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 for the return volatility of major European government bond markets. Results from HAR-type volatility forecasting models show that past short and medium-term volatility are significant predictors of the term structure of intraday volatility of European bonds with maturities ranging from 1-year up to 30-years. When we decompose bond market volatility into its continuous and discontinuous (jump) component, we find that the jump component is a significant predictor. Moreover, we show that feedback from past short-term volatility to the forecast of future volatility is stronger in days that precede monetary policy announcements.

Keywords: Bonds, Realized Volatility, Volatility Forecasting, Jumps, Monetary Policy Announcements

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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 examining 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. (2020); 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 over the period January 2005 to October 2019. Specifi-

[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.

cally, 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 show that the HAR components of realized volatility are robust predictors of European bond return volatility across different maturities at the 1-day, 5-day and 22-day horizon. The significance of HAR models also provides evidence in favour of the long memory property of bond market volatility. The models are found to be successful in explaining 40% to 80% in-sample and 20% to 70% out of-sample variation in future volatility. Moreover, the inclusion of past realized jumps in the right-hand side of the HAR model equation, has a positive and significant impact on future volatility and improves the forecasting ability of the HAR model. We also extend the model by using realized semivariances (RSV) and find the inclusion of leverage effect, semivariances and signed jumps have an additional power on the forecasting performance[2].

We proceed by examining the role of monetary policy announcements within HAR-models of bond return volatility and our analysis highlights the importance of monetary policy announcements. Our findings show that almost half of the announcements coincide with at least one statistically significant bond price jump. Moreover, we find evidence for a stronger feedback from past short-term volatility to the forecast of future volatility on pre-announcement days (relative to other days). The direct implication of this finding is that government bond volatility during monetary policy announcement days is more sensitive to the market mood in the pre-announcement day than other days. Hence, our results our consistent with a "pre-announcement effect" in bond return volatility forecasting. In addition, we show that this effect becomes more pronounced during the QE era. Furthermore, we examine whether this effect shows up both in the continuous part of the volatility and the jump variation. Our evidence is consistent only with the former. The limited and insignificant effect of pre-announcement on jumps stems from the short memory property of jump variation as opposed to the long-memory property of the diffusive (continuous) component of bond price volatility.

Our work is related and contributes to several strands of the literature. Most primarily, 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 which has been developed by following the seminal work by Corsi (2009) and identified the successful forecasting performance of HAR models for stock and commodity market volatility (Bollerslev et al. (2018); Dueker (1997); Bollerslev et al. (2016);

[2]The out-of-sample results are based upon the Diebold & Mariano (1995) test.

Bollerslev & Mikkelsen (1996); Degiannakis et al. (2020); 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 impact of jumps on future US bond volatility, we show that bond price jumps have a positive impact on European bond return volatility[3]. 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 determinants of bond market volatility and the pre-announcement effect is present in the European bond market when 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 (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))[4]. Our findings also provide further empirical insights on the strand of literature focusing on the impact of macroeconomic and monetary policy announcements on 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 (2006); Ederington & Lee (1993); Jones et al. (1998); Perignon & Smith (2007)) and FX markets (Andersen et al. (2003b); Andersen et al. (2007b)). On the European volatility forecasting

[3]The main reasons behind the difference between previous studies and our results can be linked to flat pricing and the coverage of sample period. The literature on volatility forecasting using HAR models (see Andersen et al. (2007a), Corsi (2009), Corsi et al. (2010) and Busch et al. (2011)) mainly depends on the US T-bond futures using the sample period which ends in 2002 at latest. Firstly, while Corsi et al. (2010) report nearly 30% of zero intraday (5-minute) returns in their high frequency US Treasury futures dataset, the respective percentage of zero returns in our sample is approximately 10% for most of the bonds. Due to jump detection methodology, flat prices may lead to false detection of jumps. Therefore, the contribution of jumps into volatility forecasting models becomes more prone to errors. Also, our study depends on more a more contemporary dataset, covering different markets which makes us unable to replicate and make a direct comparison with the literature.

[4]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 intraday US stock-market index price jumps.

literature, 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)).

Finally, to the best of our knowledge, our study is the first one (European data-based or otherwise) to analyse the role of the pre-announcement effect for bond return volatility forecasting using HAR models. Our results are not directly comparable with the results in the extant literature regarding the "pre-FOMC drift". In a seminal study on the US stock market, Lucca & Moench (2015) examine the stock market excess returns in a window of 24 hours leading up to scheduled FOMC statement releases and find that on overage they are positive. Moreover, they use data on Treasuries futures and show that the drift only appears in the stock market, whereas it does not show up in US fixed income markets.

The rest of the paper is structured as follows. Section 2 presents data and methodology. In Section 3, we analytically present and discuss the results. In Section 4, we briefly discuss the additional tests and methods being performed which provide robustness to our findings and analysis. Finally, 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 ranges from 5 to 10 minute intervals (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[5].

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 consider the changes in the underlying instruments on a 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 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. *Realized Volatility Measurement*

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)). The zero-coupon rates and bond prices of corresponding maturities which are obtained using the Nelson & Siegel (1987), are then used for the estimation of the realized volatility. In this study, we use bond prices (not yields) to estimate bond return volatility[6].

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

$$r(t+h,h,\tau) = p(t+h,\tau) - p(t,\tau), \tag{1}$$

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

[5] See Online Appendix ”Appendix B: Robustness” for more details.

[6] The analytical description of Nelson-Siegel model used for converting European bond yields to zero coupon bond prices is given in the Online Appendix.

according to equation 2 below:

$$r_\tau\Big(t + \frac{ih}{n}, \frac{h}{n}\Big) = -\tau\Big(s_\tau\Big(t + \frac{ih}{n}\Big) - s_\tau\Big(t + \frac{(i-1)h}{n}\Big)\Big), \tag{2}$$

where h/n shows us sampling frequency. Therefore, (2) indicates the intraday return on interval $\frac{ih}{n}$ and $\frac{(i-1)h}{n}$. Since, the returns are scaled to τ, the variance series, Var, also become proportional to τ^2 as follows:

$$Var_{r_\tau}(t+h,h) = \frac{1}{h}\sum_{i=1}^{n}\tau^2\Big(s_\tau\Big(t + \frac{ih}{n}\Big) - s_\tau\Big(t + \frac{(i-1)h}{n}\Big)\Big)^2, \tag{3}$$

where, τ is the bond maturity, $s_\tau(.)$ zero coupon interest rates, h is estimation horizon and h/n shows us sampling frequency. Therefore, intraday bond volatility increases by the square of time to maturity. We then re-scale the variance, $Var_{r_\tau}(t+h,h)$, by τ^2 to obtain comparable realized variance.

$$RV_\tau(t+h,h) = \frac{1}{\tau^2}\Big(Var_{r_\tau}(t+h,h)\Big). \tag{4}$$

The scaled estimator of volatility, as shown in equation (4), ensures that realized bond return volatility satisfies the asymptotic properties of quadratic variation. In addition to intraday variance we also focus on the importance of jumps in the intraday basis. In order to decompose realized variance 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 variance 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:

$$BV_\tau(t+h,h) = (\frac{1}{\tau^2})\mu_1^{-2}(\frac{n}{n-1})\sum_{i=2}^{n}|\Delta_{i-1}p(t+\frac{(i-1)h}{n})||\Delta_i p(t+\frac{(i)h}{n})|, \tag{5}$$

where $\mu_1 = \sqrt{2}/\sqrt{\pi}$. The first term in equation (5), $1/\tau^2$, modifies the BV parameter proposed by Barndorff-Nielsen & Shephard (2004) as an extension for bond returns which have different time to maturity[7].

[7]We provide the details regarding jump detection using ratio test of Zhang et al. (2005) in the Online Appendix.

2.3. 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 behavior, 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 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.

$$RV_{t_1:t_2} = \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} RV_t, \ where\ t_1 \leqslant t_2. \tag{6}$$

Then, weekly and monthly averages[8] are given in the (7) below:

$$RV_{t-5:t-2} = \frac{1}{4} \sum_{t=t-5}^{t-2} RV_t, \tag{7}$$

$$RV_{t-22:t-6} = \frac{1}{17} \sum_{t=t-22}^{t-6} RV_t. \tag{8}$$

Then, HAR-RV model [9] is given in (9):

$$RV_{t+h-1:t} = \beta_0 + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t, \tag{9}$$

where h corresponds to forecast horizon. We decompose the continuous and discontinuous part of RV using Barndorff-Nielsen & Shephard (2004) methodology. Then, we can employ extended HAR models such as HAR-RVJ model and HAR-CJ model of Andersen et al. (2007a) with the discontinuous jump variations. The inclusion of jump parameters in

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

[9] 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.

the volatility forecasting regressions enable us to measure the possible magnitude of daily jumps on the future volatility and its significant life span over the investment horizon.

We identify the significant jump series using jump ratio test of Huang & Tauchen (2005)[10]:

$$\hat{J}_t = I_{z_t > \psi_\alpha}(RV_t - BV_t)^+, \tag{10}$$

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 (11).

$$\hat{C}_t = RV_t - \hat{J}_t. \tag{11}$$

We also compute weekly, $\hat{C}_{t t-5:t-2}$, and monthly, $\hat{C}_{t t-22:t-6}$, continuous variation series, $\hat{C}_t$ similar to (7) and (8).

$$\hat{C}_{t t-5:t-2} = \frac{1}{4} \sum_{t=t-5}^{t-2} \hat{C}_{t t}, \tag{12}$$

$$\hat{C}_{t t-22:t-6} = \frac{1}{17} \sum_{t=t-22}^{t-6} \hat{C}_{t t}. \tag{13}$$

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

HAR-RVJ model:

$$RV_{t+h-1:t} = \beta_0 + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t. \tag{14}$$

HAR-CJ model:

$$RV_{t+h-1:t} = \beta_0 + \beta_d \hat{C}_{t-1} + \beta_w \hat{C}_{t-5:t-2} + \beta_m \hat{C}_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t. \tag{15}$$

[10] We provide more detailed information on jump identification in the Online Appendix.

3. Empirical Findings

3.1. Descriptive Statistics

In this section we present the descriptive statistics of our time series sample. Tables 1 and 2 below show 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. 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 gives the realized volatility series for the major European bond markets between January 2005 to October 2019. From top row to bottom, Swiss, German, French and the UK bond market volatility's are shown for separate maturities. 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 constitute the most important bond market disruption 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 November 2016 due to heightened riskiness in the US budget balance. Andersson et al. (2009) study the factors driving bond yield dynamics 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 Figure 2 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 to 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) which was introduced in early 2015. While, low interest rate and quantitative easing policies tame market volatility in bond markets, its impact on liquidity makes government bond markets more fragile and open to sudden volatility spikes[11]. 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 2 2nd row). These initial descriptive results are some preliminary evidence showing the significant effect of major 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. Tables 3 to 6 show the results for the Swiss, German, French and UK realized bond return

[11] 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[12][13].

[Table 3 about here.]

[Table 4 about here.]

[Table 5 about here.]

[Table 6 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. Additionally, we use Mincer-Zarnowitz (MZ) R^2 of forecasting regressions' for evaluating performance.

$$QLIKE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{RV_t}{R\hat{V}_t} - log\left(\frac{RV_t}{R\hat{V}_t}\right) - 1\right), \tag{16}$$

where RV_t is estimated using equations 9, 14 and 15.

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 6, 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

[12] We exclude the Swiss government bond with 2-year maturity from our analysis due to many (approximately 50% of the intraday observations) flat prices in the intraday intervals, resulting in 'no trade-bias' in favor of jump estimators. Bandi et al. (2020) give a detailed theoretical and empirical framework for the flat-pricing (zero returns) by linking the staleness with the transaction volume. Since the sources of flat-prices and its implications are out of the scope of our paper, we choose not to address these foundations and the staleness in the high-frequency prices could be used to improve volatility forecasts in future work.

[13] 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.

short (1-day) and medium term (weekly) and long term (monthly) horizons. In the HAR-type models of Corsi (2009), we aggregate realized volatility 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 seems to increase as the forecasting horizon extends[14].

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 measure has a significantly positive effect on the volatility forecasts and its impact on volatility is found to be persistent. 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 measure 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.

In this study, we examine the out-of-sample forecasting performance of the HAR-type direct method in multiple days ahead prediction for each 1000 observation in the rolling basis. Table 7 below report the out-of-sample forecasting results for 1-day horizon[15].

[Table 7 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

[14] See Online Appendix for longer term in-sample forecasting results.

[15] See Online Appendix for longer horizons.

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%. Moreover, realized jumps have a positive and significant impact on future volatility in the HAR models and significantly improves forecasting ability of volatility [16].

As a further assessment, we provide an analysis of realized semivariances (RSV) in the Online Appendix to see the contribution of good" and "bad" volatility in the forecasting framework. Compared to the baseline HAR model, we test for any additional forecasting power of realized semivariances and signed jumps in controlling for simple leverage effect (see Patton & Sheppard (2015)). We find that negative RSV, "bad" volatility, has a more substantial impact on future volatility than positive RSV, "good" volatility. This result implies that volatility shocks associated with an interest rate increase have a more pronounced impact than those stemming from interest rate decreases. On the other hand, the inclusion of signed jumps generates more ambiguous results. Finally, out of sample forecast results indicate improvements in forecasting power from incorporating realized semivariances and signed jumps, relative to the baseline HAR model. Therefore, jump variation, asymmetric variances, and jumps with leverage effect contribute forecasting power of HAR models[17].

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 European government bonds' realized volatility. Figure 3 reports the response of financial markets to the monetary policy announcements among major European central banks. Firstly, the announcement calendar of Swiss National Bank (SNB)

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[16]For brevity, we do not include the forecasting regression results for weekly (5-day) and monthly (22-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.

[17]Semivariance with leverage effect (HAR-RSV-L): $RV_{t+h-1} = \phi_0 + \phi_{d^+} RSV^+_{t-1} + \phi_{d^-} RSV^-_{t-1} + \phi_l RV_{t-1} I_{(r_{t-1}<0)} + \phi_w RV_{t-5:t-2} + \phi_m RV_{t-22:t-6} + \epsilon_t$, Semivariance with signed jumps and leverage effect (HAR-RSVJ-L): $RV_{t+h-1} = \phi_0 + \phi_{d^+} RSV^+_{t-1} + \phi_{d^-} RSV^-_{t-1} + \phi_l BV_{t-1} I_{(r_{t-1}<0)} + \phi_w RV_{t-5:t-2} + \phi_m RV_{t-22:t-6} + \phi_{j^+} J^+{}_{t-1} + \phi_{j^-} J^-{}_{t-1} + \epsilon_t$. We extend the model using semivariances,RSV^-_{t-1} and RSV^+_{t-1} and signed jumps, J^- and J^+ controlling with leverage effect, $I_{(r_{t-1}<0)}$ where daily bond return is negative. See Online Appendix C: Realized Semivariance section for more details.

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 3, 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 on 12:45 (GMT). It is obvious that for France (bottom left of Figure 3), and Germany (top right of Figure 3), 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 3), shows a sudden spike.

[Figure 1 about here.]

The jump variation for bond markets signals 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 important source of variation for European government bond markets. Figure 4 reports the average jumps and volatility of the yield curve on the announcement dates[18].

[Figure 2 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 the 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, which is then called as pre-FOMC drift. The excess return is justified by bearing non-diversifiable 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 effects on European bond market volatility forecasts. As to our knowledge it is the first paper trying to explain the pre-meeting impact in the HAR 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,

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

separately. Therefore, HAR-RV model[19] becomes:

$$RV_{t+h-1:t} = \beta_0 + \beta_d^1 RV_{t-1} 1(pre - announcement) + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t, \tag{17}$$

and

$$RV_{t+h-1:t} = \beta_0 + \beta_d^1 RV_{t-1} 1(announcement) + \beta_d RV_{t-1} + \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t, \tag{18}$$

where 1(.) is a dummy variable (indicator function) for pre-announcement or announcement days, which takes value of 1 on those days and takes 0 on others.

Table 8 reports 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, β_d, 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 indicate that the volatility transmission sensitivity of forecasts, $\beta_d+\beta_d^1$, increases by almost 40% in pre-announcement days. The direct implication of this finding is that volatility on the monetary policy announcement days is more sensitive to the market mood on the pre-announcement day than other days. This outcome can be interpreted as evidence of the presence of pre-announcement effect in the bond market. Therefore, the inclusion of day dummy variable highlights the importance of pre-announcement days in the European bond market.

Moreover, Table 9 shows the results for the HAR-RV model with announcement day dummy variable. Results show that there is no common impact of announcement days, β_d^1, on the one-day forward volatility and the underlying dynamics of HAR forecasting relationship after the announcement became unchanged. Although there is an ascending level of volatility around the announcements, see Figure 3, this effect is found to be short-living and not effective in the 1-day horizon.

We can link our findings to the pre-FOMC drift of Lucca & Moench (2015), who assert large positive stock market excess returns in a window of 24 hours leading to scheduled FOMC statement releases and this effect is not present in the post-FOMC period. Similarly, we find that there is an increased level of transmission of volatility from pre-announcement day to the announcement day, while the transmission from announcement

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

day to post-announcement day is found to be ineffective, see Table 8 and 9. From this perspective, although pre-FOMC drift of Lucca & Moench (2015) focus on 24-hour accumulated return and find a drift in equity markets, not in bond markets prior to FOMC release, we find an effect, or drift, in volatility in the bond market from pre-announcement day.

The difference of transmission between pre-announcement day effect and announcement day effect can be related to the information releases regarding monetary policy. The short term tension before the release 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. Similarly, Lucca & Moench (2015) emphasise the role of investors' bearing non-diversifiable risk and systemic risk around the meeting. After the monetary policy announcements generally the opportunity to speculate in the markets evaporates and markets tends to turn back its own fundamentals.

[Table 8 about here.]

[Table 9 about here.]

Moreover, we test for the source of pre-announcement drift in the integrated variation and jump variation framework using an extended model of HAR-CJ as follows:

$$\begin{aligned} RV_{t+h-1:t} = \beta_0 + \beta_d^1 \hat{C}_{t-1} 1(pre-announcement) + \beta_j^1 \hat{J}_{t-1} 1(pre-announcement) + \\ \beta_d \hat{C}_{t-1} + \beta_w \hat{C}_{t-5:t-2} + \beta_m \hat{C}_{t-22:t-6} + \beta_j \hat{J}_{t-1} + \epsilon_t, \end{aligned} \tag{19}$$

In Equation 19, 1(.) is a dummy variable, taking value of "1" on pre-announcement days and takes "0" on others. The coefficient of continuous volatility interaction variable, β_d^1, shows the transmission from integrated variation, whereas the coefficient of jump interaction variable, β_j^1 indicates contribution of jump variation on one-day future volatility.

[Table 10 about here.]

Table 10 shows 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. This outcome could be resulted by the long memory feature of volatility. Since, the continuous part reflects the long memory, while discrete jumps have short memory characteristics. Similar to these findings, Beber &

Brandt (2009) state that bond price jumps on the announcement days are not autocorrelated, while Dungey et al. (2018) find an intraday clustering in price jumps in US Treasury markets which is more intense around US macroeconomic news releases. These results are broadly in line with our findings and provide further insights on the factors driving the predictive information content of bond price jumps on European Treasury bond yield volatility.

In this paper, we also seek an answer on whether quantitative easing (QE) policies have an impact on the transmission of volatility on expected volatility, Therefore, we include an additional interaction dummy variable, $1(QE)$, which corresponds to start of asset purchase program by ECB in forms of public sector purchase program (PSPP) after January 2015. In this scope, we investigate only German and French government bond markets that are targeted by PSPP.

The estimated equations are in below. The results on β_d^{12} reveal the information regarding possible impact of QE purchases on the volatility dynamics.

$$\begin{aligned} RV_{t+h-1:t} = \beta_0 + \beta_d^{11} RV_{t-1} 1(pre-ann.) + \beta_d^{12} RV_{t-1} 1(pre-ann.) 1(QE) + \beta_d RV_{t-1} + \\ \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t, \end{aligned} \tag{20}$$

and

$$\begin{aligned} RV_{t+h-1:t} = \beta_0 + \beta_d^{11} RV_{t-1} 1(ann.) + \beta_d^{12} RV_{t-1} 1(ann.) 1(QE) + \beta_d RV_{t-1} + \\ \beta_w RV_{t-5:t-2} + \beta_m RV_{t-22:t-6} + \epsilon_t, \end{aligned} \tag{21}$$

where $1(QE)$ is the dummy variable that takes value of "1" in period after January 2015, "0" otherwise[20].

[Table 11 about here.]

The results in Table 11 reveal important shifts in the German and French bond markets volatility forecasting mechanism associated with the onset of QE. Specifically, a comparison of β_d^{11} and β_d^{12} in equation 20 show that the pre-announcement effect, whereby the feedback from past short-term volatility to the forecast of future volatility is stronger in pre-announcement days, becomes more pronounced during the QE era. Regarding the developments at the announcement window, we find some interesting changes. While prior to QE, there is no announcement effect in the sense that there is no additional feedback from past short term volatility to the forecast of future volatility on announcement

[20] We use abbreviations 1(ann.) and 1(pre-ann.) for announcement and pre-announcement dummy variables.

days, during the QE era we identify a negative announcement effect, especially in the German market. This can be interpreted as a "volatility calming" effect stemming from the additional information presented by the ECB at statements, and also the subsequent press-conferences, regarding bond purchases in the euro area.

4. Robustness

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. In addition to market microstructure noise, realized volatility models suffer from finite sample jump distortion and intraday periodicity that can result in upward bias in jump estimators. Therefore, it becomes necessary to control those bias factors in order to have more reliable results.

In the Online Appendix section, we use alternative methods to control possible bias that is resulted by volatility estimations. Firstly, we provide realized kernel (Zhou (1996)) and AC-filtered RV (Hansen & Lunde (2006)) to remedy microstructure noise. Secondly, we follow nearest neighbor truncation based estimators of MinRV and MedRV (Andersen et al. (2012)) to asymptotically more feasible estimators that also contribute to reduce bias generated by intraday periodicity. Our results show that using alternative estimators in the HAR framework would result in only a material change in the output. Therefore, the significance of HAR models and contribution of jump variation on volatility forecasts unchanged after controlling for possible bias exposures of intraday data, which indicates a minimal impact of data noise and periodicity onto our estimations.

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 analysis shows that the daily, weekly and monthly realized variance is a robust predictor of volatility in European government bond markets. In addition, the inclusion of jump variation helps to improve volatility 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%. In addition, our HAR-type models identify the significant predictive power of jumps, semivariances and signed jumps on government bond volatility. Moreover, our analysis highlights the importance of monetary policy announcements. We find that almost half of the announcements coincide with at least one statistically significant bond price jump. Our results are consistent with a pre-announcement effect in bond return volatility forecasting since there is a stronger feedback from past short-term volatility to the forecast of future volatility on pre-announcement days.

This implies that volatility on the monetary policy announcement days is more sensitive to the market mood in the pre-announcement day than other days. In addition, this effect becomes more pronounced during the QE era. Further work in this area could consider the role of the interaction between semivariances (and signed jumps) and monetary policy announcements within a volatility forecasting framework.

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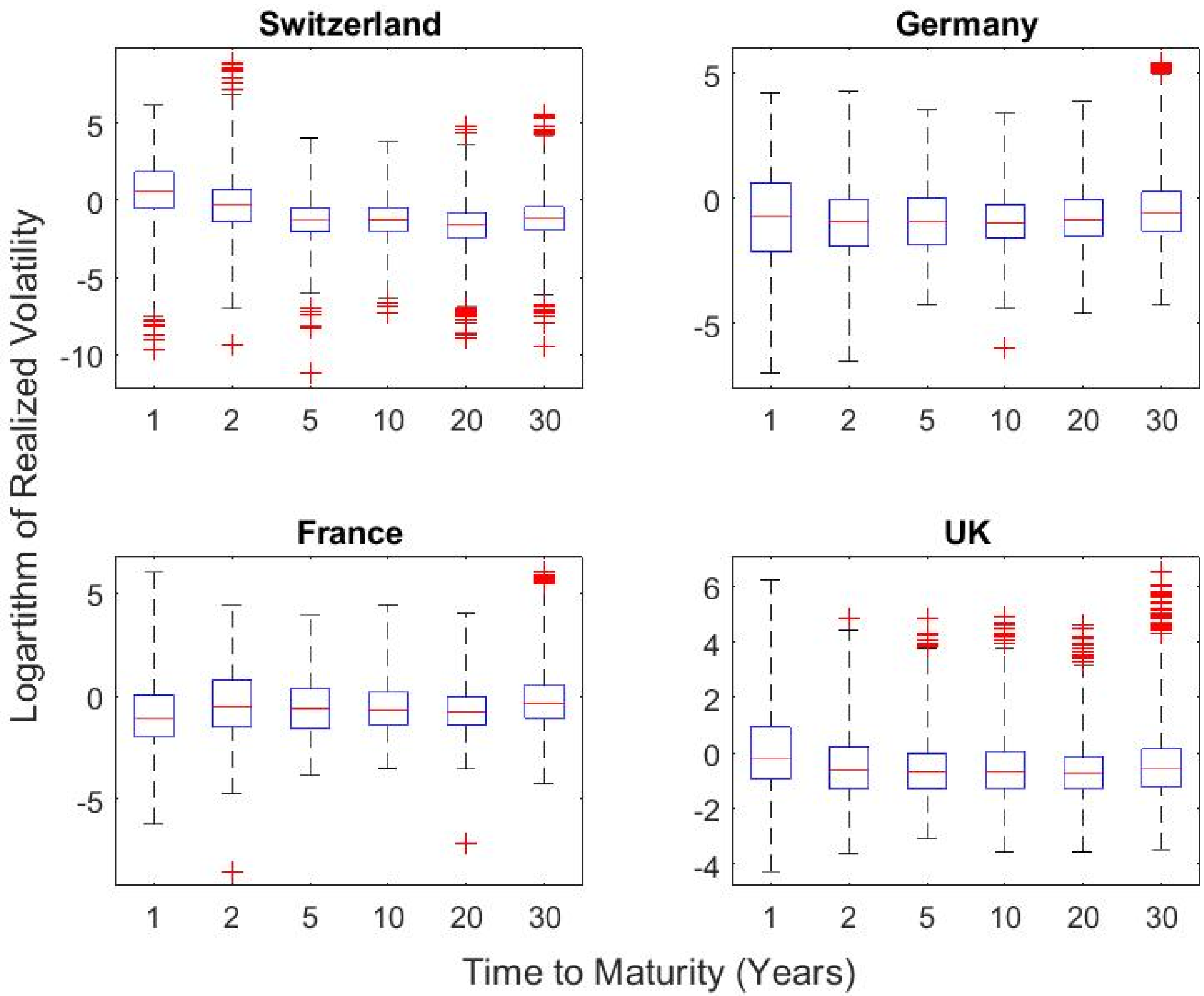

Figure 1: **Box plots for realized volatility.** The logarithms of realized volatility are given for smoothed intervals. Sub-figures depict the fence range with dashed lines and blue boxes show top to bottom quartiles with the median across markets on the maturity spectrum. Red plus signs corresponds to outliers. Sample Period: January 2005 to October 2019.

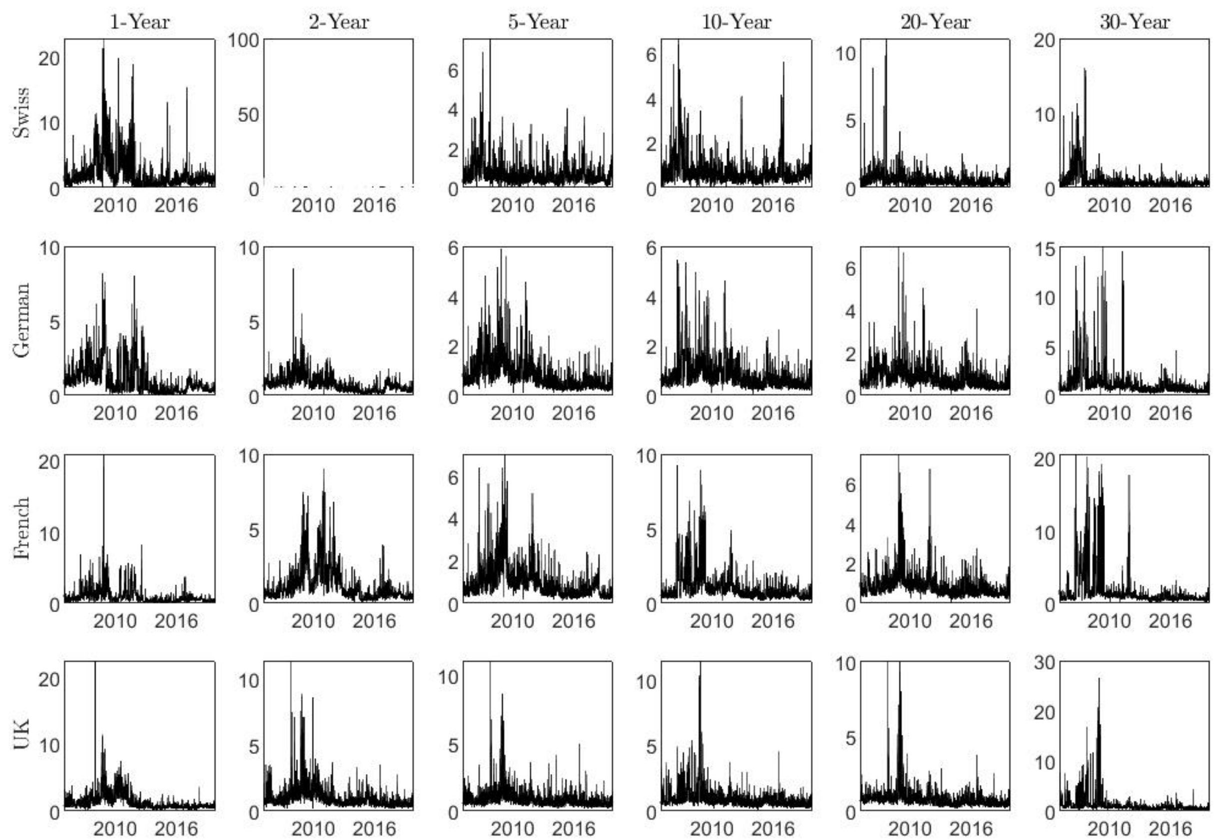

Figure 2: **Realized volatility across the maturity spectrum.** The realized volatility, $RV^{1/2}$, is given in percentages for the European Government Bond markets. 2-year Swiss bond is omitted due to flat pricing. Sample Period: January 2005 to October 2019.

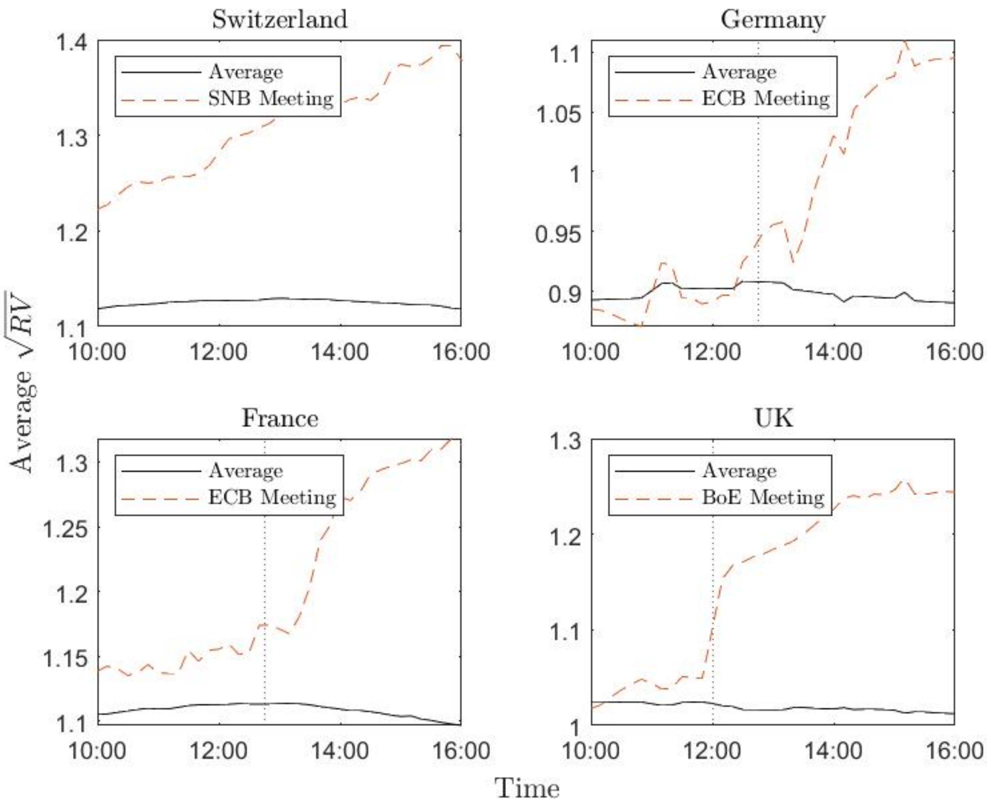

Figure 3: **Realized volatility averages by time of day.** The realized volatility, $RV^{1/2}$, is given in percentages. The averages of volatility is computed in the whole sample period of January 2005-October 2019. Dashed line represents volatility on monetary policy announcement days, solid line corresponds to non-announcement days and vertical dotted line signs the scheduled policy announcement time.

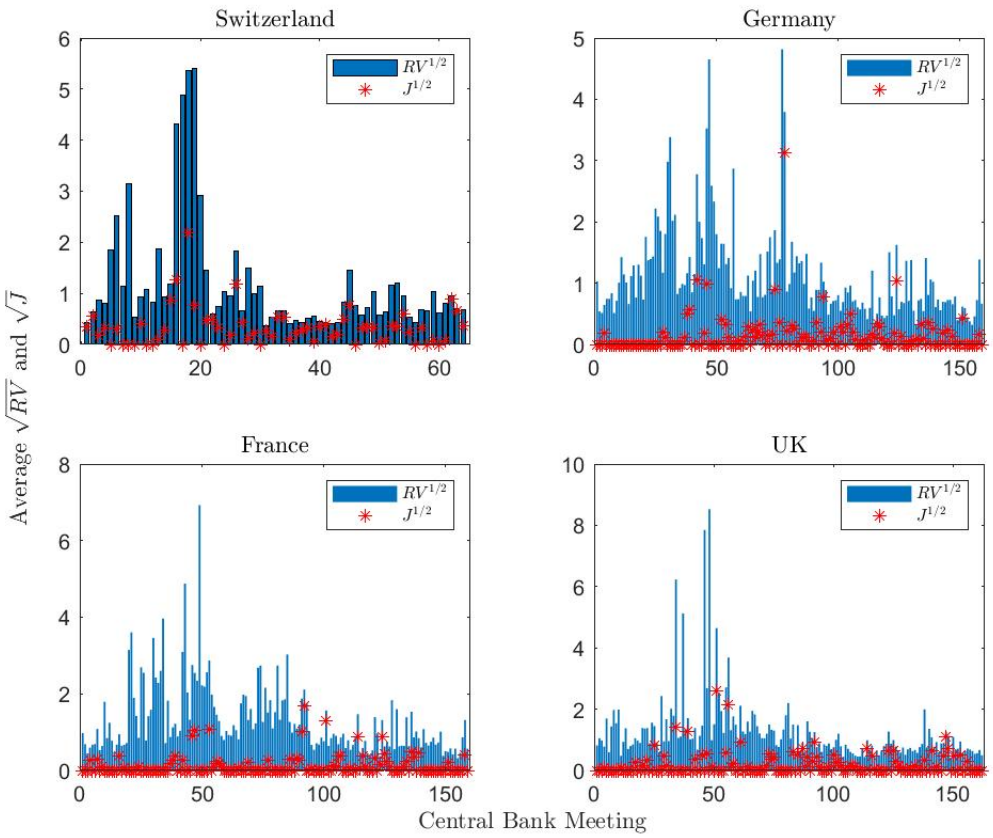

Figure 4: **Volatility and jump variation on the announcement days.** Average $\sqrt{RV}$ and $\sqrt{J}$ are given in percentages. The data points correspond to the average variation on the monetary policy committee meeting days of SNB, ECB and BoE respectively. Sample period: January 2005 to October 2019.

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: 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 8: HAR-RV Model with Pre-Announcement Dummy Variable, Equation (17)(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 9: HAR-RV Model with Announcement Dummy Variable, Equation (18) (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 10: HAR-CJ Model with Pre-Announcemet Dummy Variable, Equation (19) (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 11: HAR-RV Model with Quantitative Easing (QE) Dummy Variable (h=1)

(a) HAR-RV Model with Pre-Announcement Dummy Variable, Equation (20) (h=1)

	German						French					
	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	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.001	0.001	0.001
	(3.35)***	(3.1)***	(4.01)***	(3.91)***	(4.05)***	(4.14)***	(4.28)***	(2.59)***	(2.58)***	(3.74)***	(2.76)***	(4.72)***
β_d^{11}	-0.006	0.189	0.213	0.166	0.166	0.150	-0.015	0.124	0.062	0.131	0.064	0.098
	(-0.1)	(4.29)***	(4.91)***	(3.4)***	(3.9)***	(2.22)**	(-0.23)	(2.04)**	(1.61)	(1.45)	(0.96)	(1.17)
β_d^{12}	0.185	0.112	0.286	0.231	0.312	0.335	0.030	-0.047	0.275	0.346	0.444	0.270
	(2.23)**	(1.48)	(2.01)**	(1.38)	(1.53)	(1.58)	(0.24)	(-0.43)	(2.97)***	(2.35)***	(2.56)***	(1.64)
β_d	0.600	0.305	0.357	0.445	0.382	0.528	0.611	0.404	0.388	0.453	0.391	0.513
	(15.72)***	(8.26)***	(8.77)***	(11.52)***	(6.54)***	(8.96)***	(16.65)***	(7.88)***	(9.39)***	(10.61)***	(9.07)***	(12.23)***
β_w	0.246	0.362	0.396	0.378	0.368	0.327	0.198	0.379	0.327	0.307	0.251	0.256
	(5.37)***	(6.56)***	(7.6)***	(8.49)***	(6.6)***	(5.75)***	(2.77)***	(7.1)***	(7.86)***	(6.91)***	(4.82)***	(4.98)***
β_m	0.087	0.235	0.131	0.054	0.072	0.013	0.058	0.158	0.203	0.126	0.233	0.112
	(2.88)***	(4.23)***	(4.3)***	(1.7)*	(2.48)***	(0.56)	(1.65)*	(4.67)***	(6.16)***	(4.07)***	(5.42)***	(3.48)***
R^2	0.753	0.628	0.609	0.623	0.493	0.667	0.626	0.784	0.659	0.623	0.525	0.638
$QLIKE$	0.119	0.060	0.072	0.071	0.072	0.094	0.107	0.062	0.067	0.076	0.065	0.102

(b) HAR-RV Model with Announcement Dummy Variable, Equation (21) (h=1)

	German						French					
	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	0.000	0.001	0.001	0.001	0.001
	(3.49)***	(3.17)***	(4.3)***	(4.1)***	(4.33)***	(4.31)***	(4.4)***	(2.56)***	(2.81)***	(3.96)***	(3.08)***	(4.88)***
β_d^{11}	-0.034	0.049	0.032	0.060	0.154	0.020	-0.080	-0.013	0.015	0.070	0.170	0.028
	(-1.15)	(0.7)	(0.61)	(1.01)	(1.52)	(0.17)	(-1.01)	(-0.37)	(0.27)	(0.97)	(2.18)**	(0.23)
β_d^{12}	-0.054	-0.121	-0.145	-0.130	-0.164	-0.111	-0.203	-0.143	-0.102	-0.153	-0.230	-0.172
	(-0.98)	(-1.64)	(-2.14)**	(-1.62)	(-1.37)	(-0.89)	(-1.92)*	(-2.47)***	(-1.56)	(-1.7)*	(-2.34)***	(-1.25)
β_d	0.602	0.314	0.370	0.450	0.384	0.537	0.613	0.415	0.391	0.457	0.386	0.516
	(15.59)***	(8.24)***	(8.68)***	(11.62)***	(6.51)***	(9.29)***	(16.93)***	(7.93)***	(9.38)***	(10.45)***	(9.15)***	(12.54)***
β_w	0.247	0.358	0.388	0.373	0.362	0.320	0.197	0.376	0.325	0.303	0.248	0.254
	(5.33)***	(6.57)***	(7.26)***	(8.29)***	(6.46)***	(5.65)***	(2.77)***	(6.98)***	(7.8)***	(6.84)***	(4.79)***	(4.97)***
β_m	0.086	0.237	0.134	0.057	0.073	0.016	0.058	0.158	0.203	0.127	0.231	0.112
	(2.75)***	(4.23)***	(4.39)***	(1.78)*	(2.47)***	(0.67)	(1.66)*	(4.75)***	(6.21)***	(4.12)***	(5.39)***	(3.48)***
R^2	0.753	0.623	0.603	0.620	0.491	0.665	0.627	0.782	0.659	0.621	0.526	0.637
$QLIKE$	0.119	0.062	0.074	0.072	0.073	0.095	0.107	0.062	0.068	0.077	0.065	0.102

(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.

Online Appendix: Volatility Forecasting in European Government Bond Markets

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1 Appendix A: Data and Jump Identification

1.1 The Nelson-Siegel Model

In this paper, we use the Nelson and 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)).

$$f_{t,m} = \beta_{t,0} + \beta_{t,1} e^{\frac{-m}{\tau_{t,1}}} + \beta_{t,2} \frac{m}{\tau_{t,1}} e^{\frac{-m}{\tau_{t,1}}}, \tag{1}$$

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:

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

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

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

For each 10-minute time interval, the zero-coupon curves of European government bonds are fitted using equation (2).

1.2 Jump Detection in the RV Framework

In this article, we follow the jump separation process of Barndorff-Nielsen and 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:

$$dp(t) = \mu(t)dt + \sigma(t)dw(t) + \kappa(t)dq(t),\ 0 \leqslant t \leqslant T, \tag{4}$$

In Equation 4, $\mu(t)$ 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 and Shephard (2004) show that the quadratic variation equals to the integrated variance of instantaneous returns as given in Equation 5 below:

$$Var \to QV \equiv \int_{t-1}^{t} \sigma^2(s)ds + \sum_{t-1<s\leqslant t} \kappa^2(s). \tag{5}$$

Therefore, equation (5) 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 and 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:

$$BV \to IV \equiv \int_{t-1}^{t} \sigma^2(s)ds,\ for\ n \to \infty. \tag{6}$$

Thus, using equations (5) and (6), it is trivial to obtain an approximation of jump variation[1].

$$RV - BV \to \sum_{t-1<s\leqslant t} \kappa^2(s),\ for\ n \to \infty. \tag{7}$$

Under the assumption of absence of jumps:

$$\sqrt{n}\big(RV - BV\big) \longrightarrow MN\big(0,\ 2IQ\big), \tag{8}$$

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 and Shephard (2002) and Andersen et al. (2007)). We compute TQ as follows[2]:

$$\begin{aligned} TQ \equiv n\mu_{4/3}^{-3} \sum_{i=3}^{n} |\Delta_{i-2}p\big(t+\frac{(i-2)h}{n}\big)|^{4/3} |\Delta_{i-1}p\big(t+\frac{(i-1)h}{n}\big)|^{4/3} \\ |\Delta_{i}p\big(t+\frac{(i)h}{n}\big)|^{4/3}, \end{aligned} \tag{9}$$

where $TQ \to \int_{t-1}^{t} \sigma^4(s)ds$ for $n \to \infty$.

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. Various forms of jump detection tests are compared with those of Huang and Tauchen (2005). They find that the usage of ratio-statistics gives more powerful results than the test-statistics provided by Barndorff-Nielsen and Shephard (2004). We use the following ratio statistic to identify statistically significant bond price

[1]Barndorff-Nielsen and 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 $1/\tau^2$.

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

jumps following Huang and Tauchen (2005):

$$z = n^{-1/2} \frac{\left[RV - BV\right] RV^{-1}}{\sqrt{\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right) \max\left\{1, \frac{TQ}{BV^2}\right\}}} \sim N(0,1). \tag{10}$$

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 and Tauchen (2005); Andersen et al. (2007); Wright and Zhou (2009); and Tauchen and Zhou (2011)).

2 Appendix B: Robustness

2.1 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 and Lunde (2006)). The market microstructure noise is generally documented by providing the intraday sampling frequency impact on estimates[3]. 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 and 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. (2003)), two-scales estimator (Zhang et al. (2005)) and kernel-based techniques (Barndorff-Nielsen et al. (2008, 2009)) used in the literature in providing remedies to the market microstructure noise.

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

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:

$$RV_{Kernel} = \sum_{h=-H}^{H} k\left(\frac{h}{H+1}\right)\gamma_h, \tag{11}$$

In Equation 11, $\gamma_h = \sum_{i=1}^{n} \Delta p_{i,n} \Delta p_{i-h,n}$[4] and $k(x)$ is non-stochastic weight function[5].

In this paper, we estimate employ RV_{Kernel} as an alternative realized variance estimators in order to control possible microstructure bias[6].

Hansen and Lunde (2006) emphasize the trade-off between sampling frequency and estimation noise that 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 results indicate that there our main findings remain unaltered if we use RV_{Kernel} instead of RV in the volatility modelling[7]. Table B9 reports one-month ahead 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[8].

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

[5] Besides 11, Hansen and 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:

$$RV_{AC_1} = \sum_{i=1}^{n} \Delta p_{i,n}^2 + \sum_{i=1}^{n} \Delta p_{i,n} \Delta p_{i-1,n} + \sum_{i=1}^{n} \Delta p_{i,n} \Delta p_{i+1,n}. \tag{12}$$

Although, this estimator provides more efficient measure and reduces the noise compared to RV estimators (Hansen and Lunde (2006)), it severely suffers from negativity bias. 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.

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

[7] For brevity, we do not include in-sample forecasting results using RV_{Kernel}. In compared to RV-using models, RV_{Kernel} is only subject to material change.

[8] One-day and one-week ahead out-of-sample forecast results are available upon request.

2.2 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:

$$MinRV_\tau = \big(\frac{1}{\tau^2}\big)\frac{\pi}{\pi-2}\big(\frac{n}{n-1}\big)\sum_{i=1}^{n-1} min\Big(|\Delta_i p\big(t+\frac{(i)h}{n}\big)|, |\Delta_{i+1} p\big(t+\frac{(i+1)h}{n}\big)|\Big)^2, \tag{13}$$

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:

$$\begin{aligned} MedRV_\tau = \big(\frac{1}{\tau^2}\big)\frac{\pi}{6-4\sqrt{3}+\pi}\big(\frac{n}{n-2}\big)\sum_{i=2}^{n-1} med\Big(&|\Delta_{i-1} p\big(t+\frac{(i-1)h}{n}\big)|, \\ &|\Delta_i p\big(t+\frac{(i)h}{n}\big)|, |\Delta_{i+1} p\big(t+\frac{(i+1)h}{n}\big)|\Big)^2, \end{aligned} \tag{14}$$

In Equation 14, $med(.,.,.)$ 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).

$$\begin{aligned} \sqrt{n}\big(RV - MinRV\big) &\longrightarrow MN\big(0,\ 3.81IQ\big), \\ \sqrt{n}\big(RV - MedRV\big) &\longrightarrow MN\big(0,\ 2.96IQ\big). \end{aligned} \tag{15}$$

Also, alternative to tripower quarticity given in equation 9, we estimate

"MinRQ" and "MedRQ".

$$MinRV_\tau = (\frac{1}{\tau^4})\frac{\pi n}{3\pi - 8}(\frac{n}{n-1})\sum_{i=1}^{n-1} min\Big(|\Delta_i p\big(t+\frac{(i)h}{n}\big)|, |\Delta_{i+1} p\big(t+\frac{(i+1)h}{n}\big)|\Big)^4 \tag{16}$$

, and

$$MedRV_\tau = (\frac{1}{\tau^4})\frac{3\pi n}{9\pi + 72 - 52\sqrt{3}}(\frac{n}{n-2})\sum_{i=2}^{n-1} med\Big(|\Delta_{i-1} p\big(t+\frac{(i-1)h}{n}\big)|, |\Delta_i p\big(t+\frac{(i)h}{n}\big)|, |\Delta_{i+1} p\big(t+\frac{(i+1)h}{n}\big)|\Big)^4 \tag{17}$$

Then, we adjust the jump z-test with respect, equation 10 to the asymptotic distribution of truncation based estimators, given in equation 15.

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

3 Appendix C: Realized Semivariance

3.1 Realized Semivariance and Signed Jumps

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 of feedback effect, which is defined as the relationship between contemporaneous returns and volatility by Bollerslev and Zhou (2006), in the government bond markets [9].

[9] 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 and Wu (2000)). In addition, Bollerslev and Zhou (2006) provide empirical evidence that there is no significant relationship between

Table B1: Regression Results of Swiss Market on 22-day Forecast Horizon using MinRV (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	0.005	—	—	—	0.003	0.003	0.003
	(7.1)***	(7.11)***	(7.52)***	—	—	—	(4.48)***	(4.61)***	(4.71)***
β_d	0.212	0.211	0.213	—	—	—	0.212	0.237	0.216
	(10.35)***	(10.37)***	(10.24)***	—	—	—	(6.22)***	(6.19)***	(6.12)***
β_w	0.393	0.393	0.385	—	—	—	0.257	0.243	0.270
	(6.43)***	(6.44)***	(6.34)***	—	—	—	(4.75)***	(4.63)***	(4.68)***
β_m	0.243	0.242	0.248	—	—	—	0.208	0.204	0.216
	(4)***	(3.99)***	(4.1)***	—	—	—	(2.65)***	(2.62)***	(2.56)***
β_j		0.079	0.273	—	—	—		-0.158	0.039
		(0.94)	(3.17)***	—	—	—		(-4.19)***	(1.48)
R^2	0.695	0.696	0.694	—	—	—	0.425	0.432	0.450
$QLIKE$	0.096	0.096	0.097	—	—	—	0.058	0.058	0.056
$J-R^2$	0.571	0.569	0.569	—	—	—	0.145	0.180	0.181
$J-QLIKE$	0.185	0.187	0.186	—	—	—	0.063	0.060	0.060
$C-R^2$	0.702	0.702	0.701	—	—	—	0.444	0.445	0.463
$C-QLIKE$	0.092	0.092	0.093	—	—	—	0.057	0.057	0.055

	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	0.003	0.003	0.003	0.002	0.002	0.002
	(5.17)***	(5.21)***	(6.06)***	(5.78)***	(5.8)***	(6.66)***	(4.18)***	(4.45)***	(5.55)***
β_d	0.192	0.196	0.196	0.103	0.109	0.111	0.194	0.199	0.195
	(7.07)***	(6.92)***	(7.13)***	(3.42)***	(3.4)***	(3.45)***	(4.63)***	(4.68)***	(4.63)***
β_w	0.246	0.245	0.246	0.174	0.174	0.180	0.244	0.241	0.247
	(3.84)***	(3.82)***	(3.76)***	(2.84)***	(2.86)***	(2.87)***	(3.92)***	(3.95)***	(4.05)***
β_m	0.376	0.375	0.381	0.315	0.313	0.301	0.416	0.413	0.405
	(4.42)***	(4.42)***	(4.52)***	(3.77)***	(3.74)***	(3.59)***	(4.9)***	(4.88)***	(4.84)***
β_j		-0.036	0.131		-0.057	0.041		-0.196	-0.035
		(-1.12)	(4.03)***		(-1.96)*	(1.39)		(-4.17)***	(-0.77)
R^2	0.608	0.608	0.609	0.259	0.261	0.257	0.631	0.633	0.635
$QLIKE$	0.050	0.050	0.050	0.065	0.065	0.066	0.080	0.080	0.080
$J-R^2$	0.507	0.509	0.506	0.326	0.334	0.327	0.238	0.230	0.225
$J-QLIKE$	0.064	0.064	0.066	0.055	0.054	0.055	0.065	0.069	0.070
$C-R^2$	0.615	0.615	0.617	0.254	0.254	0.251	0.645	0.645	0.647
$C-QLIKE$	0.048	0.048	0.049	0.066	0.066	0.067	0.081	0.081	0.081

(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 B2: Regression Results of German Market on 22-day Forecast Horizon using MinRV (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	0.002
	(6.07)***	(6.11)***	(6.47)***	(4.93)***	(4.95)***	(5.31)***	(6.96)***	(7.08)***	(9.12)***
β_d	0.325	0.324	0.331	0.208	0.212	0.227	0.230	0.243	0.254
	(9.65)***	(9.62)***	(9.74)***	(8.43)***	(8.39)***	(7.55)***	(10.6)***	(9.92)***	(9.44)***
β_w	0.283	0.284	0.283	0.313	0.311	0.297	0.298	0.289	0.278
	(7.47)***	(7.5)***	(7.51)***	(6.46)***	(6.28)***	(7.17)***	(5.93)***	(5.66)***	(5.36)***
β_m	0.187	0.187	0.177	0.341	0.341	0.362	0.280	0.278	0.278
	(2.91)***	(2.91)***	(2.78)***	(6.38)***	(6.37)***	(6.81)***	(6.1)***	(6.07)***	(5.74)***
β_j		0.033	0.291		-0.018	0.138		-0.048	0.127
		(0.42)	(3.74)***		(-0.46)	(3.09)***		(-1.38)	(3.63)***
R^2	0.634	0.634	0.632	0.714	0.714	0.708	0.626	0.626	0.624
$QLIKE$	0.123	0.123	0.125	0.036	0.036	0.036	0.044	0.043	0.043
$J-R^2$	0.310	0.310	0.315	0.731	0.730	0.718	0.597	0.597	0.592
$J-QLIKE$	0.266	0.266	0.265	0.045	0.044	0.045	0.044	0.043	0.041
$C-R^2$	0.646	0.646	0.644	0.713	0.713	0.708	0.629	0.629	0.628
$C-QLIKE$	0.115	0.115	0.117	0.035	0.035	0.035	0.043	0.043	0.043

	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	0.003	0.003	0.003	0.004	0.006	0.006	0.006
	(8.15)***	(8.32)***	(9.52)***	(8.11)***	(8.36)***	(9.67)***	(8.5)***	(8.83)***	(9.43)***
β_d	0.288	0.315	0.313	0.236	0.263	0.264	0.360	0.367	0.362
	(8.83)***	(8.39)***	(8.69)***	(10.36)***	(9.82)***	(9.26)***	(9.15)***	(9.05)***	(8.66)***
β_w	0.313	0.292	0.290	0.213	0.198	0.192	0.242	0.238	0.241
	(6.4)***	(5.62)***	(5.43)***	(3.7)***	(3.55)***	(3.02)***	(4.28)***	(4.26)***	(4.19)***
β_m	0.066	0.062	0.067	0.210	0.202	0.212	0.057	0.053	0.059
	(1.09)	(1.04)	(1.09)	(5.05)***	(4.81)***	(4.47)***	(1.14)	(1.06)	(1.17)
β_j		-0.094	0.119		-0.088	0.106		-0.132	0.146
		(-2.62)***	(4.18)***		(-2.98)***	(4.3)***		(-1.34)	(1.47)
R^2	0.472	0.474	0.476	0.407	0.410	0.417	0.429	0.430	0.432
$QLIKE$	0.055	0.055	0.054	0.048	0.048	0.047	0.145	0.144	0.143
$J-R^2$	0.423	0.439	0.457	0.428	0.440	0.480	0.301	0.297	0.306
$J-QLIKE$	0.054	0.052	0.049	0.044	0.042	0.038	0.092	0.090	0.085
$C-R^2$	0.479	0.480	0.482	0.408	0.408	0.413	0.434	0.434	0.436
$C-QLIKE$	0.055	0.055	0.055	0.048	0.048	0.048	0.148	0.148	0.146

(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 B3: Regression Results of French Market on 22-day Forecast Horizon using MinRV (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)***	(7.38)***	(2.84)***	(4.49)***	(4.56)***	(2.25)**	(4.87)***	(5.13)***	(3.73)***
β_d	0.285	0.280	0.258	0.253	0.254	0.281	0.203	0.222	0.258
	(8.38)***	(8.32)***	(7.63)***	(7.27)***	(7.25)***	(9.15)***	(8.45)***	(8.27)***	(10.25)***
β_w	0.156	0.157	0.213	0.373	0.372	0.551	0.289	0.277	0.467
	(1.82)*	(1.86)*	(2.89)***	(6.51)***	(6.48)***	(13.3)***	(5.6)***	(5.39)***	(10.91)***
β_m	0.254	0.254	0.275	0.283	0.283	0.169	0.386	0.380	0.192
	(3.02)***	(3.05)***	(3.14)***	(4.44)***	(4.44)***	(3.2)***	(6.49)***	(6.4)***	(2.64)***
β_j		0.334	0.351		-0.059	0.075		-0.112	0.045
		(1.8)*	(1.96)**		(-0.84)	(1.04)		(-3.51)***	(1.64)
R^2	0.408	0.412	0.461	0.809	0.809	0.804	0.740	0.741	0.722
$QLIKE$	0.139	0.139	0.122	0.046	0.046	0.052	0.038	0.037	0.040
$J-R^2$	0.433	0.412	0.407	0.650	0.662	0.644	0.577	0.588	0.618
$J-QLIKE$	0.129	0.137	0.134	0.068	0.065	0.065	0.046	0.043	0.040
$C-R^2$	0.413	0.413	0.465	0.810	0.810	0.805	0.743	0.743	0.723
$C-QLIKE$	0.138	0.138	0.121	0.046	0.046	0.052	0.037	0.037	0.040

	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)***	(6.23)***	(3.44)***	(4.26)***	(4.39)***	(6.33)***	(5.62)***	(5.61)***	(4.2)***
β_d	0.219	0.224	0.230	0.166	0.184	0.240	0.210	0.212	0.241
	(7.7)***	(7.41)***	(9.18)***	(7.41)***	(6.37)***	(9.36)***	(7.24)***	(7.2)***	(9.21)***
β_w	0.286	0.282	0.371	0.232	0.223	0.382	0.262	0.260	0.396
	(5.04)***	(4.96)***	(6.82)***	(5.55)***	(5.56)***	(7.6)***	(4.47)***	(4.44)***	(7.71)***
β_m	0.312	0.309	0.319	0.442	0.435	0.160	0.380	0.380	0.343
	(4.99)***	(4.93)***	(4)***	(7.63)***	(7.38)***	(2.54)***	(5.12)***	(5.12)***	(3.88)***
β_j		-0.058	0.078		-0.055	0.086		-0.113	0.066
		(-1.3)	(1.89)*		(-2.02)**	(4.09)***		(-1.16)	(0.78)
R^2	0.614	0.614	0.633	0.652	0.654	0.593	0.635	0.636	0.618
$QLIKE$	0.055	0.055	0.054	0.031	0.031	0.033	0.108	0.108	0.118
$J-R^2$	0.482	0.499	0.472	0.493	0.489	0.479	0.563	0.556	0.570
$J-QLIKE$	0.078	0.076	0.078	0.039	0.039	0.038	0.058	0.057	0.061
$C-R^2$	0.618	0.618	0.638	0.660	0.660	0.597	0.634	0.634	0.616
$C-QLIKE$	0.054	0.054	0.053	0.030	0.030	0.033	0.112	0.112	0.122

(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 B4: Regression Results of UK Market on 22-day Forecast Horizon using MinRV (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)***	(3.83)***	(4.21)***	(5.66)***	(5.66)***	(8.32)***	(4.67)***	(4.7)***	(9.35)***
β_d	0.290	0.290	0.306	0.231	0.242	0.281	0.193	0.220	0.203
	(5.44)***	(5.28)***	(6.26)***	(7.27)***	(7.2)***	(9.21)***	(6.1)***	(6.15)***	(7.23)***
β_w	0.304	0.304	0.385	0.235	0.227	0.373	0.151	0.134	0.204
	(3.06)***	(3.05)***	(4.59)***	(4.66)***	(4.5)***	(7.6)***	(3.05)***	(2.75)***	(3.9)***
β_m	0.191	0.191	0.165	0.290	0.289	0.061	0.348	0.347	0.254
	(1.86)*	(1.86)*	(3.84)***	(4.57)***	(4.56)***	(3.4)***	(3.95)***	(3.92)***	(5.46)***
β_j		0.001	0.223		-0.054	0.152		-0.094	0.075
		(0.02)	(3.82)***		(-1.18)	(3.56)***		(-2.8)***	(3.05)***
R^2	0.561	0.561	0.563	0.508	0.508	0.473	0.401	0.404	0.404
$QLIKE$	0.059	0.059	0.060	0.053	0.052	0.060	0.046	0.045	0.046
$J-R^2$	0.395	0.395	0.402	0.498	0.492	0.501	0.511	0.529	0.507
$J-QLIKE$	0.113	0.113	0.107	0.059	0.058	0.059	0.037	0.036	0.036
$C-R^2$	0.566	0.566	0.568	0.509	0.509	0.472	0.394	0.395	0.396
$C-QLIKE$	0.058	0.058	0.059	0.052	0.052	0.060	0.046	0.046	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	0.002	0.004	0.004	0.005
	(3.96)***	(4.26)***	(8.24)***	(4.33)***	(4.39)***	(4.39)***	(4.34)***	(4.45)***	(7.01)***
β_d	0.228	0.250	0.226	0.213	0.227	0.190	0.279	0.282	0.250
	(4.03)***	(4)***	(3.63)***	(5.14)***	(5.19)***	(4.16)***	(4.47)***	(4.48)***	(3.76)***
β_w	0.147	0.132	0.253	0.089	0.078	0.111	0.103	0.101	0.215
	(2.15)**	(2)**	(4.58)***	(1.75)*	(1.58)	(2.05)**	(1.56)	(1.53)	(4.08)***
β_m	0.361	0.357	0.192	0.406	0.405	0.473	0.387	0.387	0.209
	(4.13)***	(4.03)***	(4.09)***	(4.32)***	(4.29)***	(4.84)***	(4)***	(3.99)***	(4.33)***
β_j		-0.148	0.012		-0.077	0.067		-0.091	0.067
		(-3.65)***	(0.58)		(-2.46)***	(2.34)***		(-1.68)*	(1.04)
R^2	0.448	0.453	0.420	0.404	0.406	0.421	0.463	0.464	0.439
$QLIKE$	0.054	0.053	0.054	0.042	0.042	0.041	0.123	0.123	0.113
$J-R^2$	0.437	0.458	0.341	0.354	0.366	0.411	0.351	0.354	0.259
$J-QLIKE$	0.030	0.029	0.034	0.037	0.036	0.033	0.076	0.074	0.070
$C-R^2$	0.447	0.448	0.418	0.408	0.408	0.420	0.466	0.466	0.444
$C-QLIKE$	0.056	0.056	0.056	0.043	0.043	0.042	0.126	0.126	0.116

(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 B5: Regression Results of Swiss Market on 22-day Forecast Horizon using MedRV (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	0.005	—	—	—	0.003	0.003	0.003
	(7.1)***	(7.1)***	(8.01)***	—	—	—	(4.48)***	(4.81)***	(5.85)***
β_d	0.212	0.211	0.213	—	—	—	0.212	0.245	0.225
	(10.35)***	(10.29)***	(10.2)***	—	—	—	(6.22)***	(5.96)***	(6.12)***
β_w	0.393	0.393	0.386	—	—	—	0.257	0.242	0.269
	(6.43)***	(6.43)***	(6.3)***	—	—	—	(4.75)***	(4.61)***	(4.56)***
β_m	0.243	0.243	0.244	—	—	—	0.208	0.200	0.201
	(4)***	(4)***	(4.03)***	—	—	—	(2.65)***	(2.58)***	(2.46)***
β_j		0.035	0.259	—	—	—		-0.133	0.071
		(0.43)	(3.23)***	—	—	—		(-3.6)***	(3.08)***
R^2	0.695	0.695	0.694	—	—	—	0.425	0.434	0.450
$QLIKE$	0.096	0.096	0.096	—	—	—	0.058	0.058	0.057
$J-R^2$	0.515	0.514	0.536	—	—	—	0.264	0.277	0.290
$J-QLIKE$	0.164	0.165	0.157	—	—	—	0.056	0.055	0.056
$C-R^2$	0.707	0.707	0.703	—	—	—	0.446	0.446	0.463
$C-QLIKE$	0.089	0.089	0.091	—	—	—	0.058	0.058	0.056

	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	0.003	0.003	0.003	0.002	0.002	0.003
	(5.17)***	(5.43)***	(8.25)***	(5.78)***	(5.87)***	(7.92)***	(4.18)***	(4.92)***	(7.61)***
β_d	0.192	0.203	0.197	0.103	0.123	0.119	0.194	0.216	0.193
	(7.07)***	(6.88)***	(7.05)***	(3.42)***	(3.21)***	(3.11)***	(4.63)***	(4.59)***	(4.3)***
β_w	0.246	0.242	0.242	0.174	0.175	0.181	0.244	0.237	0.246
	(3.84)***	(3.81)***	(3.68)***	(2.84)***	(2.9)***	(2.64)***	(3.92)***	(3.91)***	(3.75)***
β_m	0.376	0.370	0.367	0.315	0.309	0.312	0.416	0.402	0.408
	(4.42)***	(4.33)***	(4.37)***	(3.77)***	(3.7)***	(3.36)***	(4.9)***	(4.71)***	(4.57)***
β_j		-0.067	0.111		-0.069	0.058		-0.180	0.029
		(-2.31)**	(4.09)***		(-2.41)***	(2.74)***		(-4.57)***	(1.06)
R^2	0.608	0.609	0.614	0.259	0.263	0.264	0.631	0.636	0.648
$QLIKE$	0.050	0.049	0.049	0.065	0.065	0.066	0.080	0.079	0.076
$J-R^2$	0.389	0.391	0.389	0.238	0.231	0.215	0.279	0.282	0.307
$J-QLIKE$	0.052	0.052	0.053	0.051	0.051	0.053	0.066	0.066	0.064
$C-R^2$	0.634	0.634	0.640	0.271	0.270	0.275	0.660	0.660	0.671
$C-QLIKE$	0.049	0.049	0.048	0.071	0.071	0.072	0.084	0.084	0.081

(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 B6: Regression Results of German Market on 22-day Forecast Horizon using MedRV (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)***	(6.12)***	(6.66)***	(4.93)***	(5.03)***	(5.73)***	(6.96)***	(7.04)***	(10.6)***
β_d	0.325	0.324	0.336	0.208	0.199	0.246	0.230	0.233	0.271
	(9.65)***	(9.62)***	(9.91)***	(8.43)***	(7.81)***	(7.6)***	(10.6)***	(9.21)***	(9.64)***
β_w	0.283	0.284	0.276	0.313	0.318	0.278	0.298	0.296	0.255
	(7.47)***	(7.46)***	(7.37)***	(6.46)***	(6.23)***	(7.02)***	(5.93)***	(5.73)***	(5.05)***
β_m	0.187	0.187	0.176	0.341	0.341	0.369	0.280	0.280	0.275
	(2.91)***	(2.9)***	(2.79)***	(6.38)***	(6.38)***	(7.22)***	(6.1)***	(6.1)***	(5.74)***
β_j		0.030	0.281		0.026	0.177		-0.009	0.158
		(0.41)	(3.87)***		(0.75)	(4.71)***		(-0.28)	(5)***
R^2	0.634	0.634	0.629	0.714	0.714	0.696	0.626	0.626	0.613
$QLIKE$	0.123	0.123	0.127	0.036	0.036	0.038	0.044	0.043	0.046
$J-R^2$	0.229	0.231	0.228	0.729	0.729	0.711	0.590	0.590	0.582
$J-QLIKE$	0.248	0.248	0.252	0.039	0.039	0.042	0.044	0.044	0.042
$C-R^2$	0.660	0.660	0.656	0.712	0.712	0.694	0.634	0.634	0.622
$C-QLIKE$	0.108	0.108	0.112	0.036	0.036	0.037	0.043	0.043	0.046

	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)***	(8.53)***	(10.8)***	(8.11)***	(8.6)***	(11.25)***	(8.5)***	(8.66)***	(9.65)***
β_d	0.288	0.316	0.333	0.236	0.267	0.273	0.360	0.366	0.364
	(8.83)***	(7.96)***	(8.74)***	(10.36)***	(9.53)***	(9.43)***	(9.15)***	(9)***	(8.9)***
β_w	0.313	0.290	0.264	0.213	0.193	0.186	0.242	0.236	0.232
	(6.4)***	(5.57)***	(4.86)***	(3.7)***	(3.49)***	(3)***	(4.28)***	(4.13)***	(4.06)***
β_m	0.066	0.064	0.066	0.210	0.203	0.211	0.057	0.055	0.063
	(1.09)	(1.06)	(1.1)	(5.05)***	(4.82)***	(4.35)***	(1.14)	(1.1)	(1.27)
β_j		-0.077	0.131		-0.069	0.115		-0.093	0.156
		(-2.11)**	(4.82)***		(-2.51)***	(5.28)***		(-0.99)	(1.65)*
R^2	0.472	0.474	0.471	0.407	0.410	0.419	0.429	0.430	0.431
$QLIKE$	0.055	0.055	0.055	0.048	0.048	0.046	0.145	0.144	0.143
$J-R^2$	0.379	0.387	0.413	0.411	0.416	0.460	0.316	0.318	0.329
$J-QLIKE$	0.052	0.051	0.047	0.043	0.043	0.039	0.089	0.086	0.082
$C-R^2$	0.491	0.492	0.488	0.407	0.408	0.413	0.438	0.438	0.440
$C-QLIKE$	0.056	0.056	0.057	0.049	0.049	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 B7: Regression Results of French Market on 22-day Forecast Horizon using MedRV (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)***	(4.61)***	(2.52)***	(4.87)***	(5.19)***	(4.68)***
β_d	0.285	0.276	0.257	0.253	0.256	0.285	0.203	0.218	0.261
	(8.38)***	(8.28)***	(7.64)***	(7.27)***	(7.17)***	(9.12)***	(8.45)***	(7.92)***	(10.22)***
β_w	0.156	0.163	0.217	0.373	0.372	0.547	0.289	0.280	0.468
	(1.82)*	(2)**	(3.06)***	(6.51)***	(6.47)***	(13.09)***	(5.6)***	(5.45)***	(10.97)***
β_m	0.254	0.250	0.269	0.283	0.282	0.175	0.386	0.382	0.183
	(3.02)***	(3.05)***	(3.11)***	(4.44)***	(4.43)***	(3.29)***	(6.49)***	(6.4)***	(2.55)***
β_j		0.544	0.482		-0.043	0.070		-0.069	0.087
		(2.3)**	(2.01)**		(-0.86)	(1.26)		(-2.29)**	(3.34)***
R^2	0.408	0.420	0.465	0.809	0.809	0.804	0.740	0.741	0.720
$QLIKE$	0.139	0.138	0.123	0.046	0.046	0.052	0.038	0.038	0.041
$J-R^2$	0.412	0.456	0.410	0.736	0.738	0.705	0.629	0.635	0.646
$J-QLIKE$	0.132	0.186	0.151	0.053	0.052	0.056	0.047	0.047	0.045
$C-R^2$	0.422	0.422	0.476	0.810	0.810	0.805	0.746	0.746	0.724
$C-QLIKE$	0.137	0.137	0.120	0.046	0.046	0.052	0.036	0.036	0.040

	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	0.003	0.002	0.002	0.002	0.003	0.004	0.004	0.004
	(6.13)***	(6.5)***	(4.45)***	(4.26)***	(4.35)***	(7.26)***	(5.62)***	(5.2)***	(4.4)***
β_d	0.219	0.230	0.232	0.166	0.181	0.246	0.210	0.209	0.236
	(7.7)***	(7.36)***	(8.94)***	(7.41)***	(5.95)***	(9.15)***	(7.24)***	(7.18)***	(9.08)***
β_w	0.286	0.278	0.372	0.232	0.225	0.394	0.262	0.263	0.400
	(5.04)***	(4.86)***	(6.86)***	(5.55)***	(5.63)***	(7.61)***	(4.47)***	(4.48)***	(7.8)***
β_m	0.312	0.307	0.306	0.442	0.436	0.141	0.380	0.380	0.342
	(4.99)***	(4.91)***	(3.96)***	(7.63)***	(7.28)***	(2.29)**	(5.12)***	(5.12)***	(3.92)***
β_j		-0.088	0.061		-0.033	0.111		0.057	0.205
		(-2.34)***	(1.92)*		(-1.24)	(5.52)***		(0.66)	(2.25)**
R^2	0.614	0.615	0.634	0.652	0.653	0.592	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
$J-R^2$	0.497	0.511	0.526	0.582	0.585	0.572	0.631	0.631	0.631
$J-QLIKE$	0.061	0.059	0.060	0.038	0.038	0.037	0.089	0.096	0.122
$C-R^2$	0.619	0.619	0.639	0.663	0.663	0.596	0.633	0.633	0.618
$C-QLIKE$	0.055	0.055	0.052	0.030	0.030	0.033	0.116	0.116	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 B8: Regression Results of UK Market on 22-day Forecast Horizon using MedRV (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)***	(3.84)***	(4.33)***	(5.66)***	(5.69)***	(8.54)***	(4.67)***	(4.82)***	(10.46)***
β_d	0.290	0.289	0.309	0.231	0.249	0.298	0.193	0.227	0.212
	(5.44)***	(5.27)***	(6.31)***	(7.27)***	(7.15)***	(8.96)***	(6.1)***	(6.28)***	(6.78)***
β_w	0.304	0.304	0.382	0.235	0.224	0.361	0.151	0.130	0.189
	(3.06)***	(3.06)***	(4.59)***	(4.66)***	(4.56)***	(7.15)***	(3.05)***	(2.63)***	(3.67)***
β_m	0.191	0.191	0.164	0.290	0.289	0.062	0.348	0.346	0.260
	(1.86)*	(1.86)*	(3.8)***	(4.57)***	(4.56)***	(3.34)***	(3.95)***	(3.91)***	(5.6)***
β_j		0.007	0.218		-0.061	0.150		-0.092	0.066
		(0.11)	(3.81)***		(-1.5)	(4.41)***		(-2.84)***	(2.7)***
R^2	0.561	0.561	0.561	0.508	0.509	0.468	0.401	0.405	0.404
$QLIKE$	0.059	0.059	0.061	0.053	0.052	0.061	0.046	0.045	0.046
$J-R^2$	0.440	0.440	0.445	0.467	0.467	0.477	0.445	0.449	0.450
$J-QLIKE$	0.083	0.083	0.079	0.059	0.058	0.058	0.037	0.037	0.037
$C-R^2$	0.569	0.569	0.570	0.513	0.513	0.468	0.395	0.395	0.393
$C-QLIKE$	0.057	0.057	0.059	0.051	0.051	0.061	0.047	0.047	0.048

	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)***	(4.58)***	(9.62)***	(4.33)***	(4.42)***	(5.07)***	(4.34)***	(4.52)***	(7.39)***
β_d	0.228	0.258	0.232	0.213	0.227	0.198	0.279	0.282	0.251
	(4.03)***	(3.99)***	(3.52)***	(5.14)***	(5.11)***	(4.14)***	(4.47)***	(4.46)***	(3.76)***
β_w	0.147	0.122	0.242	0.089	0.078	0.098	0.103	0.098	0.211
	(2.15)**	(1.89)*	(4.36)***	(1.75)*	(1.58)	(1.77)*	(1.56)	(1.5)	(3.97)***
β_m	0.361	0.358	0.191	0.406	0.407	0.480	0.387	0.388	0.209
	(4.13)***	(4.04)***	(4.05)***	(4.32)***	(4.3)***	(4.9)***	(4)***	(3.99)***	(4.32)***
β_j		-0.151	0.011		-0.054	0.076		-0.142	0.065
		(-3.88)***	(0.55)		(-1.61)	(2.62)***		(-2.12)**	(0.83)
R^2	0.448	0.455	0.423	0.404	0.405	0.420	0.463	0.464	0.439
$QLIKE$	0.054	0.052	0.053	0.042	0.042	0.041	0.123	0.122	0.113
$J-R^2$	0.415	0.433	0.327	0.427	0.434	0.437	0.510	0.516	0.269
$J-QLIKE$	0.040	0.039	0.042	0.040	0.039	0.037	0.078	0.075	0.087
$C-R^2$	0.448	0.448	0.425	0.402	0.402	0.416	0.455	0.455	0.453
$C-QLIKE$	0.057	0.057	0.056	0.043	0.043	0.042	0.132	0.132	0.117

(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 B9: 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.

Table B10: One-Month Ahead Out of Sample Forecast Results using MinRV (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	0.999[a]	1.021	1.000	1.001	1.005	1.000	0.997[a]	0.901	1.000	0.999	1.046
2-Year	—	—	—	1.000	0.999	1.025	1.000	0.999[a]	1.202	1.000	0.998[a]	1.123
5-Year	1.000	0.995[a]	0.976[a]	1.000	0.999[a]	1.005	1.000	0.987[a]	1.155	1.000	0.996[a]	0.985[a]
10-Year	1.000	0.995[a]	0.993	1.000	0.999[a]	0.994	1.000	0.995[a]	1.021	1.000	0.994[a]	1.059
20-Year	1.000	0.996[a]	1.015	1.000	0.999	0.999	1.000	0.998[a]	1.096	1.000	0.995[a]	1.001[a]
30-Year	1.000	1.025	1.047	1.000	0.999	0.998	1.000	1.003	1.348	1.000	0.999[a]	1.039

(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%	49.9%	49.7%	49.3%	49.3%	49.6%	27.7%	28.0%	30.7%	38.8%	38.9%	37.8%
2-Year	—	—	—	52.4%	52.5%	51.5%	63.4%	63.6%	62.3%	34.3%	34.7%	33.7%
5-Year	30.0%	30.4%	31.3%	34.0%	34.1%	34.0%	55.8%	56.8%	58.8%	24.0%	24.4%	25.4%
10-Year	40.0%	40.2%	39.0%	32.3%	32.5%	33.8%	38.4%	38.6%	43.7%	33.4%	33.7%	29.5%
20-Year	20.0%	20.1%	19.3%	33.3%	33.5%	34.4%	45.9%	45.9%	44.1%	35.4%	35.4%	32.8%
30-Year	28.9%	29.1%	27.3%	36.9%	37.0%	38.3%	37.7%	37.8%	40.5%	35.4%	35.4%	29.2%

(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.

Table B11: One-Month Ahead Out of Sample Forecast Results using MedRV (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	1.002	1.015	1.000	0.999	1.011	1.000	0.995[a]	0.896	1.000	0.998[a]	1.047
2-Year	—	—	—	1.000	1.001	1.091	1.000	1.001	1.21	1.000	0.993[a]	1.127
5-Year	1.000	0.985[a]	0.979	1.000	0.998[a]	1.041	1.000	0.984[a]	1.184	1.000	0.994[a]	0.976[a]
10-Year	1.000	0.992[a]	0.977[a]	1.000	0.999	1.011	1.000	0.992[a]	1.009	1.000	0.988[a]	1.039
20-Year	1.000	0.992[a]	1.018	1.000	1.003	1.003	1.000	1.004	1.113	1.000	0.996[a]	0.995[a]
30-Year	1.000	1.035	0.974	1.000	1.005	1.008	1.000	1.006	1.259	1.000	0.999	1.04

(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%	49.8%	49.6%	49.3%	49.3%	49.4%	27.7%	28.5%	31.1%	38.8%	39.1%	38.6%
2-Year	—	—	—	52.4%	52.7%	49.7%	63.4%	63.5%	61.9%	34.3%	35.1%	34.6%
5-Year	30.0%	30.6%	30.7%	34.0%	34.2%	33.3%	55.8%	56.7%	59.3%	24.0%	24.8%	26.6%
10-Year	40.0%	40.2%	38.9%	32.3%	32.5%	32.8%	38.4%	39.1%	44.9%	33.4%	34.1%	31.8%
20-Year	20.0%	20.3%	15.0%	33.3%	33.8%	35.6%	45.9%	45.9%	43.0%	35.4%	35.5%	31.9%
30-Year	28.9%	29.2%	26.8%	36.9%	37.1%	38.0%	37.7%	38.0%	41.0%	35.4%	35.4%	28.6%

(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.

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 and Sheppard (2015) to incorporate the impact of signed jumps.

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

$$RSV_{\tau}^{+} = \frac{1}{\tau^2} \sum_{i=1}^{n} |\Delta_i p\big(t + \frac{(i)h}{n}\big)|^2 I\Bigg(\Delta_i p\big(t + \frac{(i)h}{n}\big) > 0\Bigg), \tag{18}$$

Negative Semivariance:

$$RSV_{\tau}^{-} = \frac{1}{\tau^2} \sum_{i=1}^{n} |\Delta_i p\big(t + \frac{(i)h}{n}\big)|^2 I\Bigg(\Delta_i p\big(t + \frac{(i)h}{n}\big) < 0\Bigg), \tag{19}$$

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

$$\begin{aligned} \Delta J_{\tau} &= RSV_{\tau}^{+} - RSV_{\tau}^{-}, \\ J^{+} &= \Delta J I\big(\Delta J > 0\big), \\ J^{-} &= \Delta J I\big(\Delta J < 0\big), \end{aligned} \tag{20}$$

In the equation (18), (19) adn (20), $I(.)$ corresponds to indicator function. RSV series are calculated in the intraday basis in line with RV. Figure C1 and C2 show the boxplots of the realized semivariances (RSV).

RSV series verifies U-shaped pattern in the volatility yield curve with respect to 2 and 3 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 semivariances so any feedback effect. Therefore, in line with the literature (Nelson (1991); Bekaert and Wu (2000); and Bollerslev and 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. Across the different bonds, the

contemporaneous returns and volatility, therefore they reject the presence of feedback effect.

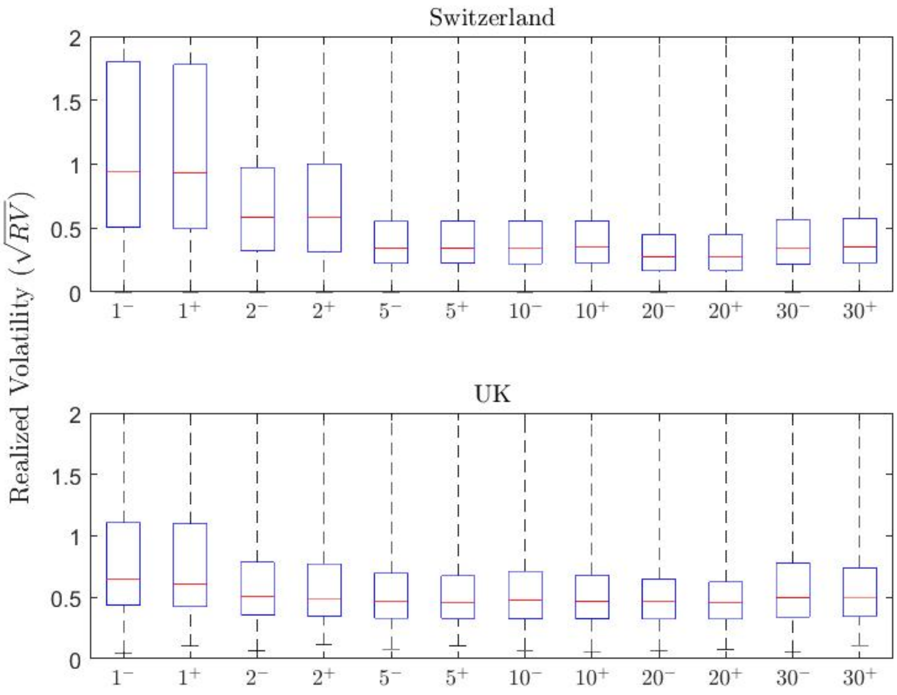

Figure C1: **Feedback Effect:** Box Plots of Negative, RSV^-, and Positive, RSV^+, Semi-variances across Maturity Span

interquartile range (Q3-Q1) of volatility for the Swiss bond market is the narrowest for 5-year and longer maturities. Therefore, long-term maturity Swiss bonds can provide a safer environment for investors.

Moreover, we test for asymmetry in the contribution of positive and negative RSV with simple leverage effect to the future volatility using the models below (see Patton and Sheppard (2015)).

HAR-RV model:

$$RV_{t+h-1} = \phi_0 + \phi_d RV_{t-1} + \phi_w RV_{t-5:t-2} + \phi_m RV_{t-22:t-6} + \epsilon_t \qquad (21)$$

HAR model incorporating realized semivariances with leverage effect (HAR-

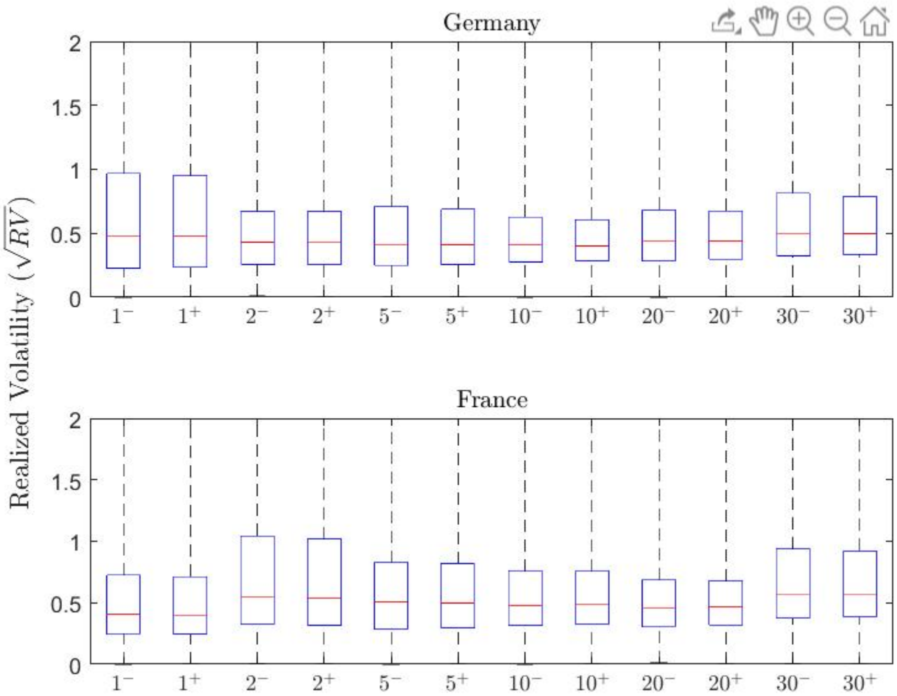

Figure C2: **Feedback Effect:** Box Plots of Negative, RSV^-, and Positive, RSV^+, Semi-variances Maturity Span

RSV-L):

$$RV_{t+h-1} = \phi_0 + \phi_{d^+} RSV^+_{t-1} + \phi_{d^-} RSV^-_{t-1} + \phi_l RV_{t-1} I_{(r_{t-1}<0)} + \phi_w RV_{t-5:t-2} + \phi_m RV_{t-22:t-6} + \epsilon_t \quad (22)$$

HAR model incorporating realized semivariances and signed jumps with leverage effect (HAR-RSVJ-L):

$$\begin{aligned} RV_{t+h-1} &= \phi_0 + \phi_{d^+} RSV^+_{t-1} + \phi_{d^-} RSV^-_{t-1} + \phi_l BV_{t-1} I_{(r_{t-1}<0)} \\ &+ \phi_w RV_{t-5:t-2} + \phi_m RV_{t-22:t-6} + \phi_{j^+} {J^+}_{t-1} + \phi_{j^-} {J^-}_{t-1} + \epsilon_t \end{aligned} \quad (23)$$

In order to assess the importance of asymmetric contribution of positive and negative variances with leverage, we extend the baseline model, Equation 21, using RSV^+_{t-1}, RSV^-_{t-1} variables and interaction term of realized volatility and negative daily bond return dummy variable, $RV_{t-1}I_{(r_{t-1}<0)}$. Patton Sheppard (2015) state that when $\phi_{d^+} = \phi_{d^-}$ and $\phi_l = 0$, then we can conclude realized semivariances have no additional information contribution to the model. Our test results show that for 1-day horizon we can reject $\phi_{d^+} = \phi_{d^-}$ in favour of $\phi_{d^+} < \phi_{d^-}$ and mostly insignificant ϕ_l (see table C1 to C4). Similar to Patton and Sheppard (2015), negative RSV has stronger impact than positive RSV on future volatility. In other words, variation due to increase in interest rates, negative returns, have more persistent impact than decrease in interest rates, positive returns. Moreover, we extend 22 in order to incorporate the impact of realized signed jumps; positive jump, ${J^+}_{t-1}$ and negative jump, ${J^-}_{t-1}$. Although, inclusion of signed jump variables contribute overall fit up to 0.9%, we find ϕ_{j^+} and ϕ_{j^-} rarely significant and the directions of contributions to future volatility is ambiguous. In addition, out of sample forecast results indicate that although models incorporating realized semivariance and signed jumps provide superior forecasts compared to baseline HAR model.

Table C1: HAR-RSV Results of Swiss Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L
ϕ_0	0.006	0.001	0.001	—	—	—	0.004	0.001	0.001
	(6.68)***	(2.93)***	(2.33)***	—	—	—	(5.35)***	(3.56)***	(4.91)***
ϕ_d	0.112			—	—	—	0.115		
	(2.9)***			—	—	—	(3.06)***		
ϕ_{d^+}		0.134	-0.086	—	—	—		0.213	0.328
		(1.2)	(-0.44)	—	—	—		(4.2)***	(2.56)***
ϕ_{d^-}		0.397	0.557	—	—	—		0.256	0.200
		(3.67)***	(2.87)***	—	—	—		(5.84)***	(1.59)
ϕ_l		0.031	0.059	—	—	—		0.017	0.040
		(0.96)	(1.59)	—	—	—		(0.46)	(0.98)
ϕ_w	0.342	0.306	0.304	—	—	—	0.101	0.334	0.328
	(3.99)***	(5.73)***	(5.69)***	—	—	—	(1.88)*	(7.32)***	(7.54)***
ϕ_m	0.232	0.214	0.209	—	—	—	0.232	0.124	0.115
	(2.84)***	(4.89)***	(4.79)***	—	—	—	(2.69)***	(2.53)***	(2.33)***
ϕ_{j^+}			0.258	—	—	—			-0.189
			(1.78)*	—	—	—			(-1.87)*
ϕ_{j^-}			0.023	—	—	—			-0.090
			(0.19)	—	—	—			(-0.72)
R^2	0.634	0.635	0.638	—	—	—	0.394	0.398	0.403
$QLIKE$	0.201	0.201	0.201	—	—	—	0.133	0.133	0.133

	10-Year			20-Year			30-Year		
	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L
ϕ_0	0.002	0.001	0.001	0.003	0.002	0.002	0.002	0.001	0.001
	(4.65)***	(3.35)***	(3.5)***	(7.52)***	(6.62)***	(7.21)***	(3.28)***	(2.77)***	(2.82)***
ϕ_d	0.131			0.072			0.132		
	(3.27)***			(3)***			(2.97)***		
ϕ_{d^+}		0.299	0.187		0.080	-0.172		0.116	-0.098
		(5.97)***	(1.51)		(1.51)	(-1)		(1.01)	(-0.35)
ϕ_{d^-}		0.193	0.337		0.114	0.318		0.316	0.540
		(4.41)***	(2.51)***		(1.38)	(1.77)*		(2.27)**	(1.85)*
ϕ_l		0.022	0.027		0.080	0.233		0.095	0.102
		(0.72)	(0.68)		(1.71)*	(3.67)***		(1.55)	(1.36)
ϕ_w	0.185	0.352	0.348	0.100	0.129	0.116	0.132	0.283	0.284
	(2.83)***	(6.41)***	(6.26)***	(2.57)***	(2.63)***	(2.4)***	(2.53)***	(4.99)***	(5.08)***
ϕ_m	0.338	0.154	0.150	0.233	0.250	0.237	0.429	0.213	0.210
	(3.84)***	(3.65)***	(3.5)***	(3.75)***	(3.55)***	(3.49)***	(4.47)***	(3.84)***	(3.7)***
ϕ_{j^+}			0.023			0.232			0.127
			(0.24)			(1.67)*			(0.63)
ϕ_{j^-}			-0.145			-0.130			-0.156
			(-1.31)			(-1.23)			(-0.91)
R^2	0.520	0.522	0.523	0.119	0.123	0.134	0.511	0.518	0.518
$QLIKE$	0.117	0.116	0.116	0.166	0.165	0.165	0.162	0.163	0.162

(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 C2: HAR-RSV Results of German Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L
ϕ_0	0.004	0.001	0.000	0.002	0.000	0.000	0.002	0.001	0.001
	(4.85)***	(3.79)***	(3.28)***	(5.57)***	(2.81)***	(2.78)***	(7.31)***	(4.63)***	(4.39)***
ϕ_d	0.222			0.153			0.141		
	(4.5)***			(5.15)***			(4.58)***		
ϕ_{d^+}		0.399	-0.013		0.202	0.219		0.190	0.225
		(5.52)***	(-0.09)		(3.74)***	(2.11)**		(4.29)***	(1.69)*
ϕ_{d^-}		0.466	0.828		0.279	0.276		0.341	0.327
		(6.38)***	(5.15)***		(6.32)***	(2.52)***		(7.15)***	(3.24)***
ϕ_l		-0.022	-0.008		0.010	0.014		0.036	0.050
		(-1.07)	(-0.34)		(0.47)	(0.65)		(1.33)	(1.6)
ϕ_w	0.093	0.247	0.249	0.161	0.343	0.340	0.164	0.371	0.363
	(1.52)	(5.43)***	(5.51)***	(3.25)***	(6.49)***	(6.53)***	(3.27)***	(6.76)***	(6.26)***
ϕ_m	0.306	0.086	0.085	0.434	0.236	0.238	0.359	0.136	0.136
	(3.65)***	(2.8)***	(2.74)***	(7.41)***	(4.2)***	(4.27)***	(6.49)***	(4.61)***	(4.65)***
ϕ_{j^+}			0.287			-0.024			-0.049
			(2.75)***			(-0.35)			(-0.52)
ϕ_{j^-}			-0.075			-0.018			-0.022
			(-0.87)			(-0.22)			(-0.3)
R^2	0.753	0.754	0.756	0.623	0.625	0.626	0.603	0.608	0.609
$QLIKE$	0.119	0.119	0.119	0.062	0.061	0.061	0.074	0.073	0.073

	10-Year			20-Year			30-Year		
	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L
ϕ_0	0.005	0.001	0.001	0.004	0.001	0.001	0.008	0.001	0.001
	(9.04)***	(4.79)***	(6)***	(9.26)***	(4.57)***	(4.75)***	(9.5)***	(5.23)***	(1.44)
ϕ_d	0.183			0.134			0.199		
	(4.36)***			(4.52)***			(3.79)***		
ϕ_{d^+}		0.338	0.611		0.327	0.336		0.381	0.049
		(8.39)***	(5.72)***		(5.66)***	(1.78)*		(3.66)***	(0.14)
ϕ_{d^-}		0.354	0.158		0.274	0.257		0.324	0.560
		(8.79)***	(1.51)		(4.3)***	(2.18)**		(3.41)***	(1.99)**
ϕ_l		-0.003	0.005		0.003	0.028		0.094	0.119
		(-0.15)	(0.19)		(0.09)	(0.79)		(1.76)*	(2.06)**
ϕ_w	0.110	0.344	0.323	0.090	0.339	0.338	0.036	0.315	0.322
	(1.92)*	(7.76)***	(7.23)***	(2.2)**	(5.75)***	(5.24)***	(0.68)	(5.56)***	(5.92)***
ϕ_m	0.118	0.056	0.055	0.257	0.070	0.070	0.109	0.016	0.019
	(1.82)*	(1.79)*	(1.85)*	(5.58)***	(2.53)***	(2.55)***	(1.81)*	(0.71)	(0.85)
ϕ_{j^+}			-0.274			-0.012			0.433
			(-3.55)***			(-0.09)			(1.7)*
ϕ_{j^-}			0.024			-0.003			0.100
			(0.31)			(-0.03)			(0.64)
R^2	0.620	0.625	0.629	0.488	0.492	0.492	0.666	0.668	0.673
$QLIKE$	0.073	0.072	0.071	0.074	0.073	0.073	0.096	0.095	0.100

(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 C3: HAR-RSV Results of French Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L
ϕ_0	0.005	0.001	0.001	0.002	0.000	0.000	0.002	0.001	0.001
	(8.13)***	(4.31)***	(2.81)***	(4.2)***	(2.69)***	(2.38)***	(4.62)***	(3.12)***	(3.3)***
ϕ_d	0.070			0.188			0.101		
	(1.02)			(4.32)***			(3.29)***		
ϕ_{d^+}		0.184	0.251		0.296	0.186		0.202	0.030
		(0.97)	(0.69)		(5.16)***	(1.27)		(4.72)***	(0.23)
ϕ_{d^-}		0.738	0.595		0.318	0.418		0.374	0.566
		(2.76)***	(1.41)		(3.82)***	(3.22)***		(7.42)***	(4.6)***
ϕ_l		-0.077	-0.100		-0.028	-0.023		0.002	0.019
		(-0.73)	(-0.92)		(-1.1)	(-0.84)		(0.07)	(0.71)
ϕ_w	0.182	0.191	0.183	0.354	0.372	0.373	0.207	0.316	0.314
	(1.47)	(2.58)***	(2.53)***	(5.23)***	(7.06)***	(7.04)***	(3.42)***	(7.59)***	(7.43)***
ϕ_m	0.214	0.062	0.052	0.259	0.156	0.155	0.462	0.199	0.199
	(4.02)***	(1.87)*	(1.49)	(3.26)***	(4.7)***	(4.65)***	(6.3)***	(6.18)***	(6.15)***
ϕ_{j^+}			0.236			0.069			0.050
			(1)			(0.74)			(0.52)
ϕ_{j^-}			0.354			-0.038			-0.169
			(1.31)			(-0.41)			(-2.22)**
R^2	0.626	0.628	0.634	0.782	0.783	0.783	0.659	0.663	0.664
$QLIKE$	0.107	0.110	0.108	0.062	0.062	0.062	0.068	0.067	0.067

	10-Year			20-Year			30-Year		
	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L
ϕ_0	0.003	0.001	0.001	0.002	0.001	0.001	0.006	0.002	0.000
	(6.7)***	(4.42)***	(3.84)***	(4.23)***	(3.29)***	(3.31)***	(5.92)***	(5.36)***	(0.11)
ϕ_d	0.118			0.066			0.091		
	(3.43)***			(2.18)**			(2.17)**		
ϕ_{d^+}		0.271	0.434		0.280	0.226		0.433	0.361
		(6.05)***	(2.24)**		(6.05)***	(1.75)*		(2.43)***	(1.32)
ϕ_{d^-}		0.358	0.205		0.331	0.404		0.306	0.263
		(7.01)***	(1.19)		(7.69)***	(4.03)***		(1.58)	(0.9)
ϕ_l		0.048	0.041		0.001	0.022		-0.015	-0.018
		(1.37)	(1.15)		(0.03)	(0.66)		(-0.29)	(-0.33)
ϕ_w	0.185	0.297	0.297	0.208	0.228	0.225	0.174	0.254	0.251
	(2.7)***	(6.72)***	(6.68)***	(3.25)***	(4.47)***	(4.32)***	(1.97)**	(4.97)***	(4.89)***
ϕ_m	0.323	0.125	0.125	0.429	0.221	0.217	0.338	0.114	0.113
	(3.64)***	(4.12)***	(4.09)***	(4)***	(5.41)***	(5.32)***	(3.22)***	(3.53)***	(3.58)***
ϕ_{j^+}			-0.103			0.005			0.464
			(-0.82)			(0.05)			(2.04)**
ϕ_{j^-}			0.086			-0.085			0.487
			(0.73)			(-1.16)			(2.63)***
R^2	0.621	0.624	0.625	0.525	0.527	0.528	0.638	0.636	0.645
$QLIKE$	0.077	0.076	0.076	0.066	0.065	0.065	0.103	0.102	0.111

(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 C4: HAR-RSV Results of UK Market on 1-day Forecast Horizon (h=1)

	1-Year			2-Year			5-Year		
	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L
ϕ_0	0.005	0.001	0.001	0.004	0.001	0.001	0.004	0.001	0.002
	(4.41)***	(2.67)***	(2.58)***	(7.48)***	(4.48)***	(4.61)***	(4.72)***	(4.37)***	(5.38)***
ϕ_d	0.155			0.061			0.024		
	(2.5)***			(1.86)*			(0.57)		
ϕ_{d+}		0.320	0.299		0.414	0.450		0.412	0.272
		(2.76)***	(0.94)		(5.23)***	(2.1)**		(5.8)***	(1.51)
ϕ_{d-}		0.431	0.415		0.336	0.405		0.436	0.752
		(3.97)***	(1.36)		(4.85)***	(1.59)		(6.46)***	(3.47)***
ϕ_l		-0.005	0.007		-0.021	-0.011		-0.096	-0.082
		(-0.13)	(0.17)		(-0.55)	(-0.25)		(-2.08)**	(-1.91)*
ϕ_w	0.141	0.241	0.244	0.143	0.235	0.218	0.172	0.172	0.143
	(1.32)	(2.53)***	(2.59)***	(2.52)***	(2.94)***	(2.71)***	(2.06)**	(2.27)**	(2.07)**
ϕ_m	0.318	0.124	0.120	0.351	0.119	0.125	0.285	0.107	0.118
	(2.76)***	(1.88)*	(1.8)*	(5.28)***	(2.85)***	(3.02)***	(2.51)***	(2.55)***	(2.89)***
ϕ_{j+}			0.076			-0.164			-0.134
			(0.42)			(-1.31)			(-1.1)
ϕ_{j-}			0.073			-0.200			-0.455
			(0.37)			(-1.09)			(-3.15)***
R^2	0.639	0.640	0.640	0.550	0.560	0.565	0.469	0.488	0.508
$QLIKE$	0.069	0.069	0.069	0.071	0.071	0.070	0.084	0.084	0.081

	10-Year			20-Year			30-Year		
	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L	RV	RSV-L	RSVJ-L
ϕ_0	0.005	0.002	0.002	0.004	0.001	0.002	0.006	0.002	0.002
	(5.68)***	(3.51)***	(5.17)***	(4.19)***	(4.61)***	(6.35)***	(5.26)***	(4.26)***	(4.46)***
ϕ_d	0.010			0.005			-0.006		
	(0.14)			(0.12)			(-0.08)		
ϕ_{d+}		0.314	0.768		0.368	0.847		0.521	0.365
		(8.3)***	(3.81)***		(9.14)***	(3.97)***		(4.79)***	(0.95)
ϕ_{d-}		0.420	0.076		0.491	0.134		0.255	0.445
		(8.12)***	(0.49)		(6.75)***	(0.78)		(2.29)**	(1.09)
ϕ_l		-0.018	-0.040		0.034	0.027		0.065	0.077
		(-0.44)	(-0.81)		(0.85)	(0.65)		(0.97)	(1.11)
ϕ_w	0.145	0.265	0.242	0.155	0.119	0.102	0.151	0.231	0.229
	(2.03)**	(6.47)***	(5.91)***	(1.51)	(1.4)	(1.26)	(1.6)	(4.84)***	(4.63)***
ϕ_m	0.292	0.050	0.055	0.319	0.088	0.097	0.281	0.029	0.032
	(3.36)***	(1.48)	(1.61)	(2.65)***	(2.16)**	(2.49)***	(2.97)***	(1)	(1.13)
ϕ_{j+}			-0.458			-0.495			-0.043
			(-3.26)***			(-3.55)***			(-0.16)
ϕ_{j-}			0.054			0.034			-0.234
			(0.47)			(0.27)			(-0.79)
R^2	0.510	0.518	0.528	0.513	0.526	0.542	0.594	0.597	0.598
$QLIKE$	0.087	0.085	0.083	0.070	0.069	0.068	0.106	0.107	0.105

(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 C5: One-Day Ahead Out of Sample Forecast Results of RSV Models (h=1)

(a) QLIKE Estimates

	Swiss			German			French			UK		
	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L
1-Year	1.000	1.006	0.999	1.000	1	0.999	1.000	1.055	1.014	1.000	0.997 [a]	0.999 [a]
2-Year	—	—	—	1.000	0.992 [a]	0.993 [a]	1.000	1.003	1.014	1.000	0.993 [a]	0.988 [a]
5-Year	1.000	0.997 [a]	0.997 [a]	1.000	0.986 [a]	0.988 [a]	1.000	0.988 [a]	0.986 [a]	1.000	0.996 [a]	0.981 [a]
10-Year	1.000	0.997 [a]	0.994 [a]	1.000	0.99 [a]	0.985 [a]	1.000	0.994 [a]	0.993 [a]	1.000	0.995 [a]	0.986 [a]
20-Year	1.000	0.996	0.99 [a]	1.000	0.996 [a]	0.999	1.000	0.992 [a]	0.994 [a]	1.000	1.013	1.004
30-Year	1.000	1.002	1.001	1.000	1.004	1.037	1.000	1.039	1.025	1.000	1.009	1.012

(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	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L
1-Year	51.5%	51.9%	52.2%	66.2%	66.2%	66.5%	57.2%	58.0%	58.8%	39.8%	40.2%	40.4%
2-Year	—	—	—	48.3%	48.9%	49.0%	63.6%	64.1%	64.3%	38.2%	39.0%	40.1%
5-Year	27.3%	27.5%	27.9%	34.9%	36.3%	36.3%	47.8%	48.6%	49.2%	26.2%	27.1%	28.2%
10-Year	37.9%	37.9%	38.1%	39.4%	40.1%	40.5%	40.9%	41.5%	41.9%	28.7%	29.0%	29.7%
20-Year	10.6%	11.0%	11.1%	37.1%	37.7%	37.8%	35.3%	35.9%	36.0%	32.2%	33.1%	33.5%
30-Year	23.3%	23.7%	23.7%	46.5%	47.3%	47.9%	37.0%	37.7%	38.6%	35.5%	36.0%	36.5%

(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.

Table C6: One-Week Ahead Out of Sample Forecast Results of RSV Models (h=5)

(a) QLIKE Estimates

	Swiss			German			French			UK		
	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L
1-Year	1.000	1.003	0.994[a]	1.000	1.006	1.002	1.000	1.012	0.981[a]	1.000	1.022	1.013
2-Year	—	—	—	1.000	0.998[a]	1.003	1.000	0.996[a]	0.994[a]	1.000	0.997[a]	0.994[a]
5-Year	1.000	0.991[a]	0.988[a]	1.000	0.991[a]	0.99[a]	1.000	0.983[a]	0.975[a]	1.000	0.99[a]	0.985[a]
10-Year	1.000	0.998[a]	0.986[a]	1.000	0.992[a]	0.989[a]	1.000	0.991[a]	0.983[a]	1.000	0.994[a]	0.985[a]
20-Year	1.000	0.995[a]	0.982[a]	1.000	0.996[a]	0.999[a]	1.000	0.993[a]	0.993[a]	1.000	0.997[a]	0.986[a]
30-Year	1.000	0.996[a]	0.993[a]	1.000	0.997[a]	0.999[a]	1.000	0.998	0.995[a]	1.000	1.002	1.013

(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	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L
1-Year	62.6%	62.6%	62.8%	64.9%	64.9%	65.0%	49.3%	49.4%	50.5%	47.9%	48.4%	48.5%
2-Year	56.7%	57.0%	59.4%	58.9%	59.1%	59.2%	70.1%	70.4%	70.5%	44.3%	45.2%	45.7%
5-Year	37.3%	37.4%	37.7%	44.5%	45.4%	45.5%	57.1%	58.1%	58.5%	28.3%	29.0%	29.5%
10-Year	48.8%	49.0%	49.0%	47.2%	48.0%	48.2%	45.9%	47.0%	47.3%	35.0%	35.6%	36.2%
20-Year	20.9%	21.1%	21.3%	45.3%	45.8%	46.1%	42.7%	43.7%	43.7%	34.7%	35.1%	35.3%
30-Year	33.7%	34.0%	34.1%	52.5%	53.3%	53.9%	41.5%	42.4%	43.2%	38.7%	39.1%	39.5%

(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.

Table C7: One-Month Ahead Out of Sample Forecast Results of RSV Models (h=22)

(a) QLIKE Estimates

	Swiss			German			French			UK		
	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L
1-Year	1.000	1.009	1.001	1.000	1.005	0.996[a]	1.000	1.003	0.976[a]	1.000	0.993[a]	0.99[a]
2-Year	—	—	—	1.000	0.999	0.991[a]	1.000	0.99[a]	0.987[a]	1.000	1.002	0.997[a]
5-Year	1.000	1.02	1.016	1.000	0.996[a]	0.985[a]	1.000	1.007	0.992[a]	1.000	1[a]	0.996[a]
10-Year	1.000	1.012	0.999[a]	1.000	0.999[a]	0.996[a]	1.000	0.996[a]	0.992[a]	1.000	1.008	1.002
20-Year	1.000	0.999	0.992[a]	1.000	0.998[a]	0.999[a]	1.000	0.996[a]	0.995[a]	1.000	1.006	1.002[a]
30-Year	1.000	1.002	0.995[a]	1.000	0.998	0.987[a]	1.000	0.994[a]	0.992[a]	1.000	1.006	1.005

(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	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L	HAR-RV	RSV-L	RSVJ-L
1-Year	50.0%	50.0%	50.5%	49.5%	49.3%	49.6%	28.1%	27.8%	28.8%	39.2%	39.1%	39.2%
2-Year	—	—	—	52.7%	52.4%	52.9%	63.5%	63.7%	63.8%	35.0%	35.0%	36.1%
5-Year	30.7%	30.3%	30.8%	34.3%	34.6%	34.7%	57.1%	56.7%	57.6%	25.0%	24.5%	25.3%
10-Year	40.1%	40.4%	40.6%	32.5%	32.6%	32.9%	38.9%	39.2%	39.9%	34.2%	33.7%	34.3%
20-Year	20.2%	20.1%	20.1%	33.8%	33.5%	34.0%	45.9%	46.4%	46.7%	35.5%	35.6%	35.9%
30-Year	28.9%	29.0%	29.1%	37.0%	37.4%	37.6%	38.1%	38.3%	39.4%	35.7%	35.8%	36.1%

(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 Appendix D: Additional Results

4.1 HAR Forecasts for 0ne-Week (h=5) and One-Month (h=22) Horizons

Table D1: Regression Results of Swiss Market on 5-day Forecast Horizon (h=5)

	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	0.002	0.002	0.003	—	—	—	0.002	0.002	0.002
	(4.19)***	(4.07)***	(6.11)***	—	—	—	(3.35)***	(3.46)***	(5.16)***
β_d	0.253	0.251	0.264	—	—	—	0.270	0.300	0.269
	(8.43)***	(8.96)***	(8.04)***	—	—	—	(6.73)***	(5.95)***	(5.73)***
β_w	0.433	0.433	0.386	—	—	—	0.408	0.402	0.446
	(9.53)***	(9.55)***	(8.32)***	—	—	—	(6.37)***	(6.08)***	(6.37)***
β_m	0.237	0.237	0.286	—	—	—	0.115	0.107	0.139
	(4.7)***	(4.71)***	(5.6)***	—	—	—	(2.13)**	(1.98)**	(2.46)***
β_j		0.021	0.231	—	—	—		-0.071	0.182
		(0.4)	(3.74)***	—	—	—		(-1.58)	(4.41)***
R^2	0.754	0.754	0.742	—	—	—	0.510	0.513	0.526
$QLIKE$	0.103	0.103	0.108	—	—	—	0.073	0.072	0.073
$J-R^2$	0.673	0.674	0.655	—	—	—	0.455	0.456	0.452
$J-QLIKE$	0.151	0.151	0.158	—	—	—	0.074	0.074	0.077
$C-R^2$	0.782	0.782	0.773	—	—	—	0.535	0.536	0.559
$C-QLIKE$	0.081	0.081	0.087	—	—	—	0.070	0.070	0.070

	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	0.002	0.003	0.003	0.004	0.001	0.002	0.003
	(3.28)***	(3.25)***	(6.4)***	(5.93)***	(6.05)***	(10.63)***	(3.17)***	(4.33)***	(8.16)***
β_d	0.300	0.301	0.301	0.107	0.126	0.132	0.281	0.303	0.288
	(9.35)***	(8.94)***	(8.88)***	(2.72)***	(2.38)***	(2.65)***	(5.71)***	(5.45)***	(5.58)***
β_w	0.335	0.335	0.327	0.123	0.123	0.154	0.294	0.286	0.321
	(5.4)***	(5.31)***	(5.21)***	(1.99)**	(2.04)**	(2.17)**	(4.17)***	(4.21)***	(4.23)***
β_m	0.239	0.238	0.245	0.343	0.338	0.281	0.296	0.288	0.259
	(3.74)***	(3.8)***	(4.01)***	(2.81)***	(2.75)***	(2.25)**	(3.52)***	(3.45)***	(2.97)***
β_j		-0.004	0.233		-0.053	0.067		-0.138	0.103
		(-0.09)	(5.64)***		(-1.42)	(2.81)***		(-3.18)***	(2.68)***
R^2	0.630	0.630	0.624	0.186	0.188	0.170	0.598	0.601	0.607
$QLIKE$	0.059	0.059	0.060	0.089	0.088	0.094	0.095	0.093	0.094
$J-R^2$	0.571	0.571	0.557	0.173	0.171	0.152	0.326	0.325	0.348
$J-QLIKE$	0.060	0.060	0.063	0.083	0.083	0.087	0.092	0.091	0.091
$C-R^2$	0.657	0.657	0.655	0.186	0.185	0.169	0.655	0.654	0.656
$C-QLIKE$	0.058	0.058	0.059	0.097	0.097	0.103	0.095	0.095	0.098

(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 D2: Regression Results of German Market on 5-day Forecast Horizon (h=5)

	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	0.001	0.002
	(4.81)***	(4.94)***	(5.85)***	(3.39)***	(3.39)***	(4.07)***	(4.83)***	(5.06)***	(8.47)***
β_d	0.449	0.453	0.452	0.276	0.288	0.324	0.318	0.342	0.354
	(12.76)***	(12.58)***	(12.86)***	(9.18)***	(7.75)***	(6.99)***	(11.04)***	(10.2)***	(9.15)***
β_w	0.325	0.326	0.323	0.353	0.346	0.336	0.397	0.380	0.382
	(6.33)***	(6.42)***	(6.65)***	(7.42)***	(7.22)***	(7.58)***	(7.94)***	(7.23)***	(6.42)***
β_m	0.130	0.127	0.129	0.287	0.287	0.292	0.175	0.174	0.158
	(2.52)***	(2.48)***	(2.53)***	(5.27)***	(5.23)***	(5.24)***	(4.7)***	(4.68)***	(3.9)***
β_j		-0.058	0.205		-0.033	0.154		-0.068	0.142
		(-1.23)	(4.4)***		(-1)	(4.36)***		(-2.23)**	(5.11)***
R^2	0.754	0.754	0.752	0.729	0.730	0.714	0.697	0.698	0.692
$QLIKE$	0.094	0.094	0.097	0.036	0.036	0.037	0.044	0.043	0.044
$J-R^2$	0.561	0.559	0.551	0.727	0.727	0.708	0.616	0.619	0.621
$J-QLIKE$	0.169	0.169	0.175	0.043	0.043	0.045	0.049	0.049	0.046
$C-R^2$	0.777	0.777	0.776	0.730	0.730	0.715	0.716	0.717	0.709
$C-QLIKE$	0.080	0.080	0.082	0.035	0.035	0.036	0.041	0.041	0.043

	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	0.002	0.002	0.002	0.002	0.003	0.003
	(5.01)***	(5.65)***	(8.04)***	(5.19)***	(5.51)***	(7.65)***	(5.66)***	(5.39)***	(6.61)***
β_d	0.389	0.439	0.449	0.365	0.403	0.418	0.476	0.488	0.484
	(12.89)***	(13.02)***	(12.47)***	(7.59)***	(8.07)***	(7.31)***	(11.11)***	(10.79)***	(10.8)***
β_w	0.393	0.356	0.350	0.305	0.282	0.270	0.356	0.350	0.350
	(7.72)***	(6.76)***	(5.86)***	(5.03)***	(4.49)***	(3.3)***	(5.8)***	(5.51)***	(5.48)***
β_m	0.061	0.057	0.045	0.126	0.120	0.118	0.012	0.009	0.012
	(1.27)	(1.19)	(0.89)	(3.95)***	(3.79)***	(3.11)***	(0.33)	(0.24)	(0.32)
β_j		-0.135	0.121		-0.082	0.165		-0.102	0.181
		(-4.61)***	(5.34)***		(-2.32)**	(4.47)***		(-0.97)	(1.65)*
R^2	0.661	0.667	0.663	0.539	0.542	0.540	0.666	0.667	0.663
$QLIKE$	0.044	0.043	0.044	0.045	0.044	0.045	0.083	0.082	0.083
$J-R^2$	0.485	0.493	0.501	0.546	0.551	0.571	0.431	0.431	0.408
$J-QLIKE$	0.050	0.049	0.047	0.046	0.046	0.045	0.074	0.073	0.075
$C-R^2$	0.698	0.700	0.694	0.541	0.543	0.536	0.694	0.694	0.694
$C-QLIKE$	0.041	0.041	0.043	0.044	0.044	0.045	0.084	0.084	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 D3: Regression Results of French Market on 5-day Forecast Horizon (h=5)

	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	0.002	0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.002
	(5.65)***	(5.27)***	(3.65)***	(2.94)***	(3.03)***	(3.15)***	(3.19)***	(3.58)***	(5.13)***
β_d	0.514	0.498	0.489	0.328	0.331	0.358	0.297	0.318	0.350
	(9.83)***	(12.02)***	(12.6)***	(8.72)***	(8.48)***	(9.97)***	(10.79)***	(10.69)***	(11.6)***
β_w	0.162	0.156	0.214	0.399	0.397	0.559	0.338	0.327	0.496
	(1.88)*	(1.76)*	(2.78)***	(7.41)***	(7.33)***	(12.16)***	(6.87)***	(6.62)***	(12.01)***
β_m	0.149	0.155	0.111	0.229	0.229	0.076	0.287	0.280	0.073
	(2.66)***	(2.59)***	(2.45)***	(4.69)***	(4.68)***	(2.55)***	(6.38)***	(6.21)***	(1.84)*
β_j		0.231	0.417		-0.041	0.141		-0.089	0.105
		(1.19)	(1.97)**		(-1.15)	(4.03)***		(-2.72)***	(3.67)***
R^2	0.571	0.576	0.570	0.850	0.850	0.844	0.749	0.751	0.739
$QLIKE$	0.100	0.100	0.101	0.040	0.040	0.042	0.041	0.040	0.042
$J-R^2$	0.349	0.357	0.331	0.850	0.855	0.832	0.647	0.655	0.673
$J-QLIKE$	0.168	0.170	0.174	0.058	0.057	0.052	0.050	0.049	0.047
$C-R^2$	0.641	0.641	0.641	0.850	0.851	0.845	0.760	0.761	0.746
$C-QLIKE$	0.092	0.092	0.092	0.040	0.040	0.042	0.038	0.038	0.041

	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	0.002	0.001	0.001	0.002	0.002	0.002	0.003
	(3.81)***	(3.92)***	(4.88)***	(2.67)***	(2.84)***	(5.8)***	(4.52)***	(3.6)***	(4.4)***
β_d	0.327	0.335	0.348	0.262	0.292	0.343	0.355	0.348	0.374
	(11.37)***	(10.79)***	(11.75)***	(9.81)***	(9.48)***	(11.04)***	(10.59)***	(10.14)***	(11.47)***
β_w	0.388	0.384	0.470	0.279	0.264	0.422	0.331	0.334	0.445
	(6.59)***	(6.47)***	(8.78)***	(5.06)***	(4.77)***	(7.23)***	(5.05)***	(5.09)***	(8.36)***
β_m	0.177	0.174	0.073	0.335	0.324	0.058	0.217	0.216	0.084
	(3.68)***	(3.63)***	(1.57)	(5.75)***	(5.55)***	(1.3)	(3.72)***	(3.72)***	(1.29)
β_j		-0.052	0.144		-0.070	0.127		0.195	0.410
		(-1.06)	(3.23)***		(-2.3)**	(5.22)***		(1.91)*	(4.28)***
R^2	0.686	0.686	0.683	0.615	0.617	0.588	0.679	0.681	0.667
$QLIKE$	0.048	0.048	0.048	0.037	0.037	0.040	0.081	0.083	0.095
$J-R^2$	0.701	0.707	0.710	0.548	0.556	0.576	0.704	0.689	0.690
$J-QLIKE$	0.057	0.056	0.051	0.045	0.045	0.046	0.087	0.100	0.092
$C-R^2$	0.683	0.683	0.679	0.629	0.630	0.593	0.682	0.682	0.667
$C-QLIKE$	0.047	0.047	0.048	0.035	0.035	0.039	0.083	0.083	0.098

(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 D4: Regression Results of the UK Market on 5-day Forecast Horizon (h=5)

	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	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.003
	(2.86)***	(2.76)***	(3.21)***	(4.13)***	(4.15)***	(5.93)***	(4.12)***	(4.38)***	(7.3)***
β_d	0.366	0.354	0.383	0.358	0.382	0.429	0.368	0.425	0.430
	(9.55)***	(9.08)***	(11.49)***	(10.32)***	(10.44)***	(10.79)***	(8.49)***	(9.87)***	(10.26)***
β_w	0.418	0.425	0.457	0.279	0.266	0.355	0.166	0.135	0.143
	(4.1)***	(4.15)***	(7.11)***	(3.27)***	(3.16)***	(5.15)***	(2.38)***	(2.04)**	(2.19)**
β_m	0.104	0.103	0.067	0.206	0.204	0.042	0.226	0.221	0.177
	(1.04)	(1.05)	(1.76)*	(2.57)***	(2.55)***	(2.41)***	(2.76)***	(2.68)***	(4.09)***
β_j		0.155	0.363		-0.070	0.198		-0.145	0.117
		(1.55)	(3.81)***		(-1.28)	(4.2)***		(-3.56)***	(3.18)***
R^2	0.693	0.695	0.688	0.579	0.581	0.557	0.441	0.451	0.442
$QLIKE$	0.042	0.044	0.046	0.048	0.047	0.053	0.051	0.050	0.052
$J-R^2$	0.769	0.775	0.784	0.548	0.551	0.582	0.362	0.368	0.332
$J-QLIKE$	0.051	0.059	0.063	0.049	0.049	0.051	0.053	0.052	0.055
$C-R^2$	0.689	0.689	0.681	0.586	0.586	0.555	0.467	0.470	0.468
$C-QLIKE$	0.043	0.043	0.045	0.047	0.047	0.054	0.049	0.050	0.050

	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	0.002	0.002	0.002	0.003	0.003	0.003
	(2.79)***	(3.52)***	(6.96)***	(4.06)***	(4.64)***	(4.46)***	(3.55)***	(3.93)***	(5.9)***
β_d	0.378	0.429	0.397	0.438	0.488	0.463	0.464	0.480	0.449
	(6.94)***	(7.38)***	(6.26)***	(9.29)***	(11.18)***	(10.82)***	(8.24)***	(8.85)***	(7.93)***
β_w	0.317	0.285	0.330	0.109	0.079	0.083	0.257	0.251	0.288
	(4.96)***	(4.52)***	(4.38)***	(1.3)	(1.05)	(1.18)	(3.73)***	(3.83)***	(4.2)***
β_m	0.114	0.110	0.102	0.205	0.207	0.282	0.110	0.112	0.095
	(1.78)*	(1.78)*	(2.84)***	(2.46)***	(2.53)***	(3.69)***	(1.71)*	(1.76)*	(2.74)***
β_j		-0.203	0.042		-0.169	0.097		-0.205	0.057
		(-5.88)***	(1.5)		(-4.2)***	(2.76)***		(-2.14)**	(0.62)
R^2	0.541	0.554	0.568	0.441	0.452	0.467	0.571	0.575	0.586
$QLIKE$	0.052	0.050	0.048	0.046	0.044	0.043	0.092	0.089	0.084
$J-R^2$	0.319	0.329	0.341	0.321	0.324	0.373	0.345	0.344	0.352
$J-QLIKE$	0.052	0.050	0.050	0.046	0.045	0.041	0.075	0.072	0.077
$C-R^2$	0.585	0.585	0.599	0.476	0.477	0.485	0.598	0.598	0.610
$C-QLIKE$	0.050	0.050	0.047	0.043	0.044	0.044	0.094	0.094	0.086

(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 D5: 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 D6: 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 D7: 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 D8: 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 D9: One-Week Ahead Out of Sample Forecast Results (h=5)

(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]	1.043	1.000	1.002	1.021	1.000	0.999[a]	0.998	1.000	1.011	1.102
2-Year	—	—	—	1.000	0.999[a]	1.055	1.000	0.999	1.113	1.000	0.997[a]	1.112
5-Year	1.000	0.994[a]	1.008	1.000	0.996[a]	1.027	1.000	0.982[a]	1.068	1.000	0.991[a]	1.014
10-Year	1.000	1.002	1.016	1.000	0.989[a]	1.011	1.000	0.991[a]	1.028	1.000	0.983[a]	0.951[a]
20-Year	1.000	0.994[a]	1.037	1.000	1.002	1.021	1.000	0.998[a]	1.093	1.000	0.983[a]	0.998[a]
30-Year	1.000	0.992[a]	0.99	1.000	0.999[a]	1.022	1.000	1.005	1.19	1.000	0.992[a]	0.963[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	62.6%	62.7%	61.7%	64.9%	65.0%	64.9%	49.3%	49.8%	49.6%	47.9%	48.2%	46.0%
2-Year	—	—	—	58.9%	59.0%	57.1%	70.1%	70.2%	69.7%	44.3%	44.9%	43.2%
5-Year	37.3%	37.4%	36.0%	44.5%	44.7%	43.8%	57.1%	58.0%	58.4%	28.3%	28.8%	28.2%
10-Year	48.8%	48.9%	45.5%	47.2%	47.7%	47.0%	45.9%	46.6%	47.5%	35.0%	35.7%	36.2%
20-Year	20.9%	21.1%	17.0%	45.3%	45.6%	44.9%	42.7%	42.7%	40.5%	34.7%	35.2%	34.1%
30-Year	33.7%	34.0%	30.7%	52.5%	52.6%	51.5%	41.5%	41.9%	41.5%	38.7%	39.1%	37.5%

(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.

Table D10: 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.

4.2 Volatility Forecast Comparison of HAR vs AR Models

Table D11: One-Day Ahead Out of Sample Forecast Results of AR(5) Model (h=1)
Model: $RV_{t+h-1} = \phi_0 + \sum_{k=1}^{5} \phi_k RV_{t-k} + \epsilon_t$

(a) QLIKE Estimates

	Swiss		German		French		UK	
	HAR-RV	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)
1-Year	1.000	0.932	1.000	0.997	1.000	0.973[a]	1.000	0.983[a]
2-Year	—	—	1.000	0.997[a]	1.000	1.006	1.000	0.979[a]
5-Year	1.000	0.98[a]	1.000	1.006	1.000	1.014	1.000	0.978[a]
10-Year	1.000	0.99[a]	1.000	0.985[a]	1.000	1.022	1.000	1.006
20-Year	1.000	1.008	1.000	0.997[a]	1.000	1.016	1.000	0.992[a]
30-Year	1.000	0.996	1.000	0.977[a]	1.000	1.012	1.000	0.983

(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	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)
1-Year	51.5%	51.5%	66.2%	66.4%	57.2%	57.7%	39.8%	40.2%
2-Year	—	—	48.3%	48.1%	63.6%	63.4%	38.2%	39.4%
5-Year	27.3%	27.7%	34.9%	34.8%	47.8%	47.4%	26.2%	26.4%
10-Year	37.9%	37.8%	39.4%	39.3%	40.9%	41.0%	28.7%	28.5%
20-Year	10.6%	9.2%	37.1%	37.9%	35.3%	34.3%	32.2%	32.1%
30-Year	23.3%	23.1%	46.5%	47.0%	37.0%	37.5%	35.5%	35.5%

(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.

Table D12: One-Week Ahead Out of Sample Forecast Results of AR(5) Model (h=5)

Model: $RV_{t+h-1} = \phi_0 + \sum_{k=1}^{5} \phi_k RV_{t-k} + \epsilon_t$

(a) QLIKE Estimates

	Swiss		German		French		UK	
	HAR-RV	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)
1-Year	1.000	1.026	1.000	0.986	1.000	0.944	1.000	1.006
2-Year	—	—	1.000	1.011[a]	1.000	1.079	1.000	1.02
5-Year	1.000	0.974[a]	1.000	1.015[a]	1.000	1.074	1.000	1.007
10-Year	1.000	1.036	1.000	0.978[a]	1.000	1.079	1.000	1.001
20-Year	1.000	1.05	1.000	0.987[a]	1.000	1.089	1.000	1.038
30-Year	1.000	1.046	1.000	0.928[a]	1.000	1.122	1.000	0.964

(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	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)
1-Year	62.6%	60.8%	64.9%	64.6%	49.3%	49.2%	47.9%	46.7%
2-Year	—	—	58.9%	57.6%	70.1%	69.2%	44.3%	44.4%
5-Year	37.3%	37.3%	44.5%	43.9%	57.1%	55.7%	28.3%	27.6%
10-Year	48.8%	47.1%	47.2%	46.5%	45.9%	45.5%	35.0%	33.8%
20-Year	20.9%	16.4%	45.3%	45.3%	42.7%	39.4%	34.7%	32.1%
30-Year	33.7%	32.2%	52.5%	52.0%	41.5%	39.4%	38.7%	36.8%

(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.

Table D13: One-Month Ahead Out of Sample Forecast Results of AR(5) Model (h=22)
Model: $RV_{t+h-1} = \phi_0 + \sum_{k=1}^{5} \phi_k RV_{t-k} + \epsilon_t$

(a) QLIKE Estimates

	Swiss		German		French		UK	
	HAR-RV	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)
1-Year	1.000	1.026	1.000	1.002	1.000	0.962	1.000	0.981
2-Year	—	—	1.000	1.009	1.000	1.103	1.000	1.042
5-Year	1.000	0.994[a]	1.000	0.974	1.000	1.139	1.000	1.111
10-Year	1.000	1.086	1.000	0.957	1.000	1.121	1.000	1.151
20-Year	1.000	1.045	1.000	0.972[a]	1.000	1.133	1.000	1.196
30-Year	1.000	1.092	1.000	0.915	1.000	1.132	1.000	1.138

(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	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)	HAR-RV	AR(5)
1-Year	49.7%	48.3%	49.3%	48.3%	27.7%	24.8%	38.8%	36.3%
2-Year	—	—	52.4%	50.5%	63.4%	59.3%	34.3%	31.7%
5-Year	30.0%	29.3%	34.0%	32.5%	55.8%	52.1%	24.0%	19.3%
10-Year	40.0%	36.3%	32.3%	30.5%	38.4%	34.4%	33.4%	26.1%
20-Year	20.0%	17.4%	33.3%	31.5%	45.9%	38.1%	35.4%	25.4%
30-Year	28.9%	26.6%	36.9%	34.6%	37.7%	30.8%	35.4%	27.1%

(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.

Table D14: Frequency of Jumps (%)

	1-Year	2-Year	5-Year	10-Year	20-Year	30-Year
Swiss	30.87	—	50.15	45.90	60.04	52.40
German	15.92	13.53	24.62	27.54	27.12	23.67
French	10.17	7.81	17.48	19.62	21.81	17.78
UK	9.45	15.00	27.01	27.42	24.37	20.81

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