Forecasting (downside and upside) realized exchange-rate volatility: Is there a role for realized skewness and kurtosis?

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Abstract

We use intraday data to construct measures of realized volatility, realized kurtosis, and realized skewness of returns of six major exchange rates vis-à-vis the dollar. The currencies under consideration are: (i) Australian dollar, (ii) Canadian dollar, (iii) Swiss franc, (iv) euro, (v) British pound, and (vi) Japanese yen. The period of the analysis spans from 1 July 2003 to 28 August 2015. We study in-sample and out-of-sample the predictive value of realized kurtosis and realized skewness for realized volatility, where we also differentiate between measures of upside realized volatility and downside realized volatility. We find that both realized kurtosis and realized skewness have in-sample predictive value in several models being studied. The out-of-sample results show that it is mainly realized kurtosis that helps to improve accuracy of one-day-ahead forecasts of realized volatility, but results depend on the assumed loss function and they differ across exchange rates.

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Keywords: Exchange rates; Realized volatility; Forecasting

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1 Introduction

The foreign exchange market is the largest and most liquid financial market in the world, with the average daily turnover being 5.1 trillion U.S. dollars.[1]. Given that exchange rates fluctuate widely, accurate forecasting of exchange-rate volatility is important to financial institutions, and traders aiming to hedge currency risks (Pilbeam and Langeland 2015). Likewise, traders of foreign currency options seek to make profits by buying (selling) options if they expect volatility to rise above (fall below) of what is implied in currency-option premiums. In addition, a large body of theoretical research has linked exchange-rate volatility to trade and welfare (Clark et al. 2004, Aye et al. 2015, Asteriou et al. 2016). Hence, forecasting exchange-rate volatility is a key element in terms of portfolio selection, option pricing, risk management, and policy decisions (Rapach and Strauss 2008). What is more, multinational managers and business practitioners evaluate their operational decisions under exchange-rate uncertainty. Thus, the profitability of multinational firms is subject to exchange-rate volatility. According to Kim and Park (2014), exchange-rate volatility can influence the internal transactions of such firms. Our results are useful for managers of such firms, and for tactical risk-management-decision making in general, because our results shed light on whether past realized volatility along with higher-order moments like realized kurtosis and realized skewness help to forecast subsequent realizations of realized volatility, thus providing useful information for currency-risk management (see Glen and Jorion 1993, Dasu and Li 1997, Ji et al. 2019, among others). Understandably, a vast methodological and empirical literature has developed that informs about the development and assessment as well as the forecasting of exchange-rate volatility (see, for example, Corsi 2009, Babikir et al. 2012, and

[1]Triennial Survey of global foreign exchange market volumes (April, 2016) of the Bank for International Settlement (BIS)

Christou et al. 2018).

In this regard, it is important to point out that foreign-exchange-market participants care not only about the nature of volatility, but also about its level, and for traders the distinction between "good" and "bad" volatility matters (Caporin et al. 2016). Good volatility is directional, persistent, and relatively easy to predict, while bad volatility is jumpy and comparatively difficult to foresee. Therefore, good volatility is generally associated with the continuous and persistent part of volatility, while bad volatility captures the discontinuous and jump component of volatility.

The objective of our study is to add to the literature on exchange-rate-volatility forecasting by analyzing, for the first time, the value of realized skewness and realized kurtosis for forecasting realized exchange-rate volatility, as well as its downside and upside components. We derive these measures based on (5 minute-interval) intraday data covering the exchange rates of six (Australian dollar, Canadian dollar, Swiss franc, euro, British pound, and Japanese yen) major currencies relative to the United States (US) dollar over the daily period from 1st July, 2003 to 28th August, 2015.[2]

The motivation to look at the role of realized skewness and kurtosis in forecasting exchange-rate volatility emanates from the large theoretical literature, starting with Kraus and Litzenberger (1976) and continuing with the macroeconomic disaster research by Rietz (1988), Longstaff and Piazzesi (2004), and Barro (2006), which hypothesises that heavy-tailed shocks in general and left-tail events in particular have an important role in explaining asset-price behaviour. Given this,

[2] All exchange rates that we study in our reseasrch are against the US dollar. The U.S. has the highest number of multinational firms around the world. Furthermore, the other countries that we study are among the group of countries that has the highest number of multinational firms around the world (except the U.S.).

studies like Harvey and Siddique (2000), Ang et al. (2006), Kelly and Jiang (2014), Amaya et al. (2015), Neuberger and Payne (2018), and Shen et al. (2018) show that realized skewness and realized kurtosis can predict aggregate and cross-sectional stock market returns. Mei et al. (2017) study the role of realized skewness and realized kurtosis for forecasting realized stock-market volatility for China and the US. In a related line of research, Demirer et al. (2018) and Gupta et al., (forthcoming a, b) provide evidence of causality from rare disaster risks to volatility of oil, bonds, and exchange rates. Since in-sample predictability does not necessarily translate into out-of-sample forecasting gains (Rapach and Zhou 2013), and the latter is considered to be a more relevant test of the validity of models and predictors (Campbell 2008), we study both the in-sample and out-of-sample predictive value of realized skewness and realized kurtosis for realized exchange-rate volatility, as well as for its downside and upside. In doing so, we analyze whether the favourable out-sample results for stock-market volatility reported by Mei et al. (2017), besides the in-sample evidence on the role of disaster risks for modeling exchange-rate volatility documented by Gupta et al. (forthcoming a), holds out-of-sample for major exchange rates.

With the availability of high-frequency, i.e., intraday data, research on modelling volatility has taken new directions, where Andersen and Bollerslev (1998) propose in their seminal work a market-microstructure effects-robust measure of realized volatility (RV). They define, for a given fixed interval, RV as the sum of non-overlapping squared high-frequency returns observed within a day, which, in turn, allows volatility to be treated as an observed rather than a latent process. Among the realized-volatility models, the heterogeneous autoregressive RV (HAR-RV) model proposed by Corsi (2009) is one of the most popular, given its ability to capture important "stylized facts" of financial-market volatility such as long memory and multi-scaling behavior. Using the HAR-RV model as the benchmark model for forecasting exchange-rate volatility, we contribute to the research on exchange-rate volatility by investigating whether adding realized skewness, realized kurtosis, or both as additional variables to the HAR-RV model can improve its forecasting performance. This has not been addressed in earlier studies of currency markets.

Our results indicate that both realized kurtosis and realized skewness have in-sample predictive value in several models being studied. The out-of-sample results show that it is mainly realized kurtosis that helps to improve accuracy of one-day-ahead forecasts of realized volatility, but results depend on the assumed loss function and they differ across exchange rates.

The remainder of the paper is organized as follows: In Section 2, we describe the methods that we use in our research. In Section 3, we describe our data. In Section 4, we describe our results. In Section 5, we conclude.

2 Methods

Volatility is defined as the second moment of the price process of a financial time series and is a measure of risk. Volatility varies over time and has latency characteristics (Gkillas et al. 2018). This means that volatility is latent. Furthermore, volatility can be estimated by parametric (e.g., GARCH models) and non-parametric methods. The use of non-parametric methods, however, allows quadratic variation to be estimated, which is the best estimator of latent volatility, and thus to separate the jump component from the continuous part. The continuous part, known as good volatility, is directional, persistent, and relatively easy to predict.

Andersen et al. (2012) propose median realized variance (MRV) as a jump-robust estimator of integrated variance using intraday data.[3] They define MRV_t as follows:

$$MRV_t = \frac{\pi}{6-4\sqrt{3}+\pi} \cdot \frac{T}{T-2} \cdot \sum_{i=2}^{T-1} med\left(|r_{t,i-1}|, |r_{t,i}|, |r_{t,i+1}|\right)^2, \tag{1}$$

where $r_{t,i}$ is the intraday return i within day t and $i = 1,..,T$ is the total number of intraday observations within a day. According to Andersen et al. (2012), MRV is robust to jumps. It is considerably less biased than other measures of realized volatility in the presence of jumps and/or market-microstructure noise. In this research, we consider MRV as a measure of daily standard RV (denoted as RV^S) in order to attenuate the effects of jumps and market-microstructure noise on our results (see Ghysels and Sinko, 2011).

Barndorff-Nielsen et al. (2010) study downside and upside semi-variance (RV^- and RV^+) as measures based entirely on downward or upward moves of returns measured using intraday data. They define RV_t^- and RV_t^+ as follows:

$$RV_t^- = \sum_{i=1}^{T} r_{t,i}^2 \cdot I_{[(r_{t,i})<0]}, \tag{2}$$

$$RV_t^+ = \sum_{i=1}^{T} r_{t,i}^2 \cdot I_{[(r_{t,i})>0]}, \tag{3}$$

where $r_{t,i}$ again is the intraday return i within day t and $i = 1,..,T$ is the total number of intraday observations within a day. Of course, $RV^S = RV^- + RV^+$. We use daily RV^- and RV^+ realized semi-variance in order to capture the sign asymmetry of the volatility process.[4]

[3] It should be noted that researchers often use the term volatility to denote the standard deviation of asset-price movements. Because there is not risk of confusion, we define in this research realized volatility as the realized variance of exchange-rate returns and use the terms realized volatility and realized variance interchangeably.

[4] It must, however, be noted that because negative (positive) currency returns actually correspond to an appreciation (depreciation) of the domestic currency relative to the dollar, RV^- (RV^+) should be representing RV^+ (RV^-) for a trader investing in domestic (foreign, i.e., US dollar) currency.

As we already mentioned, volatility is the second moment of the price process and represents a measure of risk. As a measure of risk, volatility can have unobservable behaviour and intraday events during a trading day can affect it in different ways. In the daily return distribution, there are other moments that can capture with more precision statistical forces that affect the price process. Against this backdrop, the third moment (RSU) captures conditional skewness, while the fourth moment measures kurtosis risk with tailedness around the mean (RKU). Amaya et al. (2015) study realized skewness (RSK) and realized kurtosis (RKU) as higher-order moements computed from intraday returns. They define RSK_t and RKU_t, standardized by the realized variance, as follows:

$$RSK_t = \frac{\sqrt{T} \cdot \sum_{i=1}^{T} r_{t,i}^3}{(\sum_{i=1}^{T} r_{t,i}^2)^{3/2}}, \tag{4}$$

$$RKU_t = \frac{T \cdot \sum_{i=1}^{T} r_{t,i}^4}{(\sum_{i=1}^{T} r_{t,i}^2)^2}. \tag{5}$$

We consider daily RSK as a measure of the asymmetry of the daily returns distribution, and RKU as a measure of the extremes/tails of the daily returns distribution.

Corsi (2009) introduced the HAR-RV model, which has become one of the most popular models in the literature on volatility modeling and forecasting. Several authors have proposed extensions of the HAR-RV model based on different decompositions of realized volatility (see Andersen et al. 2007, Ma et al. 2018, Ma et al. 2019, Wang et al. 2016). The HAR-RV model captures "stylized facts" of financial-market volatility such as long memory and multi-scaling behavior. The benchmark HAR-RV model, for h-days-ahead forecasting, can be written as follows:

$$RV_{t+h}^j = \beta_0 + \beta_d \cdot RV_t^j + \beta_w \cdot RV_{w,t}^j + \beta_m \cdot RV_{m,t}^j + \varepsilon_{t+h}, \tag{6}$$

where (to simplify notation) j can be either S, $+$ or $-$, and $RV_{w,t}^j$ denotes the average RV^j from day $t-5$ to day $t-1$, while $RV^j_{m,t}$ denotes the average RV^j from day $t-22$ to day $t-1$.

We use the standard HAR-RV model as the benchmark model for realized-volatility forecasting and, like Mei et al. (2017), we investigate whether adding realized skewness, realized kurtosis, or both as additional predictors to the benchmark model can improve its forecasting performance. To this end, we consider the following modified HAR-RV models:

$$RV^j_{t+h}=\beta_0+\beta_d\cdot RV^j_t+\beta_w\cdot RV^j_{w,t}+\beta_m\cdot RV^j_{m,t}+\theta\cdot RSK_t+\varepsilon_{t+h}, \tag{7}$$

$$RV^j_{t+h}=\beta_0+\beta_d\cdot RV^j_t+\beta_w\cdot RV^j_{w,t}+\beta_m\cdot RV^j_{m,t}+\eta\cdot RKU_t+\varepsilon_{t+h}, \tag{8}$$

$$RV^j_{t+h}=\beta_0+\beta_d\cdot RV^j_t+\beta_w\cdot RV^j_{w,t}+\beta_m\cdot RV^j_{m,t}+\theta\cdot RSK_t+\eta\cdot RKU_t+\varepsilon_{t+h}, \tag{9}$$

where again j denotes either S, $+$ or $-$, and RSK_t denotes realized skewness, while RKU_t denotes realized kurtosis.

3 Data

We use intraday data to construct daily measures of realized variance, realized kurtosis, and realized skewness of returns of six major exchange rates vis-à-vis the dollar. The exchange rates under consideration are: (i) Australian dollar (AUD), (ii) Canadian dollar (CAD), (iii) Swiss franc (CHF), (iv) euro (EUR), (v) British pound (GBP), and (vi) Japanese yen (JPY), all measured relative to the United States (US) dollar. Data are retrieved from Pi-Trading Inc. We define a trading day to start at 00:00 EST and to end at 23:55 EST. The sample period runs from 1 July 2003 to 28 August 2015. The sample period reflects data availability. The data comprises minute-by-minute (1-min) intraday prices, and we calculate 5-min log-returns to estimate daily realized volatility.

Following Barndorff-Nielsen et al. (2009), we apply the following data adjustment procedure to the entire dataset. First, we exclude fixed and moving holidays, including Christmas, New Year's Day etc., and thin trading days (that is, days when the trading hours did not fully cover the observation time window) from the sample. Second, we remove days with infrequent trades (less than 60 transactions at a 5-min time interval) from the sample. Third, we apply univariate filters that have been well documented in the high-frequency financial-time series literature.[5] For every day, we retrieve a daily point estimate of the daily realized volatility by employing all available intraday returns.

4 Estimation Results

Tables 1 summarizes estimation results for realized volatility for the full sample period.[6] Results show that, for all six exchange rates, the components of the benchmark HAR-RV model have significant explanatory power for realized volatility. When we add realized kurtosis to the benchmark HAR-RV model, the corresponding coefficient is significant, with the Australian dollar being the only exception. In the extended HAR-RV model that features realized skewness as an additional explanatory variable, the coefficient of realized skewness is insignificant in the models estimated for the Swiss france, euro, and pound sterling. The respective coefficient is only marginally significant in the model estimated for the yen. The significance of the coefficients of realized kurtosis and realized skewness in the extended HAR-RV model that features both realized moments largely

[5] Refer to Dacorogna et al. (2001), page 117, for more information regarding the data-cleaning procedure.

[6] Estimation results are computed using the R programming environemnt (R Core Team 2017). Newey-West robust standard errors are computed using the R packages "sandwich" (Zeileis 2004).

reflects the significance of the coefficients of the realized moments in the HAR-RV model that features only one of the two higher-order moments as an additional explanatory variable. In terms of the adjusted coefficient of determination, the extended HAR-RV models fare similar as the benchmark HAR-RV model. Most of the estimated coefficients of realized kurtosis and realized skewness are negative, in line with the results reported by Mei et al. (2017) for stock markets.

– Please include Table 1 about here. –

Inspecting the results summarized in Table 2, we find that the results for downside realized volatility are similar in terms of the significance of the estimated coefficients to the results for realized volatility. The coefficient of realized skewness, however, is also significant for the euro and the pound sterling, and stronger significant than in the model for realized volatility in case of the yen. The adjusted coefficients of determination of the models estimated on data for the Swiss franc is close to zero.[7]

– Please include Tables 2 about here. –

When we compare the results for upside realized volatility with the results for downside realized volatility, we find that the coefficients of both realized kurtosis and realized skewness become significant in the models estimated on data for the Australian dollar. As for the Swiss franc, the coefficient of realized skewness becomes significant, while the coefficient of realized kurtosis is insignificant. Realized skewness has no explanatory power in the model estimated on data for the Canadian dollar. The respective coefficient is significant only when the extended HAR-RV model features both realized kurtosis and realized skewness.

[7]It should be noted that the Swiss National Bank announced a one-sided target zone at 1.20 Swiss france/euro from September 2011 to January 2015

– Please include Table 3 about here. –

Table 4 reports the results of out-of-sample forecast comparisons based on the Diebold and Mariano (1995) test.[8] We present results for an absolute loss function (L1 loss) and squared error loss (L2 loss). The results that we report are derived using a rolling-estimation window. The first rolling window comprises data up to and including 12/31/2007 ($\approx 36\%$ of the data). We then move the rolling-estimation window forward in time on a daily basis until we reach the end of the sample period. The main message to take home from the results is that mainly realized kurtosis rather than realized skewness contributes to the accuracy of out-of-sample forecasts.[9]

Under L1 loss, adding realized kurtosis to the HAR-RV model produces significant test results for the euro, the pound sterling, and the yen in case of realized volatility. Realized skewness does not add to improve forecast accuracy, and the test results for the forecasts that result when both realized kurtosis and realized skewness are taken into account are all insignificant. Under L2 loss, only the test result for the yen is significant.

– Please include Table 4 about here. –

[8] Like Mei et al. (2017), we also compared out-of-sample forecasts for one-week-ahead (5 trading days) and one-month-ahead (22 trading days) forecasts. The test results (available upon request from the authors) turned out to be insignificant. We computed the p-values of the Diebold-Mariano test using the R package "forecast" (Hyndman 2017, Hyndman and Khandakar 2008) based on the modified Diebold-Mariano test proposed by Harvey et al. (1997).

[9] We also experimented with the popular QLIKE loss function (Patton 2011). Results of the Diebold-Mariano test for this loss function further lend support to our main result that, in case of realized volatility, it is realized kurtosis rather than realized skewness that improves the performance of out-of-sample forecasts. Interestingly, we found several significant test results for realized kurtosis when we studied one-month-ahead (22 trading days) forecasts computed by means of a somewhat longer rolling-estimation window (as in Table 6). For upside realized volatility, the evidence of improvements in forecast accuracy is more balanced between realized kurtosis and realized skewness when we use the QLIKE loss function.

According to Amaya et al. (2015), *RSK* is a measure of the asymmetry risk in the daily return distribution, while RKU helps to take into account the existence of extreme deviations in the daily distributions of the intraday returns. The prevailing view is that extremes behave fundamentally as compared to the rest of the returns distribution, and that extremes display clustering behaviour. Intraday patterns can also exhibit similar behaviour (see Gkillas et al. 2019). Hence, one can expect that *RKU* makes a more systemic and significant contribution to forecast performance than *RSK* because the former can predict a prolonged period of high volatility due to extreme fluctuations. In other words, it is possible that extreme intraday movements today can continue to the next day and that, therefore, *RKU* helps to improve forecasting performance in- and out-ofsample.

Turning next to downside realized volatility, we find significant test results under L1 loss for the Canadian dollar, the euro, and the yen. The significance of the test results also carries over to the forecasts implied by the models that feature both realized kurtosis and realized skewness. However, the forecasts produced by means of the HAR-RV model that features only realized skewness as an additional explanatory variable are only (weakly) significant in the case of the Canadian dollar. Hence, realized kurtosis is the main driver of the significant test results. The test results for realized kurtosis, though, are quite sensitive to the functional form of the assumed loss function. When we assume L2 loss rather than L1 loss, only the test result for the euro is significant.

As far as upside realized volatility is concerned, the test results under L1 loss for the Canadian dollar, pound sterling, and the yen are significant when we compare the forecasts implied by the extended HAR-RV model that features realized kurtosis with the forecasts implied by the benchmark model. None of the tests for the forecasts based on extended HAR-RV models featuring realized skewness are significant. Under L2 loss, we observe significant test results for the Canadian dollar, the euro, and the yen. In addition, we observe two significant test results for realized skewness for the euro and the yen.

As an extension, we consider a variant of the HAR-RV model extended to inlcude the daily U.S. economic policy uncertainty (EPU) index developed by Baker et al. (2016) as our benchmark model. EPU as a predictor of volatility has been studied in several studies, e.g., Ma et al. (2019). The EPU index covers a large selection of news sources tracking the frequency of various keywords related to policy uncertainty, regulatory changes as well as disagreement among economic forecasters.[10] While few details differ relative to the baseline scenario summarized in Table 4, the overall picture that emerges is that realized kurtosis matters for forecast accuracy in case of several exchange rates.

– Please include Tables 5 and 6 about here. –

As yet another extension, we present in Table 6 results for an extended rolling-estimation window. The first rolling window comprises data up to and including 12/31/2009 ($\approx$ 53% of the data), and is then moved forward in time on a daily basis until we reach the end of the sample period. On balance, the findings suggest that it is realized kurtosis rather than realized skewness that improves forecast accuracy. Moreover, for the extended rolling-estimation window, the test results for realized kurtosis are similar in terms of significance for L1 loss and L2 loss. Hence, results suggest that increasing the length of the rolling-estimation window makes the test results more robust to the choice of the functional form of the loss function. In addition, evidence that realized skewness plays a role for forecast accuracy in case of upside realized volatility strengthens somewhat relative to the baseline scenario when we consider the L2 loss function. The test yields significant results for the Australian dollor, the British pound (also for L1 loss), and the yen.

[10]The EPU index can be download at `http://www.policyuncertainty.com/`.

5 Concluding Remarks

We have assessed the importance of the realized skewness and the realized kurtosis of the daily returns distribution for realized-volatility forecasting. To this end, we have used intraday data to construct daily measures of realized volatility, realized kurtosis, and realized skewness of returns of six major exchange rates vis-à-vis the dollar. We also differentiate between measures of upside realized volatility and downside realized volatility estimated by upside and downside semi-variances, respectively. We have focused on the Australian dollar, the Canadian dollar, the Swiss franc, the euro, the British pound, and the Japanese yen relative to the US dollar. The data we have studied comprise minute-by-minute (1-min) intraday prices, and we have calculated 5-min returns. The period of the analysis covers the period of time from 1 July 2003 to 28 August 2015. We have used the popular HAR-RV model as the benchmark model. We then have studied whether adding realized skewness, realized kurtosis, or both as additional variables to the benchmark model can improve its forecasting performance. Our results indicate that both realized kurtosis and realized skewness have in-sample predictive value in several models being studied. The out-of-sample results show that it is mainly realized kurtosis that helps to improve accuracy of one-day-ahead forecasts of realized volatility, but results depend on the assumed loss function and they differ across exchange rates.

Our findings have various implications for investors and policy makers. Our results show that *RSK* and *RKU* can help to develop a better understanding of the dynamics of exchange-rate volatility, and to compute better short-term forecasts of realized volatility. Thereby, our results do not only contribute to the large literature on exchange-rate-volatility modelling, but also to the significant research on the exchange-rate-volatility risk premium. What is more, taking into account that risk managers and policy makers often have to reach decisions in periods of highly volatile financial markets, it is of central importance to develop a better understanding of key statistical features of volatility dynamics. Our results show that realized higher-order moments in general, and realized kurtosis in particular, provide useful information in this regard.

Future research may evaluate the role of volatility jumps for exchange-rate volatility forecasting, as in the study of Andersen et al. (2007) in the HAR framework, or its various extensions, as in the study by Wang et al. (2016) by including RSK and RSU. Andersen et al. (2007) decompose realized volatility into its jump components and continuous sample path and, thereby, investigate the contribution of jumps to predicting realized volatility. Furthermore, another avenue for future research is to evaluate the role of additional jump types (i.e., downside and upside jumps) for exchange-rate-realized volatility forecasting, as in the study by Duong and Swanson (2015).

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Table 1: Full Sample Estimates (Realized Volatility)

Specification	Intercept	RV	RV_w	RV_m	RKU	RSK	Adj. R2
AUD							
HAR-RV	0.0000°***	0.4029***	0.3440***	0.1729**	–	–	0.5550
p-value	0.0011	0.0001°	0.0000	0.0270	–	–	–
HAR-RV-RKU	0.0001°°**	0.4034***	0.3437***	0.1724	−0.0001°	–	0.5549
p-value	0.0215	0.0001°	0.0005	0.1274	0.1036	–	–
HAR-RV-RSK	0.0000°***	0.4029***	0.3437***	0.1731**	–	−0.0001°**	0.5550
p-value	0.0007	0.0001°	0.0000	0.0151	–	0.0156	–
HAR-RV-RKU-RSK	0.0000°**	0.4033***	0.3435***	0.1727	−0.0001	−0.0001°**	0.5549
p-value	0.0309	0.0001°	0.0003	0.1101	0.1820	0.0162	–
CAD							
HAR-RV	0.0000°***	0.2558***	0.5147****	0.1776**	–	–	0.5645
p-value	0.0033	0.0001°	0.0001°	0.0308	–	–	–
HAR-RV-RKU	0.0000°***	0.2636***	0.5084***	0.1721**	−0.0001°***	–	0.5677
p-value	0.0005	0.0001°	0.0001°	0.0287	0.0001°	–	–
HAR-RV-RSK	0.0001°**	0.2557***	0.5148***	0.1776**	–	0.0001°***	0.5647
p-value	0.0211	0.0001°	0.0001°	0.0280	–	0.0807	–
HAR-RV-RKU-RSK	0.0001°***	0.2634***	0.5085***	0.1721**	−0.0001°***	0.0001°	0.5678
p-value	0.0004	0.0001°	0.0001°	0.0284	0.0001°	0.1265	–
CHF							
HAR-RV	0.0001°***	0.2680***	0.2572***	0.2342***	–	–	0.1950
p-value	0.0070	0.0001°	0.0002	0.0034	–	–	–
HAR-RV-RKU	0.0001°***	0.2890***	0.2487***	0.2244***	−0.0001°***	–	0.1964
p-value	0.0001°	0.0001°	0.0005	0.0077	0.0009	–	–
HAR-RV-RSK	0.0001°***	0.2639***	0.2594***	0.2352***	–	−0.0001°	0.1951
p-value	0.0014	0.0000	0.0009	0.0095	–	0.1978	–
HAR-RV-RKU-RSK	0.0001°***	0.2849***	0.2509***	0.2255***	−0.0001°***	−0.0001°	0.1965
p-value	0.0001°	0.0001°	0.0006	0.0095	0.0006	0.2051	–
EUR							
HAR-RV	0.0001°***	0.3499***	0.4088***	0.1786***	–	–	0.5480
p-value	0.0083	0.0001°	0.0001°	0.0351	–	–	–
HAR-RV-RKU	0.0001°***	0.3640***	0.3945***	0.1740**	−0.0001°***	–	0.5521
p-value	0.0023	0.0001	0.0003	0.0570	0.0001°	–	–
HAR-RV-RSK	0.0001°**	0.3501***	0.4085***	0.1787**	–	0.0001°	0.5479
p-value	0.0353	0.0001	0.0001°	0.0203	–	0.7007	–
HAR-RV-RKU-RSK	0.0001°***	0.3639***	0.3948***	0.1738**	−0.0001°***	0.0001°	0.5520
p-value	0.0012	0.0001°	0.0002	0.0479	0.0001°	0.3896	–
GBP							
HAR-RV	0.0001°**	0.3175***	0.4792***	0.1513*	–	–	0.6223
p-value	0.0275	0.0001°	0.0001°	0.0569	–	–	–
HAR-RV-RKU	0.0001°***	0.3204***	0.4768***	0.1491*	−0.0001°**	–	0.6226
p-value	0.0075	0.0001°	0.0001°	0.0531	0.0101	–	–
HAR-RV-RSK	0.0001°**	0.3175***	0.4789***	0.1514*	–	−0.0001°	0.6223
p-value	0.0215	0.0001°	0.0001°	0.0563	–	0.2682	–
HAR-RV-RKU-RSK	0.0001°**	0.3203***	0.4768***	0.1493*	−0.0001°**	−0.0001°	0.6225
p-value	0.0117	0.0001°	0.0001°	0.0507	0.0271	0.6814	–
JPY							
HAR-RV	0.0001°**	0.4659***	0.1529***	0.2753***	–	–	0.4650
p-value	0.0254	0.0001°	0.0087	0.0013	–	–	–
HAR-RV-RKU	0.0001°***	0.4769***	0.1446**	0.2693***	−0.0001°***	–	0.4696
p-value	0.0073	0.0001°	0.0170	0.0019	0.0001°	–	–
HAR-RV-RSK	0.0001°*	0.4654***	0.1535***	0.2750***	–	−0.0001°*	0.4652
p-value	0.0567	0.0001	0.0503	0.0063	–	0.0703	–
HAR-RV-RKU-RSK	0.0001°***	0.4763***	0.1451**	0.2689***	−0.0001°***	−0.0001°**	0.4698
p-value	0.0064	0.0001°	0.0259	0.0021	0.0001°	0.0306	–

Note: *** (**, *) denotes significance at the 1% (5%, 10%) level. p-values are based on Newey-West standard errors. ° denotes a value smaller than 0.0001 (in absolute value). Adj. R2 = adjusted coefficient of determination.

Table 2: Full Sample Estimates (Downside Realized Volatility)

Specification	Intercept	RVB	RVB_w	RVB_m	RKU	RSK	Adj. R2
			AUD				
HAR-RV	0.0001°***	0.3802***	0.3293***	0.2030***	–	–	0.5204
p-value	0.0004	0.0001°	0.0001°	0.0011	–	–	–
HAR-RV-RKU	0.0001°***	0.3822***	0.3280***	0.2012*	−0.0001°***	–	0.5206
p-value	0.0085	0.0001°	0.0024	0.0870	0.0002	–	–
HAR-RV-RSK	0.0001°***	0.3813***	0.3289***	0.2025**	–	0.0001°**	0.5204
p-value	0.0006	0.0001°	0.0001°	0.0327	–	0.0257	–
HAR-RV-RKU-RSK	0.0001°***	0.3836***	0.3274***	0.2005	−0.0001°***	0.0001°**	0.5206
p-value	0.0103	0.0001°	0.0086	0.1323	0.0001°	0.0100	–
			CAD				
HAR-RV	0.0001°***	0.2141***	0.5047***	0.2263***	–	–	0.5386
p-value	0.0059	0.0001°	0.0001°	0.0012	–	–	–
HAR-RV-RKU	0.0001°***	0.2325***	0.4959***	0.2123***	−0.0001°***	–	0.5432
p-value	0.0007	0.0001°	0.0001°	0.0063	0.0001°	–	–
HAR-RV-RSK	0.0001°***	0.2249***	0.5027***	0.2179***	–	0.0001°***	0.5404
p-value	0.0222	0.0001°	0.0001°	0.0026	–	0.0001	–
HAR-RV-RKU-RSK	0.0001° ***	0.2441***	0.4937***	0.2033***	−0.0001°***	0.0001°***	0.5451
p-value	0.0001	0.0001°	0.0001°	0.0058	0.0001°	0.0001	–
			CHF				
HAR-RV	0.0001°***	0.0475***	0.0479***	0.1173**	–	–	0.0038
p-value	0.0001°	0.0001°	0.0043	0.0377	–	–	–
HAR-RV-RKU	0.0001°***	0.0518***	0.0479**	0.1158***	−0.0001°***	–	0.0036
p-value	0.0001°	0.0001°	0.0030	0.0047	0.0001°	–	–
HAR-RV-RSK	0.0001°***	0.0454***	0.0482**	0.1176***	–	−0.0001°	0.0035
p-value	0.0001°	0.0001°	0.0021	0.0010	–	0.3710	–
HAR-RV-RKU-RSK	0.0001°***	0.0497***	0.0482***	0.1162***	−0.0001°***	−0.0001°	0.0033
p-value	0.0001°	0.0001°	0.0027	0.0045	0.0001°	0.3968	–
			EUR				
HAR-RV	0.0001°***	0.2963***	0.3989***	0.2357**	–	–	0.5024
p-value	0.0102	0.0001°	0.0009	0.0224	–	–	–
HAR-RV-RKU	0.0001°***	0.3269***	0.3781***	0.2206***	−0.0001°***	–	0.5093
p-value	0.0001	0.0001°	0.0004	0.0099	0.0001°	–	–
HAR-RV-RSK	0.0001°***	0.3061***	0.3974***	0.2283**	–	0.0001°**	0.5038
p-value	0.0146	0.0001°	0.0004	0.0141	–	0.0178	–
HAR-RV-RKU-RSK	0.0001°***	0.3500***	0.3712***	0.2050**	−0.0001°***	0.0001°***	0.5134
p-value	0.0001°	0.0001°	0.0004	0.0153	0.0001°	0.0001°	–
			GBP				
HAR-RV	0.0001°***	0.3066***	0.4363***	0.2018**	–	–	0.5961
p-value	0.0302	0.0001°	0.0001°	0.0185	–	–	–
HAR-RV-RKU	0.0001°***	0.3149***	0.4316***	0.1954**	−0.0001°***	–	0.5971
p-value	0.0029	0.0001°	0.0001°	0.0166	0.0020	–	–
HAR-RV-RSK	0.0001°***	0.3112***	0.4353***	0.1991**	–	0.0001°**	0.5964
p-value	0.0350	0.0001°	0.0001°	0.0193	–	0.0258	–
HAR-RV-RKU-RSK	0.0001°***	0.3252***	0.4284***	0.1890	−0.0001°***	0.0001°***	0.5981
p-value	0.0007	0.0001°	0.0001°	0.0205	0.0001	0.0005	–
			JPY				
HAR-RV	0.0001°***	0.3653***	0.2018***	0.3074***	–	–	0.3724
p-value	0.0146	0.0001°	0.0006	0.0003	–	–	–
HAR-RV-RKU	0.0001°***	0.3907***	0.1868***	0.2936***	−0.0001°***	–	0.3806
p-value	0.0009	0.0001°	0.0103	0.0018	0.0001°	–	–
HAR-RV-RSK	0.0001°***	0.3745***	0.1970***	0.3048***	–	0.0001°***	0.3736
p-value	0.0211	0.0001°	0.0151	0.0027	–	0.0064	–
HAR-RV-RKU-RSK	0.0001°***	0.4008***	0.1816***	0.2907***	0.0001°***	−0.0001°***	0.3821
p-value	0.0002	0.0001°	0.0202	0.0035	0.0001°	0.0007	–

Note: *** (**, *) denotes significance at the 1% (5%, 10%) level. p-values are based on Newey-West standard errors. ° denotes a value smaller than 0.0001 (in absolute value). Adj. R2 = adjusted coefficient of determination.

Table 3: Full Sample Estimates (Upside Realized Volatility)

Specification	Intercept	RVG	RVG_w	RVG_m	RKU	RSK	Adj. R2
			AUD				
HAR-RV	0.0001°***	0.4227***	0.3138***	0.1872***	–	–	0.5613
p-value	0.0011	0.0001°	0.0001°	0.0012	–	–	–
HAR-RV-RKU	0.0001°***	0.4270***	0.3110***	0.1843**	−0.0001°***	–	0.5619
p-value	0.0071	0.0001°	0.0001°	0.0295	−0.0001°	–	–
HAR-RV-RSK	0.0001°***	0.4297***	0.3088***	0.1855**	–	−0.0001°***	0.5635
p-value	0.0184	0.0001°	0.0001°	0.0389	–	0.0001°	–
HAR-RV-RKU-RSK	0.0001°***	0.4330***	0.3067***	0.1831**	−0.0001°***	−0.0001°***	0.5639
p-value	0.0073	0.0001°	0.0001°	0.0363	0.0007	0.0001°	–
			CAD				
HAR-RV	0.0001°***	0.2309***	0.4716***	0.2436***	–	–	0.5383
p-value	0.0048	0.0001°	0.0001°	0.0075	–	–	–
HAR-RV-RKU	0.0001°***	0.2557***	0.4607***	0.2252***	0.0001°***	–	0.5437
p-value	0.0011	0.0001°	0.0001°	0.0120	0.0001°	–	–
HAR-RV-RSK	0.0001°***	0.2355***	0.4706***	0.2404***	–	−0.0001°	0.5384
p-value	0.0184	0.0001°	0.0001°	0.0064	–	0.1496	–
HAR-RV-RKU-RSK	0.0001°***	0.2617***	0.4594***	0.2210***	−0.0001°***	−0.0001°**	0.544
p-value	0.0002	0.0001°	0.0001°	0.0073	0.0001°	0.0436	–
			CHF				
HAR-RV	0.0001°***	0.2988***	0.3145***	0.2245*	–	–	0.2995
p-value	0.0001°	0.0015	0.0001°	0.0701	–	–	–
HAR-RV-RKU	0.0001°***	0.2930***	0.3174***	0.2271*	0.0001°	–	0.2994
p-value	0.0005	0.0003	0.0001°	0.0779	0.8654	–	–
HAR-RV-RSK	0.0001°***	0.3068***	0.3141***	0.2197*	–	−0.0001°**	0.3108
p-value	0.0001°	0.0001	0.0001°	0.0825	–	0.0288	–
HAR-RV-RKU-RSK	0.0001°***	0.3071***	0.3140***	0.2196*	−0.0001°	−0.0001°**	0.3106
p-value	0.0001	0.0001°	0.0001°	0.0853	0.9921	0.0115	–
			EUR				
HAR-RV	0.0001°***	0.2741***	0.3402***	0.3049***	–	–	0.4283
p-value	0.0060	0.0001°	0.0001°	0.0001	–	–	–
HAR-RV-RKU	0.0001°***	0.3309***	0.3090***	0.2735***	−0.0001°***	–	0.4411
p-value	0.0001°	0.0001°	0.0001	0.0004	0.0001°	–	–
HAR-RV-RSK	0.0001°***	0.2992***	0.3294***	0.2927***	–	−0.0001°***	0.4319
p-value	0.0063	0.0001°	0.0001°	0.0003	–	0.0002	–
HAR-RV-RKU-RSK	0.0001°***	0.3486***	0.3016***	0.2651***	−0.0001° ***	−0.0001°***	0.4434
p-value	0.0001°	0.0001°	0.0001	0.0003	0.0001°	0.0001°	–
			GBP				
HAR-RV	0.0001°***	0.3251***	0.4478***	0.1732**	–	–	0.6045
p-value	0.0278	0.0001°	0.0001°	0.0232	–	–	–
HAR-RV-RKU	0.0001°***	0.3417***	0.4383***	0.1625**	−0.0001°***	–	0.6066
p-value	0.0001	0.0001°	0.0001°	0.0258	0.0001°	–	–
HAR-RV-RSK	0.0001°***	0.3395***	0.4400***	0.1661**	–	−0.0001°***	0.6071
p-value	0.0149	0.0001°	0.0001°	0.0237	–	0.0001°	–
HAR-RV-RKU-RSK	0.0001°***	0.3497***	0.4340***	0.1591**	−0.0001°***	−0.0001°***	0.6082
p-value	0.0009	0.0001°	0.0001°	0.0347	0.0001°	0.0001°	–
			JPY				
HAR-RV	0.0001°***	0.4053***	0.1481**	0.3270***	–	–	0.3957
p-value	0.0461	0.0001°	0.0150	0.0005	–	–	–
HAR-RV-RKU	0.0001°***	0.4311***	0.1329**	0.3129***	−0.0001°***	–	0.4052
p-value	0.0006	0.0001°	0.0262	0.0007	0.0001°	–	–
HAR-RV-RSK	0.0001°***	0.4186***	0.1430**	0.3195***	–	−0.0001°***	0.4013
p-value	0.0292	0.0001°	0.0177	0.0007	–	0.0001°	–
HAR-RV-RKU-RSK	0.0001°***	0.4463***	0.1268**	0.3042***	−0.0001°***	−0.0001°***	0.4116
p-value	0.0011	0.0001°	0.0201	0.0008	0.0001°	0.0001°	–

Note: *** (**, *) denotes significance at the 1% (5%, 10%) level. p-values are based on Newey-West standard errors. ° denotes a value smaller than 0.0001 (in absolute value). Adj. R2 = adjusted coefficient of determination.

Table 4: Forecast Comparison (Out-of-Sample)

Panel A: L1 loss

Specification	AUD	CAD	CHF	EUR	GBP	JPY
Realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.9942	0.1023	0.1737	0.0864*	0.0152**	0.0169**
HAR-RV baseline vs. HAR-RV skew	0.9776	0.4112	0.9998	0.8907	0.4844	0.6211
HAR-RV baseline vs. HAR-RV both	0.9973	0.1934	0.9662	0.1506	0.1753	0.1901
Downside realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.6680	0.0904*	0.7517	0.0215**	0.2843	0.0235**
HAR-RV baseline vs. HAR-RV skew	0.6193	0.0881*	0.2279	0.5421	0.9637	0.4797
HAR-RV baseline vs. HAR-RV both	0.3720	0.0296**	0.7057	0.0227**	0.1726	0.0015***
Upside realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.5767	0.0092***	0.1608	0.1351	0.0058***	0.0505***
HAR-RV baseline vs. HAR-RV skew	0.3027	0.4621	0.9874	0.5226	0.0247**	0.1660
HAR-RV baseline vs. HAR-RV both	0.4711	0.0270**	0.8172	0.0391**	0.0055***	0.2660

Panel B: L2 loss

Specification	AUD	CAD	CHF	EUR	GBP	JPY
Realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.8408	0.1994	0.4329	0.0854	0.6353	0.0756*
HAR-RV baseline vs. HAR-RV skew	0.6028	0.8130	0.6984	0.9736	0.6726	0.2012
HAR-RV baseline vs. HAR-RV both	0.8794	0.3367	0.5640	0.1475	0.6915	0.0964*
Downside realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.8204	0.1735	0.8406	0.0303**	0.5374	0.3237
HAR-RV baseline vs. HAR-RV skew	0.9032	0.4252	0.1737	0.2010	0.6139	0.5029
HAR-RV baseline vs. HAR-RV both	0.8552	0.2061	0.8456	0.0186**	0.5237	0.3032
Upside realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.8120	0.0669*	0.4392	0.0225**	0.4893	0.0099***
HAR-RV baseline vs. HAR-RV skew	0.7041	0.4523	0.1118	0.0783*	0.2893	0.0338**
HAR-RV baseline vs. HAR-RV both	0.7875	0.0989*	0.0446**	0.0190**	0.4030	0.0288**

Note: *** (**, *) denotes significance of the Diebold-Mariano test at the 1% (5%, 10%) level. Null hypothesis: the two series of forecasts are equally accurate. Alternative hypothesis: the forecasts from the extended model is more accurate. L1: absolute loss. L2: quadratic loss. Results are based on rolling-window estimates. The first rolling window comprises data up to and including 12/31/2007. The rolling-estimation window is then moved forward in time on a daily basis until the end of the sample period is reached.

Table 5: Controlling for Economic Policy Uncertainty (Out-of-Sample)

Panel A: L1 loss

Specification	AUD	CAD	CHF	EUR	GBP	JPY
Realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.9990	0.0959*	0.2176	0.1971	0.0487**	0.0385**
HAR-RV baseline vs. HAR-RV skew	0.9726	0.6040	0.9923	0.9638	0.6100	0.7189
HAR-RV baseline vs. HAR-RV both	0.9939	0.1841	0.8834	0.3757	0.2947	0.2790
Downside realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.5301	0.0747*	0.7436	0.0331**	0.3186	0.0359**
HAR-RV baseline vs. HAR-RV skew	0.6287	0.0752	0.2595	0.4020	0.8790	0.4904
HAR-RV baseline vs. HAR-RV both	0.3089	0.0210**	0.6961	0.0274**	0.0980	0.0040***
Upside realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.7299	0.0109**	0.1054	0.1698	0.0136**	0.0932*
HAR-RV baseline vs. HAR-RV skew	0.3147	0.4671	0.9668	0.5804	0.0377	0.1559
HAR-RV baseline vs. HAR-RV both	0.5153	0.0269**	0.6646	0.0644*	0.0194**	0.3292

Panel B: L2 loss

Specification	AUD	CAD	CHF	EUR	GBP	JPY
Realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.8388	0.2174	0.4515	0.1222	0.6713	0.0637*
HAR-RV baseline vs. HAR-RV skew	0.6051	0.8727	0.6995	0.9672	0.7475	0.2248
HAR-RV baseline vs. HAR-RV both	0.8810	0.3582	0.5678	0.1912	0.7275	0.0787*
Downside realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.8186	0.1802	0.8408	0.0408**	0.5675	0.3113
HAR-RV baseline vs. HAR-RV skew	0.9059	0.4717	0.1741	0.1849	0.5962	0.5370
HAR-RV baseline vs. HAR-RV both	0.8569	0.2214	0.8456	0.0226**	0.5337	0.2997
Upside realized volatility						
HAR-RV baseline vs. HAR-RV kurt	0.8106	0.0725*	0.4101	0.0286**	0.5153	0.0083***
HAR-RV baseline vs. HAR-RV skew	0.7099	0.4578	0.1112	0.0848*	0.3109	0.0313**
HAR-RV baseline vs. HAR-RV both	0.7866	0.0999*	0.0450**	0.0231***	0.4255	0.0245**

Note: *** (**, *) denotes significance of the Diebold-Mariano test at the 1% (5%, 10%) level. Null hypothesis: the two series of forecasts are equally accurate. Alternative hypothesis: the forecasts from the extended model is more accurate. L1: absolute loss. L2: quadratic loss. Results are based on rolling-window estimates. The first rolling window comprises data up to and including 12/31/2007. The rolling-estimation window is then moved forward in time on a daily basis until the end of the sample period is reached.

Table 6: Extended Rolling-Estimation Window (Out-of-Sample)

Panel A: L1 loss

Specification	AUD	CAD	CHF	EUR	GBP	JPY
			Realized volatility			
HAR-RV baseline vs. HAR-RV kurt	0.1576	0.2556	0.3112	0.0735*	0.2808	0.0171**
HAR-RV baseline vs. HAR-RV skew	0.9594	0.5498	0.9997	0.7202	0.5610	0.7314
HAR-RV baseline vs. HAR-RV both	0.9137	0.3045	0.9952	0.1526	0.5041	0.3428
			Downside realized volatility			
HAR-RV baseline vs. HAR-RV kurt	0.0151**	0.3929	0.8380	0.0025***	0.8309	0.2051
HAR-RV baseline vs. HAR-RV skew	0.4286	0.4474	0.2425	0.4177	0.9605	0.7005
HAR-RV baseline vs. HAR-RV both	0.0026**	0.1647	0.7881	0.0393**	0.4467	0.0114**
			Upside realized volatility			
HAR-RV baseline vs. HAR-RV kurt	0.0680*	0.0287**	0.5154	0.5228	0.0207**	0.0872*
HAR-RV baseline vs. HAR-RV skew	0.6706	0.1083	0.9792	0.6686	0.0297**	0.4203
HAR-RV baseline vs. HAR-RV both	0.5304	0.0630*	0.9838	0.2603	0.0132**	0.7527

Panel B: L2 loss

Specification	AUD	CAD	CHF	EUR	GBP	JPY
			Realized volatility			
HAR-RV baseline vs. HAR-RV kurt	0.3248	0.1570	0.4062	0.0443**	0.5569	0.0007***
HAR-RV baseline vs. HAR-RV skew	0.5473	0.5334	0.7433	0.7808	0.5736	0.3242
HAR-RV baseline vs. HAR-RV both	0.5893	0.1808	0.6675	0.1119	0.6272	0.0079***
			Downside realized volatility			
HAR-RV baseline vs. HAR-RV kurt	0.0072***	0.2224	0.8398	0.0068***	0.3348	0.0809*
HAR-RV baseline vs. HAR-RV skew	0.0470**	0.3303	0.1709	0.1091	0.4225	0.5705
HAR-RV baseline vs. HAR-RV both	0.0004***	0.0693*	0.8452	0.0157**	0.1601	0.0182**
			Upside realized volatility			
HAR-RV baseline vs. HAR-RV kurt	0.0796*	0.0209**	0.7618	0.3667	0.0955*	0.0007***
HAR-RV baseline vs. HAR-RV skew	0.0666*	0.1059	0.1477	0.4436	0.0084***	0.0376**
HAR-RV baseline vs. HAR-RV both	0.0187**	0.0324**	0.1262	0.2168	0.0084***	0.0188**

Note: *** (**, *) denotes significance of the Diebold-Mariano test at the 1% (5%, 10%) level. Null hypothesis: the two series of forecasts are equally accurate. Alternative hypothesis: the forecasts from the extended model is more accurate. L1: absolute loss. L2: quadratic loss. Results are based on rolling-window estimates. The first rolling window comprises data up to and including 12/31/2009. The rolling-estimation window is then moved forward in time on a daily basis until the end of the sample period is reached.