

[18]The results of estimators using nearest neighbor truncation are given in the Online Appendix.

that the discrete jumps which are associated with monetary policy announcements, are effective in ex-post bond return volatility forecasting. Thirdly, this paper reveals the dynamics of the volatility dependency structure of major European bond markets, where findings indicate that the future volatility is significantly affected by its short and medium term trend components. We also show that the monetary policy announcements are important determinant of bond market volatility and the pre-announcement drift is present in the European bond market using HAR-model structure.

The policy recommendation which comes out of our analysis, is that since monetary policy announcements are key determinants (and significant early warning signals) of rising volatility in the respective Treasury bond markets, then the central banks are able to indirectly reduce instability in the respective bond markets if needed. For example, according to our analysis, a reduction of monetary policy announcements during a given time period, will result to less turbulence and instability in European treasury markets during this period.

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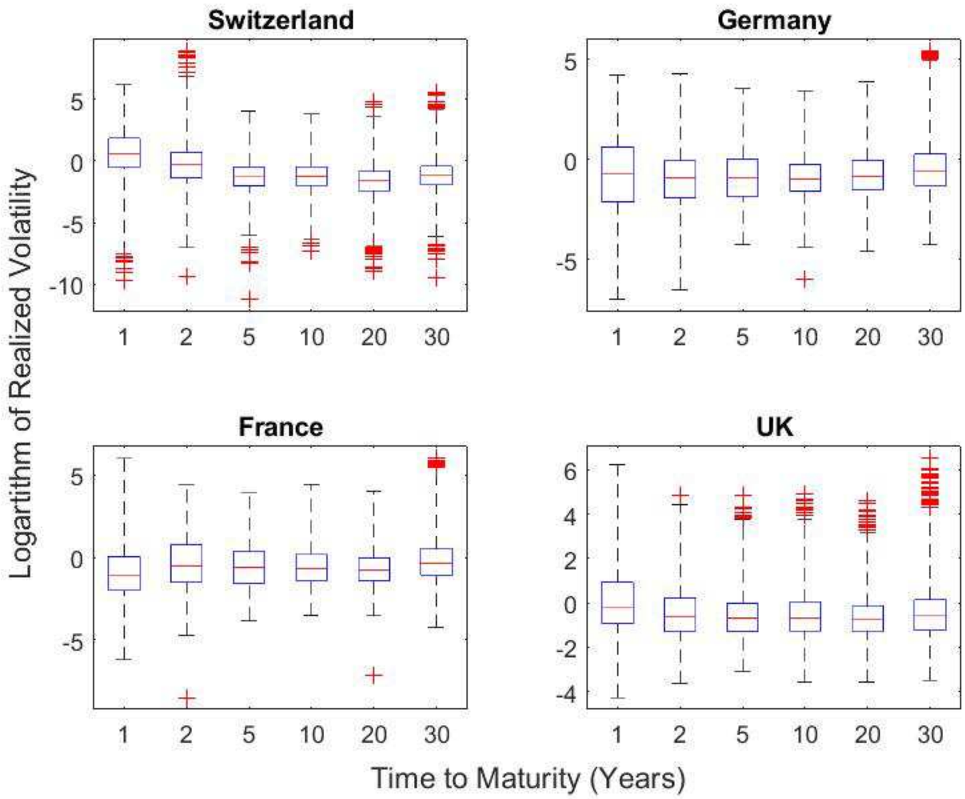

Figure 1: **Box Plot of RV**

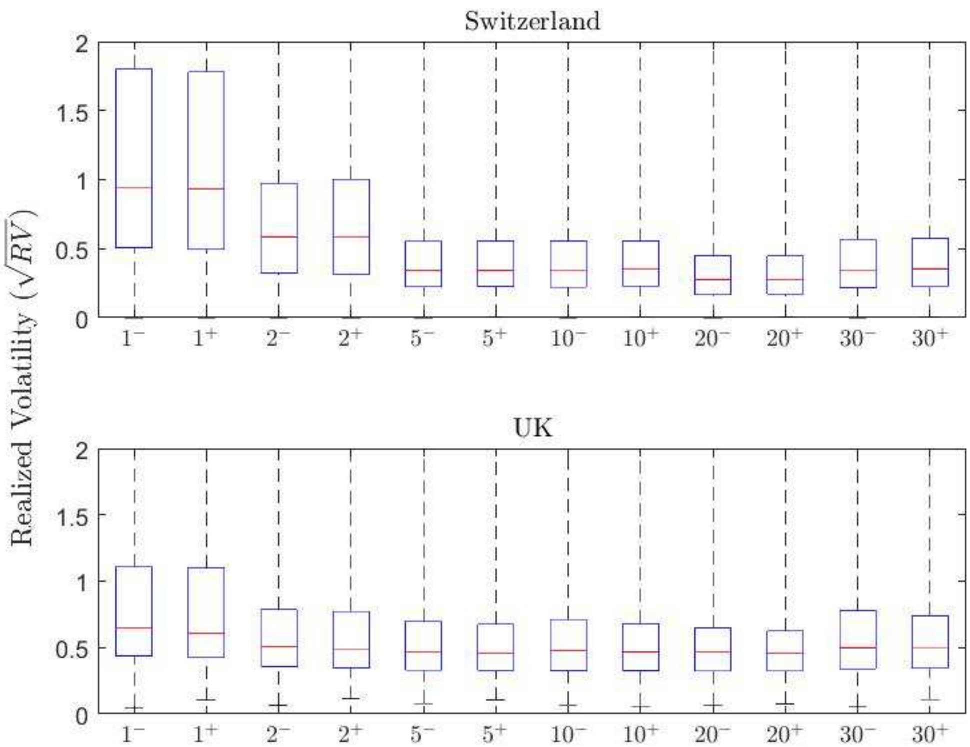

Figure 2: **Feedback Effect:** Box Plots of Negative, RSV^-, and Positive, RSV^+, Semi-variances across Maturity Span

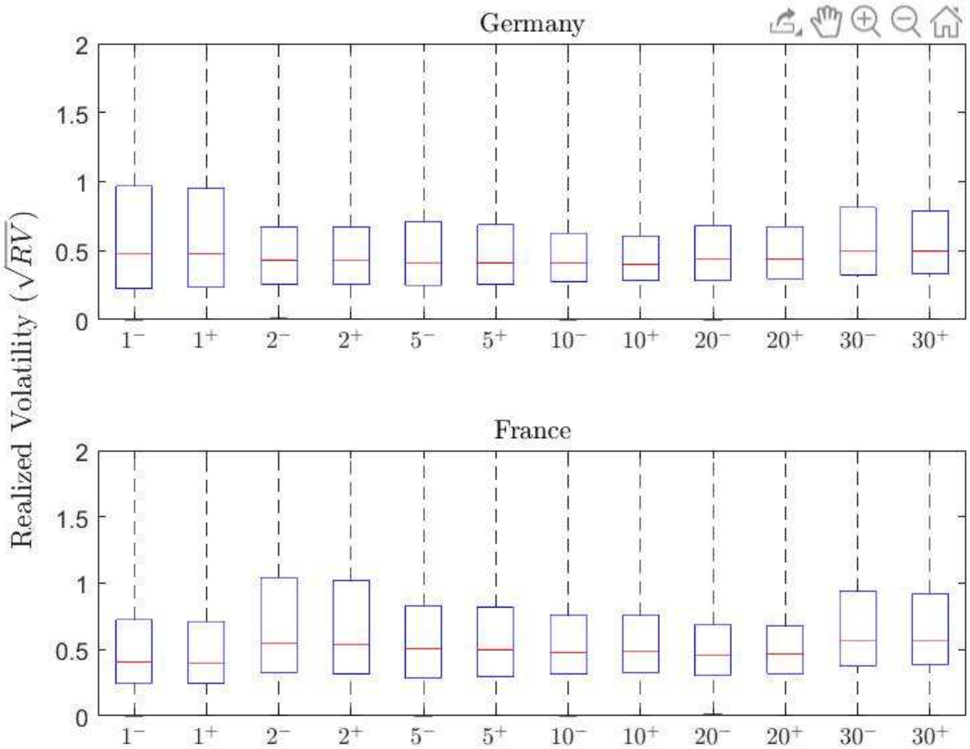

Figure 3: **Feedback Effect:** Box Plots of Negative, RSV^{-}, and Positive, RSV^{+}, Semi-variances Maturity Span

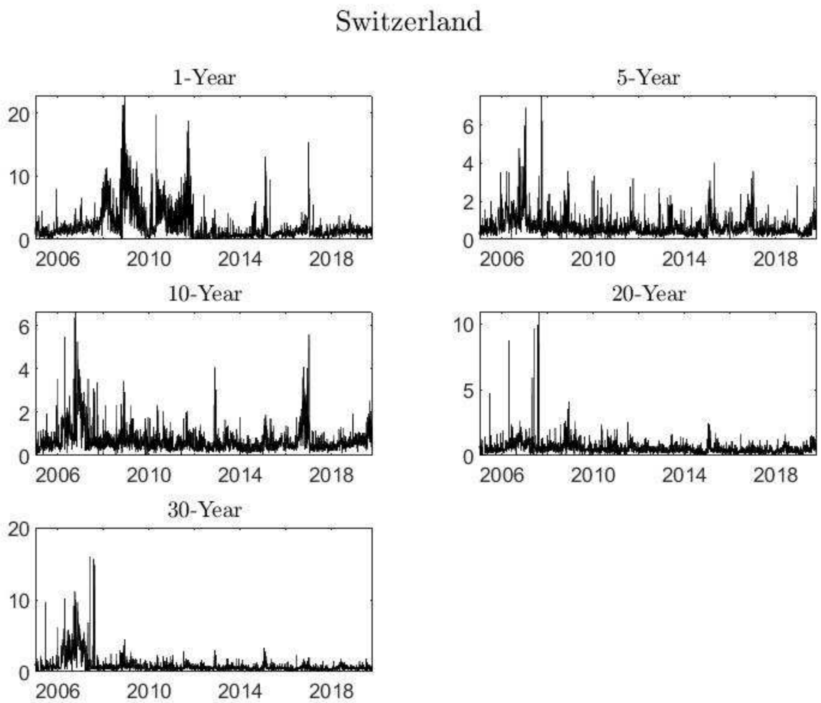

Figure 4: **Realized Volatility:** The squared root of realized volatility, $RV^{1/2}$, is given in percentages.

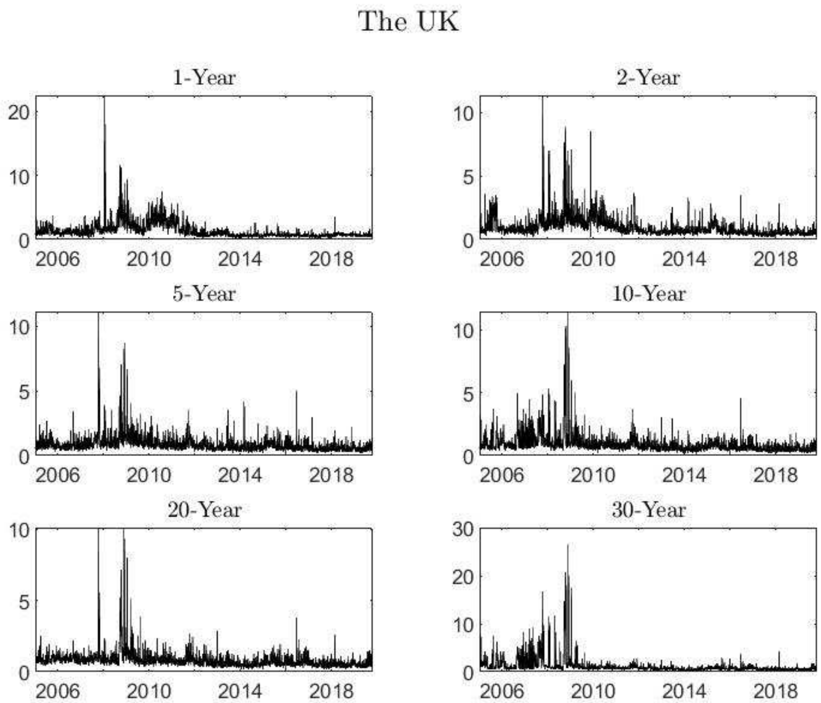

Figure 5: **Realized Volatility:** The squared root of realized volatility, $RV^{1/2}$, is given in percentages.

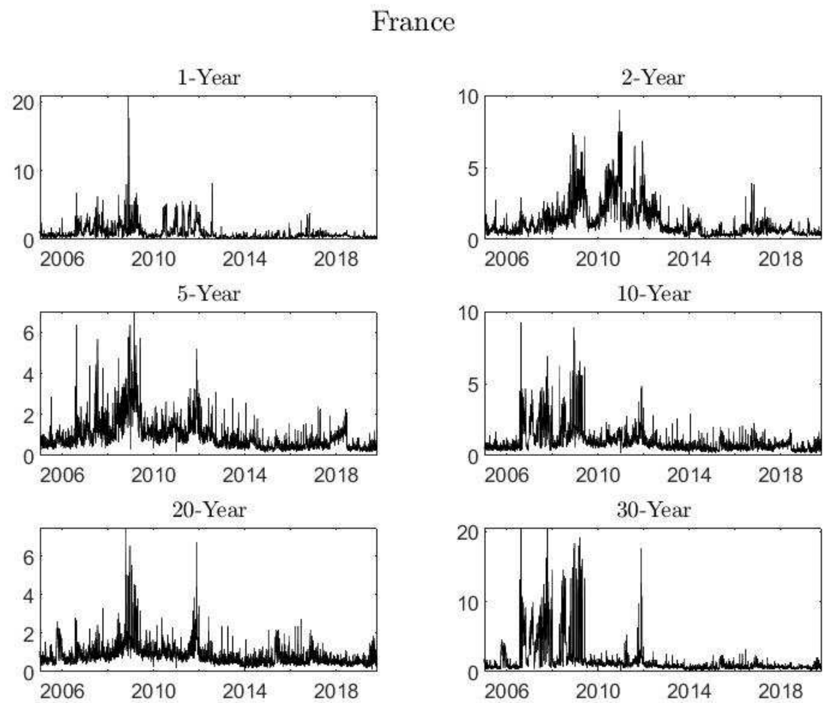

Figure 6: **Realized Volatility:** The squared root of realized volatility, $RV^{1/2}$, is given in percentages.

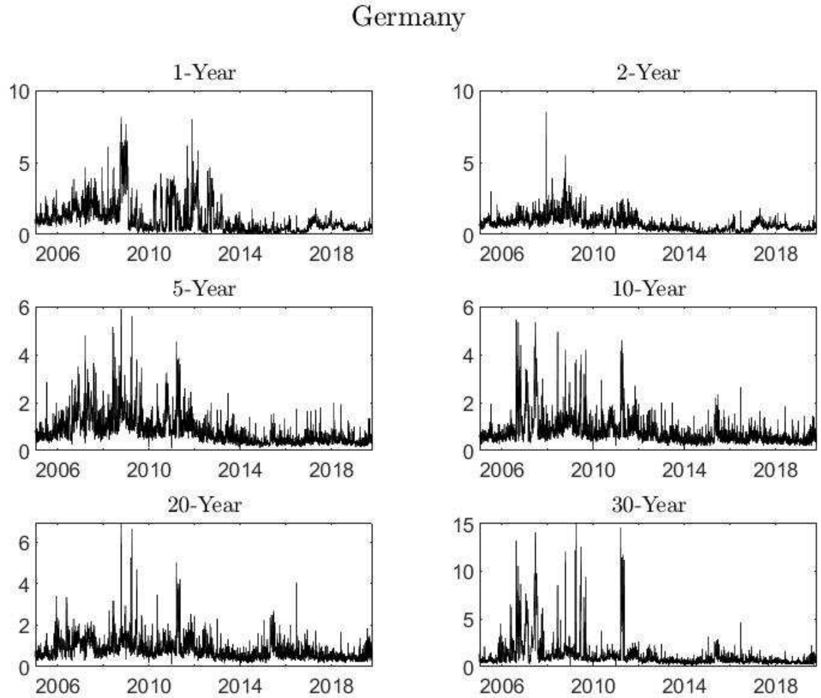

Figure 7: **Realized Volatility:** The squared root of realized volatility, $RV^{1/2}$, is given in percentages.

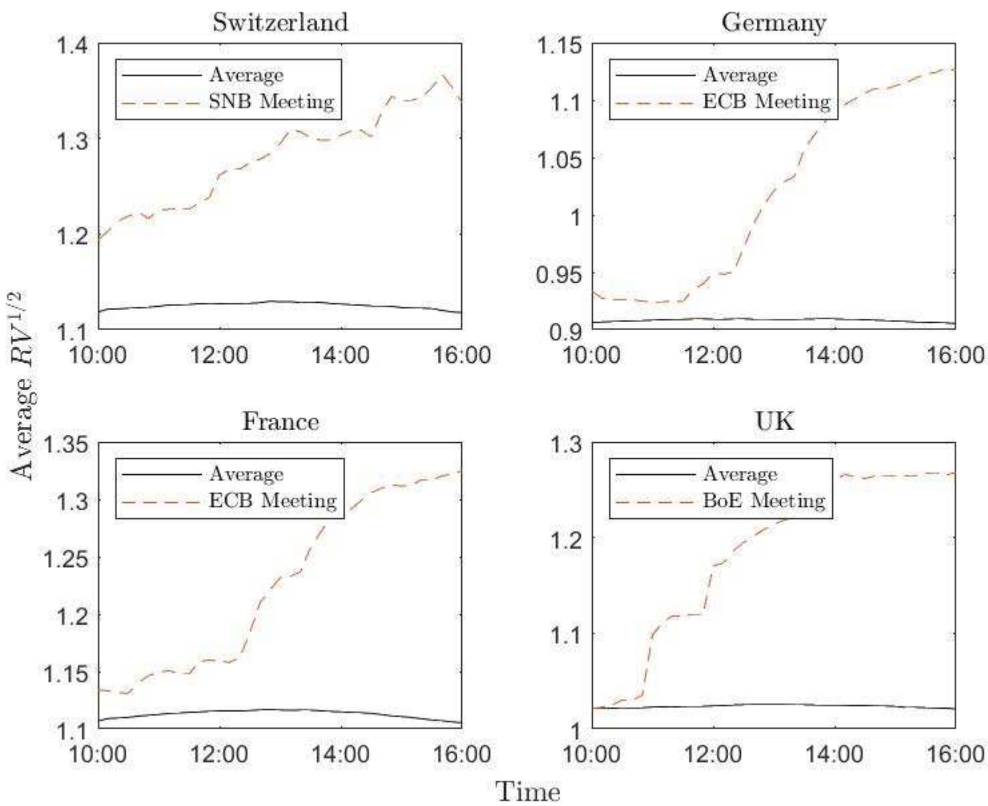

Figure 8: **Realized Volatility Averages by Time of Day:** The squared root of realized volatility, $RV^{1/2}$, is given in percentages. Averages correspond to the average of volatility in whole sample period of January 2005-October 2019. Lines represent the average volatility on the yield curves.

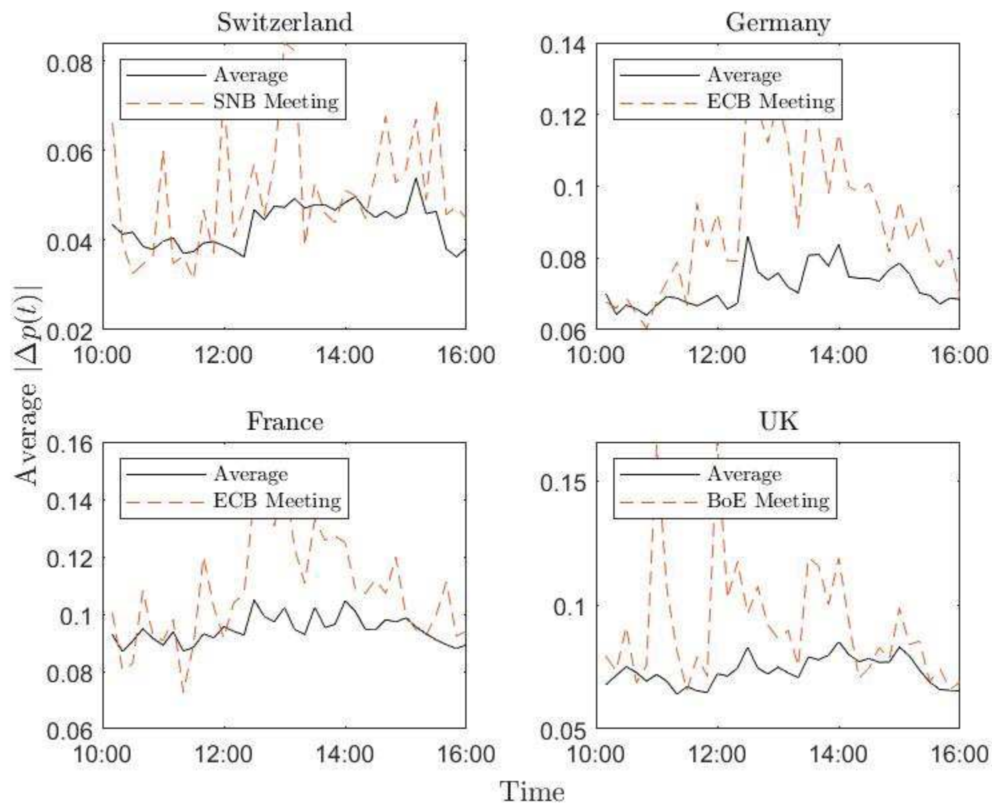

Figure 9: **Absolute Returns by Time of Day:** Averages correspond to the average absolute return in whole sample period of January 2005-October 2019.

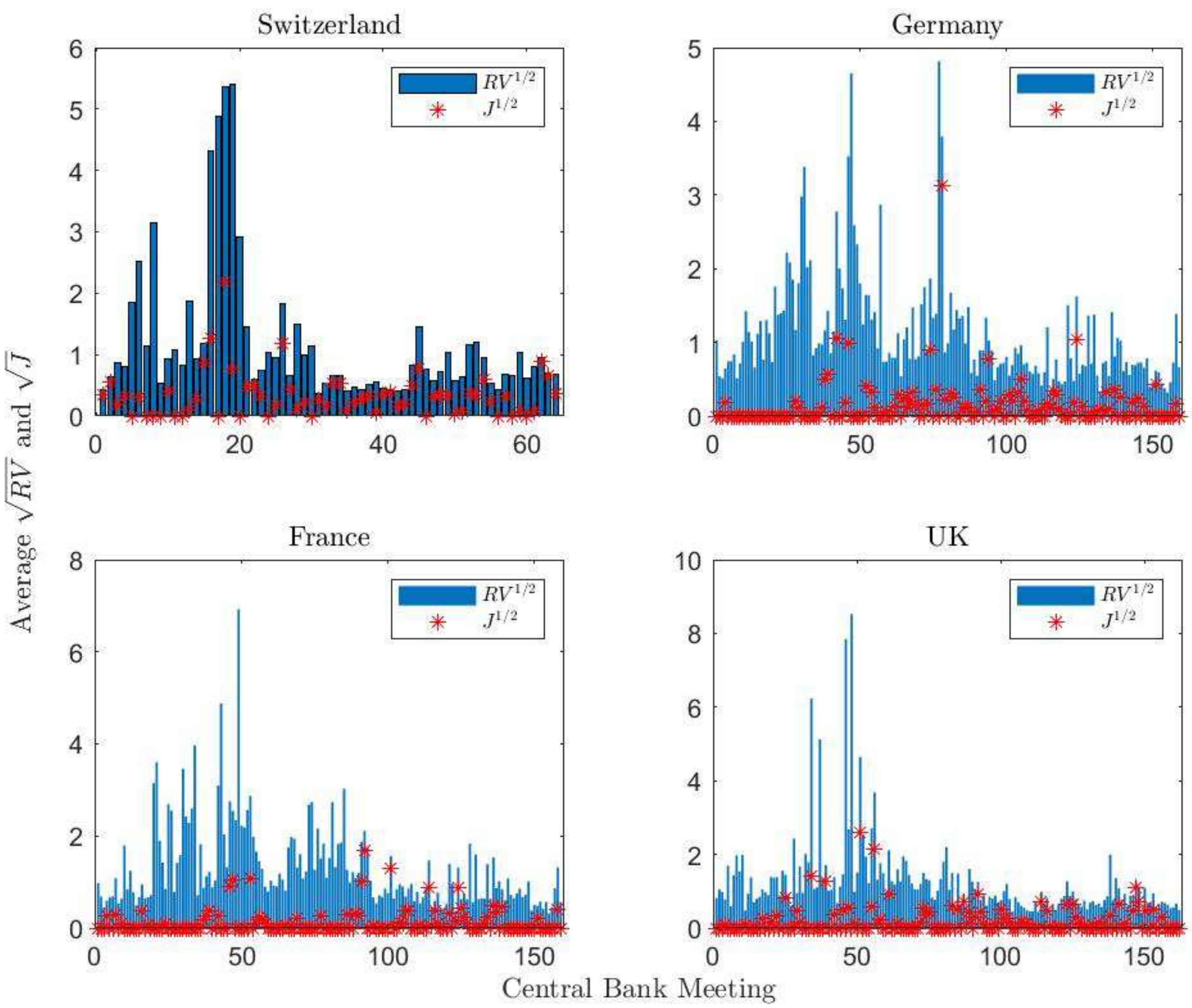

Figure 10: **Average Volatility and Jump Variation:** Averages correspond to the average variation in the date of monetary policy committee meetings of SNB, ECB and BoE respectively. Numbers represents number of meetings in the January 2005 and October 2019 period.

Table 1: Summary Statistics for Bond Price Volatility Across the Maturity Spectrum

(a) Statistics for $\sqrt{RV}$

	Swiss						German					
	1-	2-	5-	10-	20-	30-	1-	2-	5-	10-	20-	30-
Mean	0.022	—	0.007	0.007	0.005	0.008	0.011	0.007	0.008	0.008	0.008	0.012
St. dev.	0.026	—	0.006	0.006	0.005	0.011	0.011	0.005	0.006	0.006	0.006	0.016
Skewness	-0.545	—	0.113	0.393	-0.574	0.459	-0.112	-0.237	0.358	0.811	0.514	1.278
Kurtosis	4.605	—	5.277	4.620	6.902	6.677	2.549	2.907	2.725	4.066	3.523	5.073
Min	0.000	—	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.001
Max	0.228	—	0.076	0.067	0.109	0.161	0.082	0.085	0.059	0.054	0.069	0.151
DF Test St.	-16.838	—	-19.695	-17.178	-27.217	-21.631	-11.826	-13.293	-14.162	-13.401	-14.874	-15.999

(b) Statistics for $\sqrt{RV}$

	French						UK					
	1-	2-	5-	10-	20-	30-	1-	2-	5-	10-	20-	30-
Mean	0.010	0.012	0.010	0.010	0.008	0.017	0.014	0.010	0.009	0.009	0.008	0.012
St. dev.	0.012	0.012	0.008	0.009	0.006	0.025	0.014	0.009	0.007	0.008	0.006	0.018
Skewness	0.488	0.314	0.361	0.860	0.551	1.363	0.753	0.825	0.880	0.949	0.849	1.459
Kurtosis	3.211	2.718	2.734	3.695	4.087	4.613	3.398	3.924	5.001	4.906	5.865	5.886
Min	0.000	0.000	0.001	0.002	0.000	0.001	0.001	0.002	0.002	0.002	0.002	0.002
Max	0.209	0.090	0.070	0.092	0.075	0.206	0.225	0.113	0.111	0.115	0.101	0.266
DF Test St.	-15.973	-11.564	-13.309	-14.931	-14.235	-17.717	-14.848	-15.615	-15.914	-16.429	-14.658	-18.410

This table gives summary statistics of realized volatility ($\sqrt{RV}$) for European government bond markets. Daily volatility series are computed using 10-minute returns in the period of January 2005 - October 2019. The series are annualized by multiplying $\sqrt{252}$. Rows of panels represent mean, standard deviation, skewness, kurtosis, minimum, maximum and Dickey-Fuller test statistics, respectively. For skewness and kurtosis statistics, log($\sqrt{RV}$) results are reported.

Table 2: Summary Statistics for Bond Price Jumps Across the Maturity Spectrum

(a) Statistics for $\sqrt{\hat{J}}$

	Swiss						German					
	1-	2-	5-	10-	20-	30-	1-	2-	5-	10-	20-	30-
Mean	0.014	—	0.005	0.006	0.005	0.006	0.006	0.007	0.007	0.007	0.007	0.009
St. dev.	0.017	—	0.005	0.004	0.004	0.005	0.006	0.006	0.005	0.004	0.005	0.008
Skewness	-0.457	—	-0.045	0.069	-0.489	-0.074	0.074	-0.134	0.177	0.206	0.339	0.765
Kurtosis	3.829	—	5.707	3.691	5.623	5.053	2.642	2.887	2.843	3.259	3.213	4.432
Min	0.000	—	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.001
Max	0.134	—	0.063	0.035	0.058	0.095	0.056	0.051	0.038	0.035	0.055	0.088
DF Test St.	-11.916	—	-16.392	-13.375	-18.906	-17.613	-8.821	-6.411	-8.520	-9.053	-9.655	-10.287

(b) Statistics for $\sqrt{\hat{J}}$

	French						UK					
	1-	2-	5-	10-	20-	30-	1-	2-	5-	10-	20-	30-
Mean	0.007	0.009	0.007	0.008	0.008	0.010	0.010	0.009	0.008	0.008	0.007	0.008
St. dev.	0.009	0.008	0.005	0.005	0.005	0.010	0.010	0.009	0.006	0.005	0.004	0.009
Skewness	0.171	0.133	0.382	0.569	0.078	0.913	0.793	0.881	0.647	0.481	0.418	1.061
Kurtosis	3.283	2.751	2.669	3.529	4.504	4.640	3.313	4.007	3.856	3.830	3.582	5.847
Min	0.000	0.001	0.002	0.001	0.000	0.001	0.002	0.002	0.002	0.002	0.002	0.002
Max	0.123	0.046	0.034	0.053	0.069	0.118	0.093	0.081	0.060	0.068	0.044	0.127
DF Test St.	-8.980	-5.468	-7.893	-9.001	-8.682	-9.357	-7.380	-8.931	-11.221	-10.981	-9.489	-12.683

This table gives summary statistics of significant daily jumps ($\sqrt{\hat{J}}$) for European government bond markets. Daily jump series are computed using 10-minute returns in the period of January 2005 - October 2019. The series are annualized by multiplying $\sqrt{252}$. Rows of panels represent mean, standard deviation, skewness, kurtosis, minimum, maximum and Dickey-Fuller test statistics, respectively. For skewness and kurtosis statistics, log($\sqrt{\hat{J}}$) results are reported.

Table 3: Regression Results of Swiss Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.002	—	—	—	0.001	0.001	0.002
	(3.01)***	(3.05)***	(5.37)***	—	—	—	(3.07)***	(3.03)***	(4.5)***
β_d	0.386	0.391	0.397	—	—	—	0.323	0.358	0.341
	(7.68)***	(7.59)***	(7.3)***	—	—	—	(9.08)***	(8.26)***	(7.76)***
β_w	0.306	0.306	0.276	—	—	—	0.344	0.338	0.341
	(5.72)***	(5.71)***	(4.76)***	—	—	—	(7.29)***	(6.94)***	(5.88)***
β_m	0.211	0.212	0.246	—	—	—	0.129	0.119	0.160
	(4.82)***	(4.81)***	(5.19)***	—	—	—	(2.61)***	(2.36)***	(2.51)***
β_j		-0.041	0.236	—	—	—		-0.080	0.206
		(-0.8)	(4.38)***	—	—	—		(-1.63)	(4.35)***
R^2	0.634	0.634	0.630	—	—	—	0.394	0.397	0.395
$QLIKE$	0.201	0.201	0.201	—	—	—	0.133	0.133	0.136
$J-R^2$	0.518	0.518	0.515	—	—	—	0.285	0.285	0.283
$J-QLIKE$	0.324	0.324	0.328	—	—	—	0.152	0.152	0.155
$C-R^2$	0.669	0.669	0.665	—	—	—	0.474	0.475	0.473
$C-QLIKE$	0.147	0.147	0.146	—	—	—	0.114	0.114	0.116

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.001	0.002	0.002	0.003	0.001	0.001	0.002
	(2.74)***	(2.83)***	(6.31)***	(6.2)***	(6.46)***	(9.59)***	(2.38)***	(2.99)***	(5.92)***
β_d	0.349	0.358	0.364	0.148	0.159	0.159	0.341	0.350	0.331
	(8.91)***	(8.42)***	(8.31)***	(3.61)***	(3.23)***	(3.55)***	(6.08)***	(5.73)***	(5.87)***
β_w	0.358	0.355	0.331	0.137	0.137	0.167	0.293	0.289	0.326
	(6.56)***	(6.43)***	(6.05)***	(2.8)***	(2.86)***	(2.85)***	(4.88)***	(4.93)***	(5.27)***
β_m	0.159	0.156	0.168	0.258	0.256	0.219	0.214	0.210	0.186
	(3.77)***	(3.71)***	(3.9)***	(3.58)***	(3.51)***	(2.98)***	(3.8)***	(3.73)***	(3.18)***
β_j		-0.028	0.242		-0.030	0.111		-0.057	0.213
		(-0.8)	(6.93)***		(-0.67)	(2.71)***		(-1)	(3.24)***
R^2	0.520	0.520	0.510	0.119	0.120	0.116	0.511	0.512	0.517
$QLIKE$	0.117	0.117	0.119	0.166	0.165	0.168	0.162	0.161	0.161
$J-R^2$	0.431	0.432	0.412	0.128	0.127	0.126	0.259	0.257	0.273
$J-QLIKE$	0.129	0.128	0.131	0.161	0.161	0.163	0.162	0.162	0.162
$C-R^2$	0.565	0.565	0.559	0.103	0.102	0.099	0.574	0.573	0.576
$C-QLIKE$	0.108	0.108	0.110	0.170	0.170	0.174	0.159	0.159	0.158

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 4: Regression Results of German Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.001	0.000	0.000	0.000	0.001	0.001	0.001
	(3.48)***	(3.69)***	(4.89)***	(2.93)***	(2.74)***	(3.16)***	(4.07)***	(4.85)***	(8.54)***
β_d	0.600	0.603	0.602	0.319	0.355	0.388	0.372	0.412	0.427
	(15.67)***	(15.82)***	(16.45)***	(8.15)***	(6.92)***	(6.65)***	(8.84)***	(7.67)***	(7.29)***
β_w	0.246	0.247	0.247	0.356	0.337	0.328	0.389	0.361	0.353
	(5.32)***	(5.37)***	(5.83)***	(6.61)***	(6.43)***	(6.07)***	(7.35)***	(6.12)***	(5.36)***
β_m	0.087	0.085	0.085	0.237	0.236	0.242	0.135	0.133	0.123
	(2.83)***	(2.73)***	(2.76)***	(4.23)***	(4.18)***	(3.98)***	(4.42)***	(4.44)***	(3.68)***
β_j		-0.055	0.279		-0.098	0.121		-0.116	0.130
		(-0.96)	(5.3)***		(-3.07)***	(4.66)***		(-2.91)***	(5.3)***
R^2	0.753	0.754	0.755	0.623	0.626	0.616	0.603	0.607	0.603
$QLIKE$	0.119	0.119	0.121	0.062	0.061	0.062	0.074	0.073	0.074
$J-R^2$	0.596	0.596	0.605	0.648	0.652	0.641	0.487	0.493	0.494
$J-QLIKE$	0.242	0.241	0.239	0.073	0.072	0.074	0.082	0.082	0.079
$C-R^2$	0.772	0.772	0.772	0.620	0.621	0.611	0.631	0.632	0.626
$C-QLIKE$	0.097	0.097	0.098	0.059	0.059	0.060	0.071	0.071	0.072

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.002
	(4.03)***	(5.45)***	(8.37)***	(4.09)***	(4.49)***	(6.34)***	(4.28)***	(3.9)***	(4.97)***
β_d	0.454	0.528	0.531	0.396	0.429	0.442	0.538	0.551	0.541
	(11.79)***	(11.88)***	(11.68)***	(6.36)***	(5.32)***	(4.94)***	(9.32)***	(8.45)***	(8.11)***
β_w	0.372	0.317	0.319	0.359	0.339	0.345	0.320	0.313	0.326
	(8.3)***	(6.6)***	(6.02)***	(6.46)***	(4.99)***	(4.11)***	(5.68)***	(5.12)***	(5.05)***
β_m	0.058	0.051	0.038	0.075	0.069	0.050	0.017	0.013	0.009
	(1.82)*	(1.68)*	(1.14)	(2.58)***	(2.51)***	(1.77)*	(0.71)	(0.55)	(0.36)
β_j		-0.201	0.102		-0.073	0.190		-0.115	0.199
		(-5.17)***	(3.77)***		(-1.28)	(5.01)***		(-0.92)	(1.65)*
R^2	0.620	0.631	0.628	0.488	0.490	0.488	0.666	0.667	0.665
$QLIKE$	0.073	0.070	0.071	0.074	0.073	0.073	0.096	0.094	0.094
$J-R^2$	0.421	0.426	0.418	0.474	0.477	0.491	0.403	0.403	0.378
$J-QLIKE$	0.068	0.067	0.068	0.075	0.074	0.075	0.089	0.088	0.090
$C-R^2$	0.658	0.661	0.658	0.497	0.498	0.493	0.697	0.697	0.698
$C-QLIKE$	0.071	0.071	0.072	0.073	0.073	0.073	0.095	0.096	0.096

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 5: Regression Results of French Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.001	0.000	0.000	0.000	0.001	0.001	0.001
	(4.32)***	(3.89)***	(2.97)***	(2.47)***	(2.63)***	(3.1)***	(2.73)***	(3.53)***	(5.38)***
β_d	0.610	0.585	0.586	0.412	0.417	0.439	0.390	0.421	0.450
	(16.65)***	(19.01)***	(19.66)***	(8.15)***	(8.15)***	(8.87)***	(9.54)***	(9.97)***	(10.32)***
β_w	0.197	0.188	0.215	0.377	0.375	0.483	0.325	0.308	0.413
	(2.77)***	(2.57)***	(3.98)***	(7.07)***	(7.02)***	(9.34)***	(7.9)***	(7.39)***	(9.85)***
β_m	0.058	0.067	0.043	0.159	0.158	0.053	0.204	0.194	0.058
	(1.65)*	(1.75)*	(2.29)**	(4.77)***	(4.71)***	(2.88)***	(6.23)***	(6.06)***	(2)**
β_j		0.348	0.618		-0.056	0.169		-0.131	0.118
		(2.18)**	(3.92)***		(-1.13)	(3.32)***		(-3.43)***	(3.4)***
R^2	0.626	0.637	0.637	0.782	0.782	0.779	0.659	0.662	0.658
$QLIKE$	0.107	0.107	0.108	0.062	0.062	0.063	0.068	0.067	0.069
$J-R^2$	0.542	0.548	0.541	0.733	0.740	0.729	0.576	0.592	0.609
$J-QLIKE$	0.186	0.191	0.187	0.097	0.096	0.090	0.078	0.076	0.075
$C-R^2$	0.663	0.664	0.665	0.786	0.786	0.784	0.668	0.669	0.662
$C-QLIKE$	0.099	0.099	0.099	0.060	0.060	0.061	0.066	0.066	0.068

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001
	(3.81)***	(3.64)***	(4.7)***	(2.91)***	(3.33)***	(6.15)***	(4.82)***	(2.34)***	(3.34)***
β_d	0.461	0.462	0.476	0.396	0.440	0.473	0.517	0.504	0.517
	(10.23)***	(9.65)***	(10.18)***	(9.33)***	(8.53)***	(9.22)***	(12.39)***	(12.21)***	(12.7)***
β_w	0.302	0.301	0.357	0.246	0.225	0.327	0.254	0.261	0.314
	(6.8)***	(6.61)***	(7.75)***	(4.85)***	(4.24)***	(5.51)***	(4.95)***	(5.24)***	(7.09)***
β_m	0.128	0.128	0.064	0.233	0.217	0.052	0.113	0.110	0.057
	(4.16)***	(4.11)***	(2.17)**	(5.5)***	(5.19)***	(1.67)*	(3.5)***	(3.54)***	(1.54)
β_j		-0.008	0.253		-0.101	0.175		0.415	0.697
		(-0.13)	(5.11)***		(-2.44)***	(6)***		(3.5)***	(5.99)***
R^2	0.621	0.621	0.623	0.523	0.526	0.522	0.638	0.646	0.645
$QLIKE$	0.077	0.077	0.077	0.066	0.065	0.066	0.103	0.112	0.113
$J-R^2$	0.594	0.595	0.613	0.374	0.382	0.413	0.610	0.587	0.587
$J-QLIKE$	0.105	0.105	0.097	0.086	0.085	0.087	0.162	0.225	0.193
$C-R^2$	0.630	0.630	0.629	0.569	0.570	0.559	0.665	0.665	0.664
$C-QLIKE$	0.073	0.073	0.073	0.060	0.060	0.062	0.096	0.096	0.099

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 6: Regression Results of the UK Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.002	0.002
	(2.68)***	(2.65)***	(3.79)***	(4.24)***	(4.46)***	(6.19)***	(3.93)***	(4.84)***	(6.45)***
β_d	0.522	0.520	0.553	0.472	0.529	0.582	0.500	0.591	0.608
	(12.25)***	(12.1)***	(13.13)***	(6.49)***	(9.57)***	(10.66)***	(6.55)***	(8.19)***	(8.19)***
β_w	0.247	0.247	0.293	0.259	0.227	0.257	0.201	0.152	0.135
	(2.53)***	(2.53)***	(3.77)***	(3.05)***	(2.97)***	(3.79)***	(2.51)***	(1.91)*	(1.74)*
β_m	0.121	0.121	0.046	0.128	0.124	0.030	0.114	0.106	0.097
	(1.86)*	(1.87)*	(1.84)*	(2.86)***	(2.82)***	(2.82)***	(2.46)***	(2.4)***	(3.83)***
β_j		0.015	0.317		-0.173	0.180		-0.232	0.133
		(0.2)	(4.08)***		(-2.96)***	(2.71)***		(-4.68)***	(3.56)***
R^2	0.639	0.639	0.632	0.550	0.558	0.552	0.469	0.488	0.487
$QLIKE$	0.069	0.069	0.071	0.071	0.070	0.074	0.084	0.081	0.082
$J-R^2$	0.647	0.646	0.641	0.378	0.395	0.437	0.347	0.362	0.358
$J-QLIKE$	0.096	0.096	0.098	0.093	0.089	0.090	0.089	0.088	0.090
$C-R^2$	0.639	0.639	0.632	0.590	0.591	0.577	0.512	0.519	0.519
$C-QLIKE$	0.067	0.067	0.069	0.066	0.067	0.071	0.078	0.079	0.080

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.001	0.002	0.002	0.001	0.002	0.001	0.002	0.002	0.002
	(3.15)***	(4.41)***	(7.35)***	(4.12)***	(4.98)***	(4.44)***	(3.68)***	(3.78)***	(4.88)***
β_d	0.483	0.525	0.502	0.583	0.630	0.620	0.576	0.574	0.552
	(9.83)***	(9.79)***	(8.58)***	(8.46)***	(10.55)***	(9.61)***	(11.12)***	(10.54)***	(9.69)***
β_w	0.286	0.260	0.283	0.146	0.118	0.112	0.233	0.234	0.248
	(6.91)***	(6.65)***	(6.57)***	(1.65)*	(1.41)	(1.41)	(4.78)***	(4.83)***	(5.13)***
β_m	0.050	0.047	0.059	0.088	0.090	0.142	0.030	0.030	0.045
	(1.46)	(1.45)	(2.78)***	(2.1)**	(2.23)**	(3.89)***	(1.03)	(1.01)	(2.32)**
β_j		-0.163	0.137		-0.159	0.187		0.037	0.339
		(-2.89)***	(3.4)***		(-2.78)***	(2.9)***		(0.29)	(2.99)***
R^2	0.510	0.517	0.527	0.513	0.521	0.529	0.594	0.594	0.601
$QLIKE$	0.087	0.083	0.082	0.070	0.067	0.067	0.106	0.107	0.105
$J-R^2$	0.466	0.477	0.505	0.462	0.470	0.493	0.693	0.692	0.701
$J-QLIKE$	0.085	0.083	0.081	0.075	0.074	0.076	0.103	0.104	0.100
$C-R^2$	0.521	0.522	0.529	0.538	0.540	0.545	0.583	0.583	0.589
$C-QLIKE$	0.084	0.084	0.082	0.066	0.066	0.066	0.111	0.111	0.107

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 7: Regression Results of Swiss Market on 22-day Forecast Horizon (h=22)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.005	0.005	0.006	—	—	—	0.003	0.003	0.003
	(7.1)***	(7.04)***	(8.86)***	—	—	—	(4.48)***	(5.12)***	(7.55)***
β_d	0.212	0.207	0.216	—	—	—	0.212	0.275	0.224
	(10.35)***	(10.22)***	(9.69)***	—	—	—	(6.22)***	(6.05)***	(6.3)***
β_w	0.393	0.393	0.348	—	—	—	0.257	0.245	0.298
	(6.43)***	(6.43)***	(6.49)***	—	—	—	(4.75)***	(4.67)***	(5.71)***
β_m	0.243	0.242	0.294	—	—	—	0.208	0.190	0.249
	(4)***	(3.98)***	(5.17)***	—	—	—	(2.65)***	(2.47)***	(3.15)***
β_j		0.037	0.214	—	—	—		-0.145	0.071
		(0.81)	(4.23)***	—	—	—		(-3.82)***	(3.06)***
R^2	0.695	0.696	0.685	—	—	—	0.425	0.439	0.482
$QLIKE$	0.096	0.096	0.100	—	—	—	0.058	0.057	0.055
$J-R^2$	0.619	0.620	0.610	—	—	—	0.365	0.375	0.410
$J-QLIKE$	0.135	0.134	0.139	—	—	—	0.052	0.052	0.051
$C-R^2$	0.723	0.723	0.713	—	—	—	0.444	0.446	0.494
$C-QLIKE$	0.079	0.079	0.083	—	—	—	0.062	0.063	0.059

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.002	0.002	0.003	0.003	0.003	0.004	0.002	0.002	0.003
	(5.17)***	(5.34)***	(9.28)***	(5.78)***	(5.92)***	(10.47)***	(4.18)***	(4.65)***	(8.93)***
β_d	0.192	0.204	0.194	0.103	0.121	0.124	0.194	0.208	0.198
	(7.07)***	(6.12)***	(6.65)***	(3.42)***	(2.86)***	(3.18)***	(4.63)***	(4.43)***	(4.39)***
β_w	0.246	0.243	0.240	0.174	0.173	0.177	0.244	0.238	0.241
	(3.84)***	(3.83)***	(3.35)***	(2.84)***	(2.88)***	(2.71)***	(3.92)***	(3.88)***	(3.68)***
β_m	0.376	0.372	0.395	0.315	0.311	0.280	0.416	0.410	0.409
	(4.42)***	(4.33)***	(4.37)***	(3.77)***	(3.69)***	(3.3)***	(4.9)***	(4.79)***	(4.53)***
β_j		-0.039	0.132		-0.049	0.070		-0.094	0.081
		(-1.14)	(4.88)***		(-1.41)	(3.98)***		(-2.23)**	(3.43)***
R^2	0.608	0.608	0.618	0.259	0.261	0.238	0.631	0.633	0.641
$QLIKE$	0.050	0.049	0.049	0.065	0.065	0.070	0.080	0.079	0.079
$J-R^2$	0.567	0.567	0.581	0.261	0.259	0.239	0.429	0.426	0.470
$J-QLIKE$	0.046	0.046	0.045	0.059	0.059	0.063	0.079	0.078	0.074
$C-R^2$	0.616	0.615	0.624	0.243	0.241	0.217	0.672	0.671	0.670
$C-QLIKE$	0.052	0.052	0.052	0.073	0.074	0.079	0.081	0.081	0.085

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 8: Regression Results of German Market on 22-day Forecast Horizon (h=22)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.003	0.003	0.003	0.001	0.001	0.001	0.002	0.002	0.003
	(6.07)***	(6.13)***	(6.75)***	(4.93)***	(5.04)***	(5.97)***	(6.96)***	(7.04)***	(10.08)***
β_d	0.325	0.323	0.330	0.208	0.198	0.243	0.230	0.243	0.263
	(9.65)***	(9.39)***	(9.63)***	(8.43)***	(7.56)***	(7.44)***	(10.6)***	(9.3)***	(9.51)***
β_w	0.283	0.283	0.276	0.313	0.318	0.282	0.298	0.289	0.271
	(7.47)***	(7.46)***	(7.09)***	(6.46)***	(6.1)***	(6.92)***	(5.93)***	(5.55)***	(5.18)***
β_m	0.187	0.188	0.186	0.341	0.341	0.366	0.280	0.279	0.276
	(2.91)***	(2.91)***	(2.85)***	(6.38)***	(6.4)***	(7.12)***	(6.1)***	(6.1)***	(5.72)***
β_j		0.017	0.214		0.028	0.168		-0.038	0.118
		(0.33)	(4.22)***		(0.66)	(3.62)***		(-1.11)	(3.61)***
R^2	0.634	0.634	0.629	0.714	0.714	0.695	0.626	0.626	0.618
$QLIKE$	0.123	0.123	0.127	0.036	0.036	0.038	0.044	0.043	0.045
$J-R^2$	0.421	0.421	0.412	0.713	0.713	0.677	0.560	0.560	0.547
$J-QLIKE$	0.212	0.212	0.216	0.042	0.042	0.046	0.046	0.046	0.044
$C-R^2$	0.666	0.666	0.663	0.715	0.715	0.700	0.643	0.643	0.637
$C-QLIKE$	0.105	0.105	0.109	0.035	0.035	0.037	0.042	0.042	0.044

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.003	0.003	0.004	0.003	0.003	0.004	0.006	0.006	0.006
	(8.15)***	(8.52)***	(10.45)***	(8.11)***	(8.59)***	(10.91)***	(8.5)***	(8.73)***	(9.62)***
β_d	0.288	0.317	0.327	0.236	0.272	0.267	0.360	0.378	0.363
	(8.83)***	(7.81)***	(8.6)***	(10.36)***	(9.46)***	(9.04)***	(9.15)***	(8.79)***	(8.71)***
β_w	0.313	0.292	0.278	0.213	0.191	0.196	0.242	0.233	0.245
	(6.4)***	(5.63)***	(5.04)***	(3.7)***	(3.48)***	(2.97)***	(4.28)***	(4.05)***	(4.22)***
β_m	0.066	0.063	0.066	0.210	0.203	0.217	0.057	0.052	0.059
	(1.09)	(1.05)	(1.08)	(5.05)***	(4.81)***	(4.48)***	(1.14)	(1.05)	(1.17)
β_j		-0.078	0.109		-0.078	0.093		-0.149	0.070
		(-2.1)**	(4.16)***		(-2.85)***	(4.56)***		(-1.61)	(0.76)
R^2	0.472	0.474	0.473	0.407	0.411	0.422	0.429	0.432	0.434
$QLIKE$	0.055	0.055	0.055	0.048	0.048	0.046	0.145	0.144	0.142
$J-R^2$	0.377	0.382	0.390	0.442	0.447	0.478	0.296	0.298	0.290
$J-QLIKE$	0.057	0.056	0.054	0.042	0.041	0.038	0.099	0.098	0.098
$C-R^2$	0.497	0.499	0.496	0.398	0.399	0.406	0.442	0.442	0.446
$C-QLIKE$	0.054	0.054	0.055	0.049	0.050	0.048	0.154	0.154	0.152

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 9: Regression Results of French Market on 22-day Forecast Horizon (h=22)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.004	0.004	0.002	0.001	0.001	0.001	0.001	0.002	0.002
	(7.4)***	(7.19)***	(2.92)***	(4.49)***	(4.58)***	(2.4)***	(4.87)***	(5.25)***	(4.54)***
β_d	0.285	0.273	0.249	0.253	0.255	0.287	0.203	0.221	0.260
	(8.38)***	(7.91)***	(7.4)***	(7.27)***	(7.16)***	(9.39)***	(8.45)***	(7.85)***	(10.21)***
β_w	0.156	0.151	0.224	0.373	0.372	0.550	0.289	0.279	0.473
	(1.82)*	(1.76)*	(3.16)***	(6.51)***	(6.48)***	(13.21)***	(5.6)***	(5.44)***	(10.95)***
β_m	0.254	0.258	0.283	0.283	0.283	0.178	0.386	0.381	0.186
	(3.02)***	(3)***	(3.19)***	(4.44)***	(4.44)***	(3.3)***	(6.49)***	(6.38)***	(2.56)***
β_j		0.170	0.151		-0.023	0.106		-0.075	0.063
		(1.34)	(1.33)		(-0.64)	(2.47)***		(-2.35)***	(2.46)***
R^2	0.408	0.411	0.463	0.809	0.809	0.804	0.740	0.741	0.721
$QLIKE$	0.139	0.138	0.122	0.046	0.046	0.052	0.038	0.038	0.040
$J-R^2$	0.327	0.322	0.369	0.842	0.843	0.810	0.641	0.648	0.647
$J-QLIKE$	0.174	0.179	0.148	0.052	0.052	0.053	0.046	0.046	0.045
$C-R^2$	0.431	0.431	0.484	0.807	0.807	0.803	0.749	0.749	0.728
$C-QLIKE$	0.134	0.134	0.118	0.046	0.046	0.052	0.036	0.036	0.039

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.002	0.002	0.002	0.002	0.002	0.003	0.004	0.004	0.004
	(6.13)***	(6.34)***	(4.11)***	(4.26)***	(4.36)***	(7.08)***	(5.62)***	(5.2)***	(4.26)***
β_d	0.219	0.228	0.233	0.166	0.182	0.240	0.210	0.207	0.235
	(7.7)***	(7.45)***	(9)***	(7.41)***	(5.89)***	(8.93)***	(7.24)***	(7.14)***	(9.09)***
β_w	0.286	0.281	0.383	0.232	0.224	0.400	0.262	0.264	0.405
	(5.04)***	(4.98)***	(7)***	(5.55)***	(5.63)***	(7.62)***	(4.47)***	(4.49)***	(7.82)***
β_m	0.312	0.309	0.305	0.442	0.436	0.145	0.380	0.379	0.344
	(4.99)***	(4.94)***	(3.81)***	(7.63)***	(7.29)***	(2.3)**	(5.12)***	(5.11)***	(3.82)***
β_j		-0.060	0.065		-0.038	0.097		0.105	0.240
		(-1.65)*	(2.01)**		(-1.33)	(4.84)***		(1.33)	(3.17)***
R^2	0.614	0.615	0.632	0.652	0.653	0.595	0.635	0.636	0.620
$QLIKE$	0.055	0.055	0.053	0.031	0.031	0.033	0.108	0.109	0.117
$J-R^2$	0.606	0.610	0.610	0.584	0.586	0.581	0.715	0.712	0.701
$J-QLIKE$	0.057	0.056	0.056	0.038	0.038	0.036	0.071	0.075	0.072
$C-R^2$	0.612	0.612	0.631	0.664	0.664	0.597	0.625	0.625	0.609
$C-QLIKE$	0.055	0.055	0.053	0.030	0.030	0.033	0.117	0.117	0.126

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 10: Regression Results of the UK Market on 22-day Forecast Horizon (h=22)

	1-Year			2-Year			5-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.004	0.004	0.003	0.003	0.003	0.004	0.003	0.003	0.004
	(3.82)***	(3.86)***	(4.4)***	(5.66)***	(5.68)***	(8.56)***	(4.67)***	(4.82)***	(10.36)***
β_d	0.290	0.288	0.309	0.231	0.242	0.292	0.193	0.229	0.214
	(5.44)***	(5.17)***	(6.36)***	(7.27)***	(6.48)***	(8.75)***	(6.1)***	(6.28)***	(6.69)***
β_w	0.304	0.305	0.384	0.235	0.229	0.370	0.151	0.131	0.196
	(3.06)***	(3.07)***	(4.6)***	(4.66)***	(4.66)***	(7.22)***	(3.05)***	(2.71)***	(3.73)***
β_m	0.191	0.191	0.168	0.290	0.289	0.061	0.348	0.345	0.258
	(1.86)*	(1.86)*	(3.83)***	(4.57)***	(4.55)***	(3.27)***	(3.95)***	(3.89)***	(5.57)***
β_j		0.028	0.194		-0.033	0.151		-0.092	0.048
		(0.48)	(4.08)***		(-0.73)	(4.26)***		(-3.02)***	(2.09)**
R^2	0.561	0.561	0.562	0.508	0.508	0.469	0.401	0.405	0.403
$QLIKE$	0.059	0.059	0.060	0.053	0.053	0.061	0.046	0.045	0.046
$J-R^2$	0.544	0.546	0.560	0.465	0.466	0.487	0.405	0.412	0.391
$J-QLIKE$	0.063	0.063	0.060	0.059	0.059	0.060	0.040	0.039	0.041
$C-R^2$	0.562	0.562	0.562	0.515	0.515	0.468	0.401	0.401	0.403
$C-QLIKE$	0.058	0.058	0.060	0.051	0.051	0.061	0.047	0.047	0.047

	10-Year			20-Year			30-Year		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
β_0	0.003	0.003	0.004	0.003	0.003	0.003	0.004	0.004	0.005
	(3.96)***	(4.51)***	(9.42)***	(4.33)***	(4.45)***	(5.01)***	(4.34)***	(4.81)***	(8.05)***
β_d	0.228	0.266	0.239	0.213	0.237	0.196	0.279	0.300	0.254
	(4.03)***	(4.41)***	(3.55)***	(5.14)***	(5.25)***	(4.16)***	(4.47)***	(4.83)***	(3.88)***
β_w	0.147	0.122	0.247	0.089	0.075	0.105	0.103	0.095	0.228
	(2.15)**	(1.93)*	(4.31)***	(1.75)*	(1.5)	(1.91)*	(1.56)	(1.48)	(4.26)***
β_m	0.361	0.359	0.199	0.406	0.407	0.482	0.387	0.389	0.207
	(4.13)***	(4.09)***	(4.31)***	(4.32)***	(4.32)***	(4.91)***	(4)***	(4.05)***	(4.23)***
β_j		-0.152	-0.004		-0.082	0.046		-0.283	-0.092
		(-3.73)***	(-0.1)		(-2.39)***	(1.5)		(-3.92)***	(-1.91)*
R^2	0.448	0.456	0.425	0.404	0.407	0.423	0.463	0.471	0.446
$QLIKE$	0.054	0.053	0.053	0.042	0.042	0.040	0.123	0.121	0.111
$J-R^2$	0.320	0.334	0.262	0.337	0.336	0.398	0.366	0.399	0.288
$J-QLIKE$	0.049	0.048	0.053	0.042	0.042	0.037	0.083	0.082	0.085
$C-R^2$	0.477	0.477	0.455	0.422	0.421	0.427	0.472	0.472	0.457
$C-QLIKE$	0.054	0.054	0.053	0.042	0.042	0.042	0.131	0.131	0.118

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 11: One-Day Ahead Out of Sample Forecast Results (h=1)

(a) QLIKE Estimates

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	1.000	1.001	1.006	1.000	0.998[a]	1.003	1.000	1.008	1.013	1.000	1.003	1.043
2-Year	—	—	—	1.000	0.998[a]	1.017	1.000	1.004	1.037	1.000	0.994[a]	1.05
5-Year	1.000	0.996[a]	1.02	1.000	0.992[a]	1.013	1.000	0.979[a]	1.014	1.000	0.981[a]	0.999[a]
10-Year	1.000	0.999[a]	1.015	1.000	0.977[a]	0.993[a]	1.000	1.001[a]	1.009	1.000	0.99[a]	0.978[a]
20-Year	1.000	0.997[a]	1.006	1.000	1.003	1.015	1.000	1.000	1.033	1.000	0.996[a]	1.01
30-Year	1.000	0.996[a]	0.99	1.000	1.002[a]	1.014	1.000	1.016	1.047	1.000	1.016	0.999[a]

(1) QLIKE ratios are given in the table. (2) The ratios are scaled to QLIKE estimators of HAR-RV model. (3) Rolling window, 1000 observation, forecasts are estimated. (4) [a] corresponds to significant Diebold-Mariano Test at 5% level.

(b) Average R^2

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	51.5%	51.5%	51.1%	66.2%	66.2%	66.3%	57.2%	58.5%	58.5%	39.8%	40.1%	38.8%
2-Year	—	—	—	48.3%	48.7%	47.9%	63.6%	63.8%	63.7%	38.2%	39.5%	38.6%
5-Year	27.3%	27.3%	26.0%	34.9%	35.4%	34.6%	47.8%	48.6%	48.6%	26.2%	27.2%	26.8%
10-Year	37.9%	37.9%	34.8%	39.4%	40.3%	39.5%	40.9%	41.5%	42.0%	28.7%	29.1%	29.0%
20-Year	10.6%	10.7%	9.7%	37.1%	37.6%	36.9%	35.3%	35.4%	35.2%	32.2%	32.5%	32.1%
30-Year	23.3%	23.4%	22.2%	46.5%	46.6%	46.1%	37.0%	38.2%	38.2%	35.5%	36.0%	35.4%

(1) Average R^2's are given in the table. (2) Rolling window, 1000 observation, forecasts are estimated.

Table 12: One-Month Ahead Out of Sample Forecast Results (h=22)

(a) QLIKE Estimates

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	1.000	0.994[a]	1.041	1.000	0.997[a]	1.009	1.000	1.001	0.897	1.000	0.999[a]	1.049
2-Year	—	—	—	1.000	1.002	1.087	1.000	0.999	1.208	1.000	0.995[a]	1.129
5-Year	1.000	0.974[a]	0.932	1.000	0.999	1.028	1.000	0.978[a]	1.167	1.000	0.993[a]	0.981[a]
10-Year	1.000	0.99[a]	0.953[a]	1.000	0.998[a]	1.008	1.000	0.994[a]	1.016	1.000	0.99[a]	1.039
20-Year	1.000	0.996[a]	1.044	1.000	1.001	0.995	1.000	1.004	1.109	1.000	0.994[a]	0.999[a]
30-Year	1.000	0.994[a]	0.973	1.000	0.999[a]	0.999[a]	1.000	1.005	1.312	1.000	0.991[a]	1.032

(1) QLIKE ratios are given in the table. (2) The ratios are scaled to QLIKE estimators of HAR-RV model. (3) Rolling window, 1000 observation, forecasts are estimated. (4) [a] corresponds to significant Diebold-Mariano Test at 5% level.

(b) Average R^2

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	49.7%	50.0%	49.1%	49.3%	49.5%	49.7%	27.7%	28.1%	30.7%	38.8%	39.1%	38.4%
2-Year	—	—	—	52.4%	52.7%	50.1%	63.4%	63.5%	61.9%	34.3%	35.0%	34.4%
5-Year	30.0%	30.7%	31.0%	34.0%	34.3%	33.7%	55.8%	57.1%	59.5%	24.0%	24.8%	26.1%
10-Year	40.0%	40.1%	38.7%	32.3%	32.5%	32.8%	38.4%	38.9%	44.2%	33.4%	34.0%	31.5%
20-Year	20.0%	20.2%	16.0%	33.3%	33.8%	35.6%	45.9%	45.9%	43.5%	35.4%	35.5%	32.4%
30-Year	28.9%	28.9%	26.2%	36.9%	37.0%	37.9%	37.7%	38.1%	40.9%	35.4%	35.8%	29.6%

(1) Average R^2's are given in the table. (2) Rolling window, 1000 observation, forecasts are estimated.

Table 13: HAR-RV Model with Pre-Announcement Dummy Variable, Equation (29)(h=1)

	Swiss						German					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.001	—	0.001	0.001	0.002	0.001	0.001	0.000	0.001	0.001	0.001	0.001
	(3.21)***	—	(3.07)***	(2.74)***	(6.27)***	(2.38)***	(3.48)***	(3.19)***	(4.26)***	(4.05)***	(4.18)***	(4.27)***
β_d^1	0.159	—	0.021	0.051	0.288	0.070	-0.001	0.195	0.223	0.180	0.187	0.157
	(1.13)	—	(0.18)	(0.37)	(1.72)*	(0.35)	(-0.03)	(4.6)***	(5.22)***	(3.88)***	(4.46)***	(2.37)***
β_d	0.377	—	0.323	0.348	0.145	0.340	0.600	0.304	0.356	0.444	0.380	0.527
	(7.27)***	—	(8.95)***	(8.86)***	(3.59)***	(6.02)***	(15.72)***	(8.28)***	(8.77)***	(11.51)***	(6.56)***	(8.97)***
β_w	0.309	—	0.344	0.358	0.135	0.292	0.246	0.362	0.396	0.379	0.368	0.328
	(5.71)***	—	(7.28)***	(6.55)***	(2.76)***	(4.84)***	(5.37)***	(6.56)***	(7.61)***	(8.51)***	(6.61)***	(5.76)***
β_m	0.210	—	0.129	0.160	0.258	0.214	0.087	0.235	0.130	0.053	0.071	0.013
	(4.79)***	—	(2.6)***	(3.76)***	(3.59)***	(3.8)***	(2.88)***	(4.22)***	(4.26)***	(1.67)*	(2.46)***	(0.54)
R^2	0.635	—	0.393	0.520	0.121	0.511	0.753	0.628	0.609	0.623	0.493	0.667
$QLIKE$	0.201	—	0.133	0.117	0.166	0.162	0.119	0.060	0.073	0.072	0.073	0.095

	French						UK					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002
	(4.32)***	(2.57)***	(2.75)***	(3.88)***	(2.94)***	(4.83)***	(2.7)***	(4.36)***	(3.98)***	(3.11)***	(4.08)***	(3.6)***
β_d^1	-0.014	0.123	0.075	0.144	0.091	0.101	0.141	0.155	0.212	0.262	0.264	0.346
	(-0.21)	(2.08)**	(2)**	(1.67)*	(1.34)	(1.22)	(1.68)*	(2.08)**	(2.63)***	(3.01)***	(3.18)***	(3.36)***
β_d	0.611	0.404	0.388	0.452	0.387	0.513	0.514	0.461	0.490	0.477	0.577	0.567
	(16.65)***	(7.88)***	(9.37)***	(10.58)***	(8.99)***	(12.24)***	(11.79)***	(6.22)***	(6.4)***	(9.7)***	(8.25)***	(11.05)***
β_w	0.198	0.379	0.327	0.307	0.251	0.255	0.251	0.266	0.203	0.285	0.142	0.229
	(2.77)***	(7.1)***	(7.86)***	(6.91)***	(4.85)***	(4.98)***	(2.56)***	(3.08)***	(2.55)***	(6.82)***	(1.63)	(4.67)***
β_m	0.058	0.158	0.202	0.125	0.232	0.112	0.118	0.124	0.111	0.049	0.087	0.029
	(1.65)*	(4.68)***	(6.13)***	(4.04)***	(5.39)***	(3.46)***	(1.82)*	(2.76)***	(2.42)***	(1.43)	(2.1)**	(1.01)
R^2	0.626	0.784	0.659	0.623	0.523	0.638	0.641	0.552	0.473	0.515	0.519	0.600
$QLIKE$	0.107	0.062	0.068	0.076	0.065	0.102	0.068	0.070	0.083	0.086	0.069	0.106

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 14: HAR-RV Model with Announcement Dummy Variable, Equation (30) (h=1)

	Swiss						German					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.001	—	0.001	0.001	0.002	0.001	0.001	0.000	0.001	0.001	0.001	0.001
	(2.71)***	—	(3.06)***	(2.74)***	(6.2)***	(2.37)***	(3.49)***	(3.02)***	(4.12)***	(4.03)***	(4.2)***	(4.28)***
β_d^1	-0.134	—	0.127	0.027	0.037	0.186	-0.036	0.039	0.022	0.045	0.128	0.014
	(-2.88)***	—	(1.39)	(0.37)	(0.47)	(2.06)**	(-1.26)	(0.6)	(0.44)	(0.84)	(1.48)	(0.12)
β_d	0.394	—	0.320	0.348	0.147	0.338	0.602	0.314	0.369	0.449	0.382	0.537
	(7.71)***	—	(8.9)***	(8.76)***	(3.56)***	(5.99)***	(15.59)***	(8.24)***	(8.68)***	(11.62)***	(6.53)***	(9.29)***
β_w	0.304	—	0.345	0.358	0.137	0.293	0.247	0.358	0.389	0.374	0.365	0.320
	(5.68)***	—	(7.29)***	(6.56)***	(2.8)***	(4.86)***	(5.34)***	(6.56)***	(7.29)***	(8.35)***	(6.54)***	(5.67)***
β_m	0.211	—	0.129	0.159	0.258	0.214	0.086	0.238	0.135	0.057	0.073	0.016
	(4.84)***	—	(2.62)***	(3.77)***	(3.58)***	(3.8)***	(2.76)***	(4.25)***	(4.43)***	(1.8)*	(2.5)***	(0.68)
R^2	0.635	—	0.394	0.519	0.119	0.512	0.753	0.623	0.603	0.620	0.491	0.666
$QLIKE$	0.201	—	0.133	0.117	0.166	0.162	0.119	0.062	0.074	0.072	0.073	0.095

	French						UK					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002
	(4.36)***	(2.46)***	(2.72)***	(3.83)***	(2.93)***	(4.84)***	(2.68)***	(4.28)***	(3.98)***	(3.23)***	(4.22)***	(3.92)***
β_d^1	-0.094	-0.018	0.006	0.056	0.130	0.023	0.127	0.215	0.185	0.003	0.036	0.067
	(-1.27)	(-0.52)	(0.12)	(0.83)	(1.89)*	(0.2)	(1.07)	(1.73)*	(1.14)	(0.02)	(0.22)	(0.29)
β_d	0.613	0.415	0.390	0.456	0.384	0.516	0.512	0.452	0.476	0.483	0.577	0.569
	(16.9)***	(7.93)***	(9.37)***	(10.43)***	(9.08)***	(12.54)***	(11.74)***	(6.72)***	(7.41)***	(10)***	(10.15)***	(11.37)***
β_w	0.198	0.376	0.325	0.304	0.252	0.254	0.250	0.269	0.211	0.286	0.149	0.236
	(2.77)***	(6.98)***	(7.81)***	(6.87)***	(4.87)***	(4.98)***	(2.54)***	(3.27)***	(2.87)***	(6.73)***	(1.77)*	(4.81)***
β_m	0.059	0.159	0.204	0.128	0.233	0.113	0.121	0.126	0.113	0.050	0.088	0.029
	(1.67)*	(4.77)***	(6.24)***	(4.15)***	(5.42)***	(3.5)***	(1.86)*	(2.8)***	(2.42)***	(1.49)	(2.1)**	(1.03)
R^2	0.627	0.782	0.659	0.621	0.525	0.637	0.641	0.556	0.474	0.510	0.512	0.594
$QLIKE$	0.107	0.062	0.068	0.077	0.066	0.102	0.069	0.071	0.083	0.087	0.070	0.106

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 15: HAR-CJ Model with Pre-Announcemet Dummy Variable, Equation (31) (h=1)

	Swiss						German					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.002	—	0.002	0.001	0.003	0.002	0.001	0.000	0.001	0.001	0.002	0.002
	(5.51)***	—	(4.47)***	(6.43)***	(9.73)***	(6)***	(4.8)***	(3.34)***	(8.79)***	(8.43)***	(6.63)***	(4.98)***
β_d^1	-0.003	—	0.005	-0.010	0.007	-0.019	0.002	0.015	0.017	0.014	0.015	0.010
	(-0.59)	—	(0.29)	(-1.21)	(0.54)	(-3.14)***	(0.46)	(4.9)***	(5.91)***	(3.56)***	(3.61)***	(2.23)**
β_j^1	0.976	—	-0.013	0.355	0.330	0.656	-0.182	0.070	-0.011	0.037	-0.009	0.054
	(4.79)***	—	(-0.09)	(1.79)*	(1.09)	(4.91)***	(-1.42)	(1.02)	(-0.16)	(0.46)	(-0.14)	(0.36)
β_d	0.393	—	0.340	0.366	0.158	0.333	0.599	0.379	0.411	0.522	0.430	0.529
	(7.04)***	—	(7.68)***	(8.4)***	(3.53)***	(5.86)***	(16.73)***	(6.66)***	(7.11)***	(11.57)***	(4.95)***	(7.77)***
β_w	0.287	—	0.341	0.331	0.165	0.327	0.251	0.326	0.362	0.325	0.352	0.334
	(4.9)***	—	(5.85)***	(6.04)***	(2.85)***	(5.26)***	(6.01)***	(6.1)***	(5.62)***	(6.22)***	(4.23)***	(5.13)***
β_m	0.241	—	0.161	0.166	0.219	0.182	0.083	0.240	0.115	0.030	0.043	0.005
	(5.12)***	—	(2.51)***	(3.88)***	(2.99)***	(3.11)***	(2.75)***	(4.02)***	(3.52)***	(0.94)	(1.48)	(0.2)
β_j	0.195	—	0.206	0.232	0.102	0.194	0.300	0.109	0.130	0.095	0.182	0.200
	(3.55)***	—	(4.2)***	(6.41)***	(2.54)***	(2.78)***	(5.28)***	(3.88)***	(5.19)***	(3.73)***	(5.28)***	(1.63)
R^2	0.637	—	0.394	0.511	0.118	0.519	0.755	0.623	0.609	0.631	0.493	0.666
$QLIKE$	0.202	—	0.136	0.119	0.168	0.161	0.120	0.060	0.072	0.070	0.072	0.094

	French						UK					
	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
β_0	0.001	0.000	0.001	0.001	0.002	0.001	0.002	0.001	0.002	0.002	0.001	0.002
	(2.84)***	(3.19)***	(5.43)***	(4.65)***	(6.03)***	(3.03)***	(3.79)***	(6.26)***	(6.91)***	(7.02)***	(4.42)***	(4.47)***
β_d^1	0.005	0.009	0.007	0.015	0.016	0.004	0.011	0.013	0.014	0.017	0.020	0.021
	(1.51)	(2.14)**	(3.04)***	(2.69)***	(5.12)***	(0.82)	(1.81)*	(2.71)***	(2.18)**	(2.29)**	(2.53)***	(2.09)**
β_j^1	-0.879	-0.155	0.038	-0.288	-0.148	-0.169	-0.015	0.046	0.227	0.176	0.062	0.167
	(-5.04)***	(-1.25)	(0.47)	(-3.39)***	(-2.73)***	(-0.79)	(-0.1)	(0.46)	(1.29)	(1.1)	(0.35)	(0.91)
β_d	0.582	0.432	0.448	0.467	0.468	0.517	0.547	0.574	0.605	0.499	0.619	0.548
	(19.48)***	(8.67)***	(10.19)***	(10.56)***	(9.24)***	(12.56)***	(12.79)***	(10.28)***	(8.14)***	(8.52)***	(9.62)***	(9.88)***
β_w	0.213	0.482	0.412	0.358	0.328	0.312	0.294	0.259	0.130	0.278	0.104	0.243
	(3.88)***	(9.37)***	(9.73)***	(7.9)***	(5.51)***	(7.02)***	(3.77)***	(3.76)***	(1.72)*	(6.29)***	(1.37)	(5)***
β_m	0.046	0.052	0.057	0.063	0.049	0.057	0.044	0.028	0.094	0.057	0.138	0.043
	(2.29)**	(2.82)***	(1.97)**	(2.15)**	(1.56)	(1.55)	(1.76)*	(2.7)***	(3.87)***	(2.64)***	(3.8)***	(2.22)**
β_j	0.671	0.178	0.113	0.275	0.186	0.727	0.307	0.171	0.106	0.123	0.176	0.293
	(4.43)***	(3.26)***	(3.06)***	(5.07)***	(5.22)***	(5.11)***	(3.29)***	(2.35)***	(3.51)***	(3.1)***	(2.63)***	(2.46)***
R^2	0.640	0.781	0.659	0.627	0.527	0.645	0.633	0.555	0.495	0.532	0.537	0.606
$QLIKE$	0.107	0.062	0.068	0.076	0.065	0.114	0.071	0.073	0.081	0.081	0.066	0.103

(1) The results in the parenthesis indicates t-statistics. (2) ***, **, * show 1%, 5% and 10% statistically significant coefficients, respectively. (3) Newey-West standard errors are used to calculate the t statistics.

Table 16: Microstructure Bias Corrected One-Month Ahead Out of Sample Forecast Results (h=22)

(a) QLIKE Estimates

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	1.000	0.996[a]	1.042	1.000	1	1.016	1.000	1.003	0.903	1.000	0.999[a]	1.041
2-Year	—	—	—	1.000	1.002	1.083	1.000	0.998	1.205	1.000	0.994[a]	1.115
5-Year	1.000	0.968[a]	0.929[a]	1.000	1.001	1.032	1.000	0.973[a]	1.127	1.000	0.993[a]	0.977[a]
10-Year	1.000	0.985[a]	0.947[a]	1.000	0.996[a]	1.004	1.000	0.994[a]	1.003[a]	1.000	0.989[a]	1.02
20-Year	1.000	0.996[a]	1.05	1.000	0.999[a]	0.987[a]	1.000	1[a]	1.08	1.000	0.995[a]	1.004[a]
30-Year	1.000	0.99[a]	0.967	1.000	0.999[a]	0.999[a]	1.000	1.004	1.207	1.000	0.99[a]	1.017

(1) QLIKE ratios are given in the table. (2) The ratios are scaled to QLIKE estimators of HAR-RV model. (3) Rolling window, 1000 observation, forecasts are estimated. (4) [a] corresponds to significant Diebold-Mariano Test at 5% level.

(b) Average R^2

	Swiss			German			French			UK		
	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ	HAR-RV	HAR-RVJ	HAR-CJ
1-Year	50.5%	50.7%	49.7%	48.6%	48.8%	49.0%	27.4%	27.7%	30.4%	36.8%	37.1%	36.6%
2-Year	—	—	—	54.1%	54.3%	51.5%	62.8%	63.0%	61.5%	31.5%	32.2%	31.9%
5-Year	29.3%	30.2%	30.5%	34.0%	34.2%	33.5%	53.4%	55.1%	57.7%	23.4%	24.0%	25.7%
10-Year	39.6%	39.7%	38.6%	31.9%	32.1%	32.2%	37.2%	37.7%	43.2%	32.4%	33.0%	30.7%
20-Year	19.6%	19.7%	15.3%	33.0%	33.7%	35.6%	46.1%	46.1%	43.8%	36.2%	36.2%	33.4%
30-Year	28.1%	28.3%	25.5%	36.5%	36.7%	37.5%	38.9%	39.0%	41.5%	36.2%	36.6%	30.7%

(1) Average R^2's are given in the table. (2) Rolling window, 1000 observation, forecasts are estimated.