The Effect of Uncertainty on Volatility and Correlation *

Hossein Asgharian, Lund University[a]

Charlotte Christiansen, Aarhus University[b]

Ai Jun Hou, Stockholm University[c]

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[a]Hossein Asgharian, Department of Economics and Knut Wicksell Center for Financial Studies, Lund University, Box 7082, 22007 Lund, Sweden. Hossein.Asgharian@nek.lu.se.

[b]Corresponding author. Charlotte Christiansen, CREATES, Aarhus BSS, Aarhus University, Fuglesangs Allé 4, 8210 Aarhus V, Denmark. cchristiansen@econ.au.dk. Phone: +4587165576. Lund University.

[c]Ai Jun Hou, Stockholm Business School, Stockholm University, SE-106 91 Stockholm, Sweden. Aijun.Hou@sbs.su.se.

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Abstract: We use an extension of the heterogeneous autoregressive model to investigate the influence of time-varying risk aversion and a number of macroeconomic, financial, and economic-policy uncertainty measures on stock-return volatility and correlations. Our results indicate strong in-sample and out-of-sample predictive ability of risk aversion and economic uncertainty constructed from financial information for the realized volatility. In contrast, economic-policy uncertainty, the *TED* spread, the leading indicator, and industrial production do not provide useful information once we account for risk aversion and economic uncertainty. We also provide evidence on the strong forecasting ability and considerable economic value of risk aversion and economic uncertainty for international-portfolio analysis.

Keywords: economic uncertainty; HAR-RV-X model; international-portfolio analysis; stock market correlation; stock market volatility

JEL classifications: C32; G11; G15; G17

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1. Introduction

It is important for academics, policymakers, and financial practitioners to understand how different types of uncertainty affect financial markets. This paper aims to provide the first comprehensive empirical study of the relative importance of different sources of uncertainty proposed in existing literature on predicting international stock market volatility and correlation and to investigate if this information is useful for international-portfolio analysis.

According to Shiller's (1981) present-value model, the conditional volatility of stock market returns depends on the conditional volatility of expected future cash flows and future discount rates. Thus, it is plausible that uncertainty about fundamentals, such as consumption or dividend growth, which provide information about either expected future cash flows or future discount rates, can help explain stock-return volatility. Many studies provide evidence on the effect of uncertainty about fundamentals on variations of financial-asset returns (see Bansal and Yaron; 2004; Bansal et al., 2005; Bekaert et al., 2009; Bansal et al., 2014, among others).[1] In addition to economic uncertainty, existing literature finds that changes in risk aversion or risk preferences also play a crucial role for stock returns. For example, Bekaert et al. (2009) show that risk aversion affects dividend growth and the equity risk premium.[2]

The key role of the variations in the two state variables, economic uncertainty and risk aversion, in determining financial returns is recently emphasized by Bekaert et al. (forthcoming). They suggest a dynamic no-arbitrage asset-pricing model according to which the conditional

[1] Bansal and Yaron (2004) provide evidence that the volatility of dividend and consumption growth are countercyclical and, consequently, generates countercyclical stock market volatility. Bansal et al. (2005) show that economic uncertainty, measured as the conditional volatility of consumption, is an important channel for variations in asset prices. Bekaert et al. (2009) show that variations in economic uncertainty account for a very large portion of the variations in the conditional volatility of stock returns. Bansal et al. (2014) show that the time variation in economic uncertainty plays a fundamental role in explaining the variation over time in the financial risk premium.

[2] Campbell and Cochrane (1999) show that their consumption-based model with external habit formation that accounts for countercyclical risk aversion generates long-run predictability of stock and bond returns and explains the equity premium. Several other studies also show the impact of the changes in risk aversion on stock prices and the risk premium (see, e.g., Barsky, 1989; Kandel and Stambaugh, 1990; Bansal and Lundblad, 2002; Bansal and Yaron, 2004).

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volatility of asset returns is mainly driven by variations in these two state variables. While economic uncertainty is mainly linked to fundamental factors, the dynamics of risk aversion are driven not only by fundamental shocks (e.g., consumption shocks in Campbell and Cochrane, 1999), but also by nonfundamental shocks linked to sentiment induced by news, as developed in the behavioral finance literature (see, e.g., Baker and Wurgler, 2006), and reflect investor mood and anxiety. The nonfundamental measure of risk aversion is consistent with Bekaert et al. (2010), who show that accounting for the changes in risk aversion that are not driven by fundamentals is essential to capture asset-price dynamics. Jurado et al. (2015) suggest that stock market volatility might change if uncertainty about economic fundamentals remains unchanged and either risk aversion or sentiment changes.

It is crucial to define and quantify economic uncertainty, as it is unobservable and can originate from a variety of factors that impose shocks not only to the real economy, but also to financial markets. Several important sources of uncertainty are considered in the existing literature, mainly macroeconomic, financial, and economic-policy uncertainty. Ludvigson et al. (2021) construct two measures of uncertainty that quantify predictability about future macroeconomic and financial uncertainty. They show that their financial-uncertainty measure is more important than their macroeconomic-uncertainty measure for explaining economic fluctuations. Another type of uncertainty, economic-policy uncertainty, is related to but distinct from general economic uncertainty (Brogaard and Detzel, 2015). Pástor and Veronesi (2013) show that economic-policy uncertainty increases volatility and stocks are more correlated in times of high uncertainty (see also Kelly et al., 2016). A well-known representative for economic-policy uncertainty is the Baker et al. (2016) newspaper-based uncertainty index. They show that greater economic policy uncertainty yields higher stock volatility.

We use the economic uncertainty index (*EU*) proposed by Bekaert et al. (forthcoming) as the main measure of economic uncertainty. In our benchmark model, we also include the risk-aversion measure (*RA*) from the same paper. We first investigate to what extent volatility and

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correlation are determined by economic fundamentals through the economic-uncertainty index and through risk aversion, which may also reflect investor sentiment. Then, we investigate if alternative measures and sources of uncertainty also help explain and predict return variations. We use the Ludvigson et al. (2021) macroeconomic- and financial-uncertainty indexes (*MAC* and *FIN*) and the Baker et al. (2016) economic-policy uncertainty index (*EPU*). For comparison, we use several additional variables that reveal specific features of uncertainty or economic conditions. These variables include the *TED* spread and the volatility index (*VIX*), two important variables that reflect uncertainty in the stock and credit markets, respectively, and have been reported to be useful predictors of stock market volatility (Mittnik et al., 2015; Bekaert et al., 2013). We also include the industrial-production growth (*IP*) which is a popular macroeconomic variable for modeling business cycles and is widely used for forecasting stock-return volatility (see, e.g., Schwert, 1989; Hamilton and Lin, 1996; Engle et al., 2013). Similarly, the OECD composite leading indicator (*CLI*) is used as a business-cycle indicator.

Understanding international stock-return correlations is important for asset allocation and portfolio diversification.[3] Barberis et al. (2005) indicate that, without frictions, the returns of two assets are correlated because changes in the assets' fundamental values are correlated. In economies with frictions, such as limits to arbitrage, the comovement can be generated through shocks to discount rates and expected earnings. They further suggest that behavioral factors may induce excessive correlation between US stock returns. Since uncertainty about fundamentals and risk aversion linked to both fundamentals and nonfundamentals provide information on future discount rates, analogously, shocks to uncertainty and risk aversion are expected to affect the comovement of stock returns.

However, only a few studies address the relevance of risk aversion for predicting global stock market comovements. For instance, Xu (2019) studies the impact of the Bekaert et al.

[3] A number of empirical studies document that the correlation between international stock returns are higher during bear than bull markets (see, e.g., Longin and Solnik, 2001; Ang and Bekaert, 2002).

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(forthcoming) risk-aversion measure on global stock- and bond-return comovements and find that risk aversion explains a large portion of their variations. Demirer et al. (2018) show that global risk aversion is a significant determinant of international stock correlations, consistently across all emerging markets examined. However, neither has studied the impact of uncertainty combined with risk aversion. Our paper aims to investigate if information on the degree of risk aversion and different sources of uncertainty can be useful for predicting stock volatility and correlation, and for international-portfolio analysis. Since most of the uncertainty measures discussed above are only available for the US, our primary analysis is on US stock-return volatility. We conclude the analysis by investigating the global impact of the US uncertainty variables by including several international stock markets and thereby demonstrating the practical benefits of using these variables for portfolio selection.

We use Corsi's (2009) heterogeneous autoregressive model of realized volatility (HAR-RV). The model has a fairly simple and straightforward structure, but it still conveniently captures such financial-return properties as long memory and fat tails (Corsi et al., 2008). Due to its simplicity, the model is easily extended by including additional predictors, denoted as the HAR-RV-X model. We use the HAR-RV-X model to describe the realized volatility (RV) and Audrino and Corsi's (2010) parallel extension to describe the realized correlation (RC), denoted HAR-RC-X. Our models enable us to investigate and compare the influence of various uncertainty measures on the stock market RV and RC. Because the predictive ability of different measures and sources of uncertainty may change across horizons, we study the daily (short-run) and the monthly (long-run) impact of uncertainty on US stock market volatility. Due to differences in trading hours and the unavailability of intradaily data for all countries, the international part of the analysis is conducted with monthly data.

For the daily frequency, we use intradaily returns to obtain the daily RV and investigate the influence of daily, weekly, and monthly lagged predictor variables (for those that are available at the daily frequency). For the monthly frequency, we use daily returns to construct the

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monthly *RV* and *RC* and investigate the impact of monthly, quarterly, biannually, and annually lagged predictor variables. We compare the performance of the models with different combinations of predictor variables, both in and out of sample.

Our main empirical findings are as follows. For the US volatility, statistical tests reject the Corsi (2009) model (HAR-RV) against all the HAR-RV-X models for both daily and monthly frequency. However, only at the monthly frequency, augmenting the Corsi (2009) model with additional variables considerably enhances the model's explanatory power. The benchmark variables, *RA* and *EU*, are important for explaining the future *RV* at both the daily and monthly frequencies, yet *RA* shows a much stronger performance than *EU* in the in-sample analysis and remains robust in all possible model specifications. The stronger effect of *RA* on volatility can be explained by the fact that *RA* reflects, in addition to variations in economic fundamentals, changes in investor sentiment embedded in financial data. Augmenting the benchmark model with the variables *VIX* and *FIN*, which are also constructed from financial data, improves the models' explanatory power at both the daily and monthly frequencies. On the other hand, the uncertainty measures *EPU*, *IP*, *TED*, and *CLI* do not contribute to *RV* prediction when added to the benchmark specification.

The strong in-sample performance of the HAR-RV-X model and its relative advantage over the HAR-RV model diminishes in the out-of-sample analysis, particularly for the daily frequency. The relatively weaker out-of-sample performance of the augmented models may to some extent be related to the effect of parameter instability on forming forecasts when the number of parameters increases. With the monthly frequency, the benchmark model augmented with *FIN* gives the lowest mean square error (MSE). In general, the better performance of HAR-RV-X at the monthly frequency may be because the fluctuations in economic uncertainty follow a smoother path than the changes in stock market volatility. This excess variation can be due to the shocks to demand and supply of stocks that is unrelated to the fundamentals. This finding is in line with the results of Chiu et al (2018). They decompose

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the conditional volatility into a short run transitory component and a long run persistent component and find that only the persistent component of volatility is linked to the fundamental factors that affect expectations of future cash flows and discount rates.

Both our in-sample and out-of-sample analyses of the international stock markets confirm the findings for US *RV* and show the importance of the variables *RA* and *FIN* for predicting stock market volatility. For the forecast of *RC* between the US and world (excluding the US) markets, the benchmark model significantly outperforms the HAR-RC model for most of the forecasting horizons. International-portfolio analysis validates the importance of the benchmark variables and shows that augmenting the HAR-RV/RC model with the two benchmark variables, *EU* and *RA*, either separately or jointly, yields the best model performance based on all the portfolio-performance metrics used in the paper. That is, they result in lower risk in terms of portfolio volatility and beta and offer the highest utility. The most important effect of uncertainty and risk aversion for international-portfolio performance stems from their effect on volatility, not on correlation.

We contribute to the existing literature with comprehensive in-sample and out-of-sample analyses that compare the influence of many uncertainty measures—capturing economic, financial, and economic-policy sources of uncertainty—on stock market volatility and correlation. In addition, to the best of our knowledge, this is the first comparative study of the relative importance and economic value of uncertainty and risk aversion for international-portfolio management. Our empirical findings provide new understandings of the importance of uncertainty measures in predicting stock-return volatility and international stock-return comovements. Among other things, we find stronger predictive ability of risk aversion and uncertainty variables at the monthly than at the daily frequency. More importantly, we provide empirical evidence on the strong predictive ability and economic value of the recently proposed measure of risk aversion from Bekaert et al. (forthcoming) by itself as well as in combination with uncertainty measures. We also show that, in contrast to earlier results, *EPU* does not

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provide useful information for stock market volatility once we account for risk aversion and economic uncertainty.

The rest of the paper is structured as follows. We introduce the data in Section 2 and the econometric framework in Section 3. In Section 4, we discuss the in-sample and out-of-sample volatility and correlation results, while Section 5 includes international-portfolio analysis before we conclude in Section 6.

2. Data

In this section, we present the data used to calculate stock returns (Section 2.1) and the predictor variables (Section 2.2). The sample period is from January 1990 to July 2020.[4]

2.1. Stock Returns

We use daily closing price indexes: S&P 500 (US), S&P/TSX composite index (Canada), CAC 40 (France), DAX 30 (Germany), SMI (Switzerland), TOPIX (Japan), Hang Sang index (Hong Kong), FTSE 100 (UK), and MSCI World (excluding US). We also use the 5-minute US S&P 500 price index.[5] The stock returns are calculated as log-first-differences of the price indexes.

The international stock markets do not have identical opening hours. The North American and European stock markets have overlapping opening hours, but the Asian markets do not have overlapping opening hours with the US. To accommodate this, we follow Jondeau and Rockinger (2006) and use the 1-day leading returns for the Asian countries.[6]

Throughout the paper, we define the RV as the square root of the realized variance, similar to Corsi (2009). The 1-day RV is calculated from the 5-minute intraday returns and the 1-month

[4]The beginning of the sample period is determined by the availability of the VIX index, and the end of the sample period is determined by the availability of the uncertainty indexes from Ludvigson et al. (2021).

[5]All daily indexes are collected from DataStream, except for Hong Kong, which is collected from Yahoo Finance. The intraday data is collected from Refinitiv Datascope.

[6] The unconditional correlations of the US–Asian stock returns are higher for the 1-day leading Asian stock returns than for the same-day closing returns and 1-day leading opening prices for the Asian markets. The unconditional correlations between the US and European markets are higher using the same-day closing price returns than with the 1-day leading prices of the European markets.

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RV and *RC* are calculated from the daily returns. The 1-day (1-month) *RV* is calculated as the square root of the sum of the squared 5-minutes intraday (daily) returns in the given day (month). The 1-month *RC* is calculated as the 1-month realized covariance divided by the product of the 1-month *RV*s. The 1-month realized covariance is the sum of the cross-multiplied daily returns within the month.

2.2. Predictor Variables

In addition to the Bekaert et al. (forthcoming) *RA* index, we use several uncertainty measures proposed by the existing literature: the Bekaert et al. (forthcoming) *EU* index, the Baker et al. (2016) *EPU* index, and the Ludvigson et al. (2021) *MAC* and *FIN* for the 1-month horizon.[7]

- The *RA* index measures the time-varying relative risk-aversion coefficient in an asset pricing model with external habit formation and is constructed from various financial variables.
- The *EU* index is based on the predicted conditional variance of the *IP* growth from a dynamic no-arbitrage asset-pricing model.
- The *EPU* index is a news-based uncertainty measure quantifying the newspaper coverage of policy-related economic uncertainty in 10 major US newspapers.
- The 1-month *MAC* measure is constructed from the common component of a large set of macroeconomic variables.
- The 1-month *FIN* measure is constructed from the common component of a large set of financial variables.

Furthermore, we consider several other important predictor variables frequently used in the existing literature.[8]

[7] The *RA* and *EU* indexes are available from Xu's webpage. The *EPU* index is available from www.policyuncertainty.com. The *FIN* and *MAC* indexes are available from Ludvigson's webpage.
[8] The *TED* spread is from DataStream, the *IP* index is from the FRED database, *VIX* is from the CBOE webpage, and *CLI* is from the OECD.

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- The *TED* spread is the difference between the 3-month LIBOR and the 3-month T-bill rate. The *TED* spread measures the default risk on interbank loans and is used as a proxy for credit risk in the general economy (see, e.g., Cornett et al., 2011).
- A business-cycle variable, *IP* growth, is calculated as the log difference of US industrial production.
- The *VIX* volatility index is traded on the CBOE as a representation of the market's expectations of future volatility and is seen as a measure of market fear.
- The OECD composite leading indicator, *CLI*, predicts economic activity relative to its trend.

For illustration, we plot the predictor variables and the US *RV* in Figure 1 (monthly in Panel A and daily in Panel B). The variables are all highly volatile with peaks during the 2007–2008 financial crisis and the recent COVID-19 crisis, similar to the pattern of the US daily *RV*. The *EPU* varies even more. All the predictor variables follow the *RV* except for *IP* growth and *CLI* which, as expected, mirror the *RV*. Panel A of Table 1 shows the correlation matrix of the monthly *RV* and the uncertainty measures. The uncertainty measures, as anticipated, are all significantly and positively correlated with each other and with the US *RV*, and negatively and significantly correlated with the two measures of economic activity, *IP* and *CLI*. The US *RV* has the highest correlation with *VIX*, *RA*, and *FIN*, which is natural as these variables are constructed from financial data. In fact, the correlations between *VIX* and *RA* (0.92) and *FIN* (0.88) are higher than the correlations between the *RV* and these two variables (0.75 and 0.74, respectively), which may indicate the forward-looking properties of *RA* and *FIN*. Panel B of Table 1 shows the correlation matrix for daily *RV* and the available daily predictors; all correlations are positive. As with the monthly data, the *RV* is highly correlated with *VIX* and *RA*.

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3. Econometric Methodology

In Corsi's (2009) HAR-RV model, the dependent variable is the daily RV, and the independent variables are the lagged daily, weekly, and monthly RVs. Haugom et al. (2011) and Haugom et al. (2014) add 1-day lagged daily exogenous variables to the HAR-RV model.

We extend the HAR-RV model further by including exogenous variables at more lags, calling it the HAR-RV-X model. We have two data frequencies for the dependent variable, i.e., daily and monthly. The dependent variable for the daily (monthly) frequency is the 1-day (1-month) RV denoted $RV_{i,t}$ for asset i on day (month) t. The first set of independent variables are a straightforward extension of Corsi (2009): the lagged 1-day, 5-day, and 22-day RVs for the daily frequency and lagged 1-month, 3-month, 6-month, and 1-year RVs for the monthly frequency. The lagged RVs for different time lengths are calculated similar to Corsi (2009) by taking a rolling average of lagged RVs over an integer number of h days (months) for the model with daily (monthly) frequency:

$$RV_{i,t-1}^{(h)} = \frac{1}{h}\sum\nolimits_{j=1}^{h} RV_{i,t-j}, \tag{1}$$

where $h = \{1,5,22\}$ for daily and $h = \{1,3,6,12\}$ for monthly.

Further, we extend the model with the lagged exogenous variables for similar time periods as for RVs. More specifically, for each predictor variable k, we use a rolling average of lagged values of the variable over an integer number of h days (months) for the model with daily (monthly) frequency:

$$X_{k,t-1}^{(h)} = \frac{1}{h}\sum\nolimits_{j=1}^{h} X_{k,t-1}. \tag{2}$$

To ensure that the predicted RV is always positive, we consider the logarithmic version of the HAR-RV model (without changing notation), taking the natural logs of the RV and the

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uncertainty variables.[9] Previous papers have also used the logarithmic version of the HAR-RV model (Corsi et al., 2008; Fengping et al., 2017; Buccheri and Corsi, 2019). The extended HAR-RV model used in this paper, denoted HAR-RV-X, is

$$RV_{i,t} = a + \sum_h b_h RV_{i,t-1}^{(h)} + \sum_h \sum_k \gamma_{h,k} X_{k,t-1}^{(h)} + e_{it}, \tag{3}$$

where $RV_{i,t}$ is the 1-day (1-month) RV for asset i on day (month) t, and e_{it} is the residual of the OLS regression estimated with Newey and West (1987) standard errors. The set of included predictor variables, due to their availability, are different for the daily and monthly frequencies. In the most general specification, we have $k = \{\text{RA,EU,EPU,TED,VIX}\}$ for daily and $\{\text{RA,EU,EPU,MAC,FIN,IP,TED,VIX,CLI}\}$ for monthly. However, we also consider restricted specifications with fewer exogenous variables.

For the daily frequency, we estimate the volatility model of Bollerslev et al. (2016) that takes into account that the RV may be measured with error (see also Bollerslev et al., 2018; Clements and Preve, 2021). The model extends the HAR-RV model in eq. (3) by including the lagged integrated realized quarticity (RQ) at the same frequencies as the lagged RVs. We include the predictor variables as before, and denote it as HARQ-RV-X:[10]

$$RV_{i,t} = a + \sum_h b_h RV_{i,t-1}^{(h)} + \sum_h c_h \sqrt{RQ_{i,t-1}^{(h)}} + \sum_h \sum_k \gamma_{h,k} X_{k,t-1}^{(h)} + e_{it}. \tag{4}$$

The 1-day RQ is calculated as the sum of the power-four of M intraday returns in the given day:

$$RQ_t = \frac{M}{3} \sum_{j=1}^{M} r_{t,j}^4$$

[9] We use the natural log of one plus the variables' value as variables can have zero or negative values in some periods.

[10] The standard deviation of the realized volatility error is $\sqrt{\frac{1}{2M} \frac{RQ_t}{(RV_t)^2}}$, cf. Bollerslev et al. (2016).

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We estimate the monthly RC between different assets using Audrino and Corsi's (2010) HAR-RC model. The 1-month RC for assets i and j is denoted $RC_{ij,t}$. The RC depends on the lagged RCs and the lagged exogenous variables. The HAR-RC-X model follows eq. (3), where we simply exchange the RVs with RCs, on the left and right side.

We estimate all the RV and RC models with and without the 1-period lagged NBER recession indicator included as an exogenous variable to account for potential level shifts during recessions. The benchmark specification for the RV (RC) uses the lagged RV (RC) in combination with RA and EU. In other specifications, we add further uncertainty variables. To identify the additional contribution from additional predictors, we orthogonalize the variables using the residuals from univariate regressions of each of the variables on RA and EU of the same lag.[11] Further, we estimate a model with only the lagged RV or RC.

We report a number of metrics for in-sample comparison of the models –the adjusted R^2, the Bayesian information criterion (BIC), the likelihood ratio test (LR), the partial determinant coefficient (PDC), and the F-test.[12] PDC is calculated as the percentage difference between the sum of squared residuals of two models and measures the proportion of variation explained by the general model that cannot be explained by the nested model. We use the LR test and PDC to compare the full model, that includes all the predictors, with different nested models, and we use F-test for comparing two models to analyze the contribution of different predictors in the HAR-RV-X (HAR-RC-X) models to the HAR-RV (HAR-RC) model.

The out-of-sample analysis is based on a rolling window of 250 days for the daily RV and 10 years for the monthly RV and RC. For the out-of-sample evaluations, we consider the Fischer transformation of the RC and of the predicted RC to ensure that the correlations are within the

[11] We also estimate all the models without orthogonalization, and the results remain qualitatively the same.

[12] We do not report the Akaike information criterion (AIC) as the AIC and BIC rank models identically.

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$[-1; 1]$ interval.[13] For this analysis, we compare the suggested models to two simple models, random walk and constant volatility or correlation. The random-walk model uses the first lag of RV (RC) as the predicted value, while the constant model uses the average of the observations over a rolling 250-day and 10-year window of historical daily and monthly RV (RC) values, respectively. The out-of-sample predictions consider different horizons, 1 day, 1 week, and 1 month (1 month, 3 months, 6 months, and 12 months) for the daily (monthly) frequency. To compare the out-of-sample performance of the various models, we report the MSE and mean absolute errors (MAE) calculated from comparing the forecasts from the various models with the realized volatility (correlations). Further we follow Diebold and Mariano (1995) to compare the different models' MSEs with the lowest MSE for a given horizon.

4. In-Sample and Out-of-Sample US Volatility Estimation

In this section, we discuss the estimation results for the US RV. We first briefly consider daily RV for which we only have a limited set of uncertainty variables available to show how the daily volatility differs from the monthly volatility. We then consider the monthly RV.

4.1. Daily Volatility

Table 2 shows 12 different in-sample specifications for the model of US daily RV. Specification (1) only includes the recession indicator, demonstrating that the RV is twice as large in recessions than in expansions.[14] Specification (2) shows the HARQ-RV model without any uncertainty variables. The current daily RV depends positively and significantly on the lagged daily RV and the lagged weekly RV. This is similar to the findings in Corsi (2009) except for the insignificant lagged monthly RV (which is significant in all our other specifications). In

[13] Audrino and Corsi (2010) apply this same transformation for the same reason. They find qualitatively identical results for the two methods.
[14] The coefficient of the recession indicator is equal to the size of the intercept, implying that the RV is about double in recessions compared to expansions.

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addition, the still significantly positive, but much smaller, recession indicator suggests that a major part of the additional volatility during recession periods is captured by the lagged *RV*.

For specification (3) (as well as for (4) to (12)), the lagged *RQ* is only significant for the daily lag which implies that the uncertainty about the *RV* measure can be disregarded at the lower frequencies. This is consistent with the findings in Bollerslev et al. (2016), where the weekly and monthly *RQ* lags are not significant and only induce a minimal improvement in the in-sample fit of the model of the *RV* of the S&P500. As this is the case for all our specifications, we do not include the lagged *RQ*s at the monthly frequency *RV* models and turn to the simpler HAR-RV-X model for monthly *RV*.

Specifications (3) and (4) show the HARQ-RV-X model extended with *RA* and *EU* separately, while specification (5) shows the benchmark HARQ-RV-X model with both *RA* and *EU* variables included. Both *RA* and *EU* enter significantly, with positive effects of their 1-day lags, while we observe a reversion for the weekly and monthly lags. The *RA* is more important than *EU* as judged from these three specifications (the adjusted R^2, the PDC, and the *F*-test are all in favor of adding *RA* rather than *EU*).

Specifications (6) to (12) show the results with all possible combinations of the other three uncertainty variables (*EPU*, *TED*, and *VIX*) available at the daily frequency. Adding the other variables changes neither *RA*'s sign nor its significance for the daily and monthly lags and improves its effect for the weekly lag. *EU* becomes insignificant in all specifications that include *VIX*. This may be caused by the relatively high correlation between these two variables (see Table 1, Panel B). All the three other predictor variables show positive effects on *RV* with 1-day lag, but the effect turns to negative in weekly or monthly lags.

Although the *F*-test rejects the HARQ-RV model against all the HARQ-RV-X models, in general, augmenting the HARQ-RV model with additional variables does not considerably enhance the model's explanatory power. The adjusted R^2 of the HARQ-RV-X model with all

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the predictor variables is 0.68 (specification (12)) compared to 0.63 for the HARQ-RV model (specification (2)). This increase is partly due to *RA* and *EU* and partly due to *VIX*: The R^2 of the benchmark model (specification (5)) increases from 0.66 to 0.67 when augmented with the *VIX* (specification (8)). *TED* and *EPU* add no explanatory power, as the model which includes these two variables (specification (9)) gives the same R^2 as the benchmark model and dropping both from the model (specification (8)) gives the same R^2 as the full model with a zero PDC compared to the full model.

Table 3 shows the out-of-sample results for the various HARQ-RV-X models for the daily *RV*. The lowest MSE is achieved by including just the *RV*, i.e., HARQ-RV model, for all the three forecast horizons. The MAE is also lowest for the HARQ-RV model. The magnitudes of MSE and MAE are substantially greater for the random-walk model and the constant-volatility model than for all the other models, showing the advantage of modeling the daily *RV* using HARQ-RV. For instance, the 1-day MAE for the random walk model is around 0.04 (17%) higher than for the HARQ-RV model. For all the three forecast horizons, the second lowest MAE values belong to HARQ-RV-X model that includes only *EU*. Interestingly, all the models have their lowest out-of-sample MSE and MAE for the weekly forecast horizon, which shows that the forecast of 1-day ahead realized volatility might be too noisy and the 1-month horizon is too long, when using daily data. For the weekly horizon, HARQ-RV significantly outperforms all the models except HARQ-RV-X models that include only *RA* and *EU*.

4. 2. Monthly Volatility

We start our monthly analysis by estimating the HAR-RV-X model for each variable at a time, while including all four lags of that variable (1-, 3-, 6-, and 12-month) to determine how many lags to include in the subsequent analysis. Since the parameters of 6- and 12-month lagged

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values of all the variables are insignificant, we only include the 1- and 3-month lags in the subsequent analyses. Results are not reported but is available upon request.[15]

To assess the robustness of the variables, we use Leamer's (1983) extreme-bound analysis. More specifically, we consider the variables in the benchmark model as "important" variables to be included in all the specifications, and the other variables as "doubtful," to be either included or omitted. We estimate all the possible regression models which may result from inclusion of the important variables and all 128 combinations of the doubtful variables. Extreme bounds of each coefficient are defined as the lowest and highest estimated values resulting from 128 regressions. We define a coefficient as sensitive or fragile if it changes sign or becomes insignificant at the extreme bounds (Levine and Renelt, 1992). Table 4 summarizes the results. The coefficients of *RA* and *FIN*, for both lags, and the coefficient of *VIX* for the 1-month lag are all robust and remain significant in all the possible combinations (128 for *RA* and 64 for *FIN* and *VIX*). All other coefficients can be considered fragile. *EPU*, *IP*, and *TED* are not significant in any combination and *CLI* almost never. The insignificance of *EPU* goes against the previous findings, cf. the references in the Introduction including Pástor and Veronesi (2013). However, since this variable is significant in univariate estimation (see footnote 15), and becomes insignificant when added to the benchmark model, we conclude that this variable does not provide useful information over and above that communicated by risk aversion and macroeconomic uncertainty.

Table 5 shows the estimation results of selected models out of the 128 estimated combinations for the monthly *RV*, in addition to the two specifications that include only one of the benchmark predictors (*RA* and *EU*) at a time. The selected models clearly illustrate the importance of including exogenous variables. The models not shown in this table are qualitatively the same

[15] The LR test that compares the model including all the four lags with the model including only the first two lags, supports this exclusion. Further, the 1-month lags of all the variables are significant with the expected sign (except TED and CLI), while the parameters of the 3-month lags are significant only for MAC and FIN.

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and suggest similar conclusions. Specification (1) shows that the monthly *RV* is almost twice as large in recessions as in expansions. Specifications (2) and (3) show the HAR-RV-X model with either *RA* or *EU*, while specification (4) shows the benchmark HAR-RV-X model with *RA* and *EU*. As for the daily *RV*, the *RA* is more important than *EU*, still *EU* is significant when included alone. Specifications (5) to (11) show the models where we include one additional uncertainty variable at a time. Specification (12) extends the benchmark with *MAC*, *FIN*, and the *VIX* volatility index and is the most parsimonious model not rejected by the LR test against the full model with all the predictor variables, shown in column 13, and has almost the same explanatory power as the full model (1% PDC). The one-month lagged *RV* becomes insignificant when either *FIN* or *MAC* are included in the model, which may be due to the relatively high correlation between *RV* and these variables (see Table 1 Panel A). On the other hand, *RA*, *VIX*, and *FIN* remain highly significant in the full model, despite their high pairwise correlations. Including predictor variables increases the explanatory power from an adjusted R^2 of 0.48 for the HAR-RV model, and 0.59 for the benchmark HAR-RV-X model, to 0.67 for the model in specification (12). So, even when we have already accounted for *RA* and *EU*, there is room for further improvement by including additional predictor variables. The additional explanatory power is mainly due to the variable *FIN* (seen from the F-test and the adjusted R^2). In the full model (specification (13)), the coefficients of the 1-month lag of *RA*, *FIN*, and *VIX* are all positive and significant (at 10% level or higher). We observe a reversal in the effect of these variables for the 3-month lags.

The preferred variables differ between the daily and monthly frequency because the daily *MAC* and *FIN* are not available. However, we conclude from the combined results of the daily and monthly in-sample analyses that the variables *FIN* and *VIX*, which are constructed from financial variables, have additional information about uncertainty in stock market that is not captured entirely by *EU*, which is mainly constructed from macroeconomic variables. In addition, by comparing R^2 values, we conclude that adding predictor variables in the HAR-

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RV-X model is more beneficial at the monthly than the daily horizon; the adjusted R^2 increases from 0.63 (HARQ-RV) to 0.66 (benchmark HARQ-RV-X) for daily *RV* (see Table 2) and from 0.48 (HAR-RV) to 0.59 (benchmark HAR-RV-X) for monthly *RV* (see Table 5).

Table 6 shows the out-of-sample results for predicting the monthly *RV* with the models above, as well as the random walk and constant volatility models. The results are in line with the in-sample findings and show that the benchmark model extended with *FIN* has the lowest MAE for all horizons and the lowest MSE, except for the 12-month horizon for which the MSE is lowest for the constant-volatility model.[16] According to the Diebold and Mariano (1995) test for the 1-month horizon, the benchmark extended with *FIN* significantly outperforms all the other models except the random walk, HAR-RV, and HAR-RV extended with *EU*. The constant volatility model has an MAE which is 60% larger than the benchmark extended with *FIN*, while for the full model the MAE is 8% larger and for the benchmark it is 10% larger. At the medium horizon (3 and 6 months), the benchmark extended with *FIN* has significantly lower MSE than all the other models except HAR-RV and HAR-RV extended with *EU*. The predictive power of the models is lower at the long 12-month horizon. The constant-volatility model, which is constructed using a longer window of past *RV* information, has the lowest MSE, but according to the Diebold and Mariano (1995) test it does not significantly outperform any of the other models, except the random walk model. This shows that the contribution of conditioning on recent information is low when we forecast far into the future.

4.3. Summing Up

Overall, the analysis shows that the uncertainty variables are more helpful for predicting *RV* at the monthly frequency than the daily frequency. This may partly be due to the fact that fluctuations in economic uncertainty follow a much smoother path than the changes in stock market volatility.

[16]The model with only FIN also gives the smallest MSE when comparing the models that include only the lagged values of each exogenous variable, excluding the lagged RVs.

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In-sample analysis shows that that the benchmark variables, *RA* and *EU*, are important for explaining the future *RV* both at the daily and monthly frequency. However, *RA* is shown to be more important than *EU* and remains robust in all possible model specifications. The effects of *RA* on the volatility are representative of behaviorally induced time variation in the volatility, which reflects not only the variations in economic fundamentals, but also changes in investors' sentiment, while the effects of *EU* are representative of fundamentally induced time variation in the volatility. Augmenting the benchmark model with the variables *VIX* and *FIN* greatly improves the explanatory power of the models at the daily and monthly frequencies, respectively.

In the out-of-sample analysis, we find considerable benefits in using the HARQ-RV model for predicting volatility at the daily frequency, whereas at the monthly frequency the smallest MSE is for the benchmark model with the additional predicator *FIN*.[17]

5. International Analysis

We now consider international stock markets and their relationship with the US stock market. We analyze the world market (excluding US) as well as seven major international stock markets to obtain an overall assessment of the predictive ability of US uncertainty measures for non-US markets. We expect the predictor variables to be of less importance for the world and international stock markets because they are directly related to the US economy and indirectly to the world economy.[18] Our aim is to investigate if using US predictor variables is helpful for international diversification from the perspective of a US investor.

[17] To account for the leverage effect, greater volatility in the periods with negative returns, we also estimate an extension of Corsi and Renò's (2012) LHAR-RV model by including the lagged negative stock returns (results not tabulated). In addition, we extent the model to consider the asymmetric impact of the predictor variables by allowing the parameters of the exogenous variables to differ when the stock returns are positive and negative. The leverage is significant in-sample but has low explanatory power and does not improve the predictive ability out-of-sample. We do not find any asymmetric effect from the predictors.

[18] We also consider using local exogenous predictor variables when estimating the local RV. The results are restricted in the sense that only EPU, IP, and CLI are available for the international stock markets and only for shorter sample periods. We find that using local exogenous variables perform worse, both

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We first estimate the HAR-RV-X and HAR-RC-X models for international stock markets (section 5.1), followed by international-portfolio analysis (section 5.2), and we end by summing up (section 5.3).

5.1. International Volatility and Correlation Estimation

Table 7 shows the in-sample results for the international stock market *RV*s and their *RC* with the US. The predictor variables are the lagged local *RV* and lagged local-US *RC* and the same exogenous variables as for the US *RV* above. To save space, we only show the results from estimating the full model which includes all exogenous predictor variables. The table also leaves out exogenous variables that are insignificant for all countries, as well as the intercept term.

For the *RV*s the results are shown in Panel A. As expected, the explanatory power of predictor variables is higher for the US than for the international stock markets, e.g., for the UK, the adjusted R^2 is 0.57 compared to 0.68 for the US. Like the US results, the lagged *RA* is significant for all international stock markets. The lagged *FIN* is also significant for most international stock markets, whereas *VIX* is only important for the North American stock markets. For the *RC*s (Panel B), the significant exogenous variables differ from market to market. For instance, for the Canada-US *RC*, the lagged *VIX* is significant, whereas for the Germany-US *RC*, the lagged *EU* and *TED* are significant. Overall, the explanatory power of predictor variables for the *RC* estimations is lower than for the *RV*s. The *F*-test is significant for all the markets, which shows that the augmented models with *RA* and uncertainty variables, i.e., HAR-RV-X and HAR-RC-X outperform the HAR-RV and HAR-RC models, respectively.

To save space, for the out-of-sample analysis, we only show the result of the world market (excluding US), which gives an overall assessment of the models' forecasting ability.[19] Table

in-sample and out-of-sample, in international-portfolio analysis than using US ones. Detailed results are available upon request.

[19]The results for individual international stock market are available upon request.

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8 shows the MSEs for the world *RV* and world–US *RC*. The results for the world *RV* are similar to those for the US *RV*. The benchmark model extended with the *FIN* has the lowest MSE for the 1-month, 3-month, and 6-month horizon, and it significantly outperforms most of the other models. The constant volatility has the lowest MSE for the 12-month horizon, but its difference with MSE of the other models is in general insignificant.

For the world–US *RC*, the benchmark model and the augmented benchmark models with predictors all give very low MSEs. For the 1-month horizon, the simple random walk, the constant volatility/correlation, the benchmark models augmented with *VIX* and *CLI*, as well as the full model, significantly underperform the benchmark extended with *TED*. For the longer horizons (i.e., 3-, 6-, and 12 month), the benchmark model has the lowest MSE, and it significantly outperforms the HAR-RC model, among several other models.

5.2. International-Portfolio Analysis

In this section, we investigate if exogenous predictor variables are helpful for international-portfolio analysis from the perspective of a US investor. We use the out-of-sample *RV* and *RC* predictions from each model to form portfolios. We use four statistics to compare the international-portfolio performance across models:

- Minimum variance portfolio (MVP): Each month we use the out-of-sample predicted *RV*s and *RC*s of all country pairs to form the predicted covariance matrix for each model. We then obtain the corresponding weights that minimize the portfolio variance for this estimation window. These weights are used to construct the MVP portfolio for the following month. To ensure that the covariance matrices are positive definite, as in Voev (2008), we first use Cholesky decompositions of the realized covariance matrices and predict the Cholesky series and then reconstruct the variance and covariance forecasts. We provide the yearly standard deviation for the MVP portfolio for each model.

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- Engle and Colacito's (2006) test: This approach examines the relative performance of two covariance matrices, by minimizing the predicted variance subject to a required return for a range of hypothetical required returns. The predicted positive-definite covariance matrix for each model is defined like that in constructing the MVP. We use the generalized method of moments with a heteroscedasticity- and autocorrelation-consistent covariance matrix to define the test statistics.

- Economic value: We use the framework of Fleming et al. (2001), Fleming et al. (2003), and Bollerslev et al. (2018) to estimate the economic value of choosing the model with the highest utility instead of an alternative model, for an investor with quadratic utility with a given degree of risk aversion. The economic value is denoted delta and measures the maximum return an investor would be willing to pay in order to capture the performance gains associated with switching to the best model (with highest utility) from an alternative model.

- Cosemans et al. (2019) market-neutral minimum-variance portfolio test:[20] We use the forecasted realized betas to predict the covariance matrix implied by the single-factor model and construct the market-neutral minimum-variance portfolio by minimizing the portfolio variance with an additional constraint that the ex-ante market beta of the portfolio should be equal to zero. An advantage of this test compared to the conventional minimum-variance test is that, in addition to the realized volatility of each country, we only estimate the countries' realized beta against the US market, instead of correlations among all countries.

Table 9 shows the results of out-of-sample portfolio analysis for each of the models using the four statistics described above. We show the results when we use the exogenous variables for both RV and RC (HAR-RV-X & HAR-RC-X, in the left columns) and when we only use the

[20]We thank an anonymous referee for this helpful suggestion.

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exogenous variables in the *RV* (HAR-RV-X & HAR-RC, in the right columns). The two sets of results are mainly similar and show that the HAR-RV models augmented with the two benchmark variables, *EU* and *RV*, either separately or jointly, are the best performing models. We therefore mainly focus on the HAR-RV-X and HAR-RC-X results. The results are thereby robust to excluding the exogenous predictors in the *RC* model.

The first column shows the yearly standard deviations of the MVPs for the different models. For comparison we also report the standard deviation of an equally-weighted portfolio (last row). The MVP from the HAR-RV-X model that includes *EU* as its only exogenous variable gives the lowest out-of-sample standard deviation, while the largest out-of-sample standard deviation belongs to the MVP from the random walk and constant volatility/correlation models. These results underscore the usefulness of including exogenous variables in the HAR-RV-X model to predict covariance matrices. The standard deviation of the equally weighted portfolio is around ten times larger, indicating the risk of an unoptimized portfolio.

The second column shows the Engle and Colacito (2006) test. For each model, we use the forecasted covariance matrix to construct a portfolio that minimizes the portfolio variance with a given vector of expected returns and compare the resulting portfolio performance under the various models with the best-performing model (empty entry in the table). Similar to the result for the MVP, the best model is again the HAR-RV-X model that includes the *EU*. But in general, the results of Engle and Colacito (2006) portfolio test show that only a few of the models perform significantly worse than the best model.

The third column shows the economic value, delta, namely the percentage yearly return that the investor would be willing to sacrifice to choose another model than the one with the highest utility. We follow Rapach et al. (2016) and use a risk aversion parameter equal to 3 in the table, but we also use risk aversion coefficient equal to 1 and 5 and the results remain qualitatively the same. The HAR-RV-X model with *RA* as exogenous variable has the highest utility, but its difference with the HAR-RV-X model that includes *EU* is negligible (less than 0.01% yearly

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return). The difference in economic value is large across some models, like the random walk (3.17%), constant volatility/correlation (1.06%), the benchmark extended with *TED* (0.93%), and the full model (1.93%). For instance, the investor would be willing to pay 3.17% yearly return in order to invest in a portfolio constructed based on the HAR-RV-X with *RA* instead of the portfolio formed based on the random walk approach. The corresponding value is 0.5% yearly return for not switching to the HAR-RV/RC model from the best model.

The fourth column shows the means of the average of the estimated realized betas from the Cosemans et al. (2019) market-neutral minimum-variance portfolio for each model. The market beta should be close to zero if the model successfully predicts the volatility and correlation. The lowest realized beta is obtained for the benchmark HAR-RV-X/HAR-RC-X model. The realized beta of the benchmark model is significantly lower than those for the random walk and the benchmark HAR-RV-X/HAR-RC-X model extended with *MAC*, *FIN*, and *VIX*, as well as the full model. The beta of the equally-weighted portfolio is around six times that of the benchmark model, which shows the degree of risk reduction from applying the optimization algorithm with a proper model.

5.3. Summing Up

The in-sample estimation results show that the international *RV* and *RC* with the US depend significantly on the exogenous predictors, though not so much as for the US *RV*. The out-of-sample estimation results provide the same conclusions for the world *RV* and the US *RV*, namely that the benchmark model extended with the *FIN* provides the lowest prediction error for short- and medium-term forecast horizons. For the US-world *RC*, the largest out-of-sample prediction errors belong to the simple models, such as the random walk and constant volatility/correlation model, and the full model that has the largest number of the parameter.

Our portfolio analysis documents the importance for a US investor of considering the influence of *RA* and uncertainty when estimating second-order moments. However, including too many variables may lead to overfitting and suboptimal portfolio compositions. Interestingly, the

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random-walk model, which is based on the lagged values of *RV* and *RC* performs much worse than the HAR-RV/HAR-RC and its extension the HAR-RV-X/HAR-RC-X model, which reveals that a proper modeling of the information is crucial for satisfactory results.

6. Conclusion

We have studied the influence of three sources of economic uncertainty (macroeconomic, financial, and economic policy) on return volatility and comovements, while controlling for the time variation in risk aversion. Further, we control for the effects of additional predictors, including alternative measures of uncertainty and macroeconomic conditions. We use the HAR-RV model from Corsi (2009) extended with exogenous predictors, HAR-RV-X. The in-sample analysis shows that the benchmark model with *RA* and *EU* performs well in explaining the future *RV* and that augmenting the benchmark model with uncertainty measures constructed from financial information improves its explanatory power at both the daily and monthly frequency. At the daily frequency, we find considerable benefits in using the HAR-RV model for predicting volatility and augmenting the model with additional uncertainty variables does not significantly improve its predictability. However, at the monthly frequency there are significant improvements in using the HAR-RV-X model, i.e., adding additional predicators such as the *RA*, *EU*, and *FIN*.

International volatility and correlation depend on the exogenous predictor variables similarly to the US volatility. We have also conducted international-portfolio analysis. A US investor benefits from taking *RA* and *EU* into account when deciding on portfolio composition. However, including additional uncertainty measures does not improve portfolio performance.

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Table 1. Correlation matrix of variables

The table reports the correlation coefficients between the US realized volatility (*RV*) and the following predictor variables: the Bekaert et al. (forthcoming) risk-aversion (*RA*) and economic-uncertainty (*EU*) indexes, the Baker et al. (2016) economic-policy-uncertainty (*EPU*) index, the Ludvigson et al. (2021) macroeconomic-uncertainty (*MAC*) and financial-uncertainty (*FIN*) indexes for the one-month horizon, the *TED* spread, industrial-production growth (*IP*), the volatility index (*VIX*), and the composite leading indicator (*CLI*). Panel A is for the monthly frequency and Panel B is for the daily frequency. The sample period is from January 1990 to July 2020. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Number of observations: 355 (monthly) and 6219 (daily).

Panel A. Monthly frequency

	RV	***RA***	***EU***	***EPU***	***MAC***	***FIN***	***IP***	***TED***	***VIX***	***CLI***
RV	1.000									
RA	0.771***	1.000								
EU	0.597***	0.601***	1.000							
EPU	0.381***	0.365***	0.508***	1.000						
MAC	0.614***	0.646***	0.712***	0.224***	1.000					
FIN	0.732***	0.729***	0.585***	0.382***	0.660***	1.000				
IP	-0.358***	-0.424***	-0.658***	-0.269***	-0.706***	-0.430***	1.000			
TED	0.491***	0.374***	0.208***	-0.011	0.429***	0.336***	-0.119**	1.000		
VIX	0.886***	0.918***	0.558***	0.368***	0.601***	0.808***	-0.332***	0.440***	1.000	
CLI	-0.438***	-0.521***	-0.477***	-0.534***	-0.517***	-0.560***	0.730***	-0.035	-0.492***	1.000

Panel B. Daily frequency

	RV	***RA***	***EU***	***EPU***	***TED***	***VIX***
RV	1.000					
RA	0.698***	1.000				
EU	0.573***	0.691***	1.000			
EPU	0.358***	0.350***	0.426***	1.000		
TED	0.403***	0.442***	0.385***	0.052***	1.000	
VIX	0.793***	0.773***	0.652***	0.444***	0.474***	1.000

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Table 2. In-sample HARQ-RV-X models for daily US realized volatility

The table reports the estimated parameters for various HARQ-RV-X models for the daily US realized volatility (*RV*). The right-side variables are the 1-, 5-, and 22-day lags of the natural logarithms of the exogenous variables in addition to the lagged NBER recession indicator. The exogenous variables are *RV*, realized quarticity (*RQ*), the risk-aversion (*RA*) index, the economic-uncertainty (*EU*) index, the economic-policy-uncertainty (*EPU*) index, the *TED* spread, and the volatility index (*VIX*). The table reports the adjusted R^2, the Bayesian information criterion (BIC), the likelihood ratio (LR) test statistics compared to model (12), the partial determination coefficient (PDC) compared to model (12), and the *F*-test compared to model (2). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on Newey and West (1987) standard errors. The estimations are based on 6219 daily observations.

Model:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Intercept	0.008***	0.000	-0.004***	0.000	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
Recession	0.008***	0.001***	0.000*	0.001***	0.000**	0.001**	0.001**	0.000*	0.001**	0.000**	0.000*	0.000*
***RV* 1d**		0.414***	0.286***	0.350***	0.281***	0.279***	0.278***	0.170***	0.276***	0.168***	0.166***	0.163***
***RV* 5d**		0.529***	0.396***	0.505***	0.391***	0.384***	0.387***	0.323***	0.380***	0.323***	0.317***	0.317***
***RV* 22d**		0.047	0.226***	0.107**	0.215***	0.221***	0.213***	0.336***	0.221***	0.337***	0.335***	0.337***
***RQ* 1d**		-0.674***	-0.621***	-0.583***	-0.600***	-0.597***	-0.594***	-0.324***	-0.592***	-0.320**	-0.315**	-0.311**
***RQ* 5d**		-0.281	-0.296	-0.326*	-0.301*	-0.291	-0.309*	-0.179	-0.299*	-0.178	-0.184	-0.183
***RQ* 22d**		0.037	0.072	-0.016	0.050	0.035	0.053	-0.088	0.038	-0.105	-0.083	-0.101
***RA* 1d**			0.019***		0.017***	0.018***	0.019***	0.032***	0.020***	0.032***	0.035***	0.035***
***RA* 5d**			-0.006*		-0.005	-0.005	-0.007*	-0.013***	-0.007*	-0.013***	-0.015***	-0.016***
***RA* 22d**			-0.009***		-0.008***	-0.008***	-0.008***	-0.016***	-0.008***	-0.016***	-0.016***	-0.016***
***EU* 1d**				0.037***	0.011**	0.011**	0.011**	-0.002	0.011**	-0.001	-0.002	-0.002
***EU* 5d**				-0.034***	-0.009	-0.009	-0.009	0.002	-0.009	0.002	0.002	0.002
***EU* 22d**				-0.002	-0.002	-0.002	-0.002	0.001	-0.002	0.000	0.001	0.001
***EPU* 1d**						0.001***			0.001***	0.001***		0.001***
***EPU* 5d**						0.000			0.000	0.001		0.001
***EPU* 22d**						-0.001**			-0.001**	-0.001**		-0.001**
***TED* 1d**							0.005*		0.004		0.005**	0.005**
***TED* 5d**							-0.004		-0.004		-0.005	-0.005
***TED* 22d**							0.000		0.000		0.000	0.000
***VIX* 1d**								0.011***		0.011***	0.011***	0.011***
***VIX* 5d**								-0.006***		-0.006***	-0.006***	-0.006***
***VIX* 22d**								-0.004***		-0.004***	-0.004***	-0.004***
Adj R^2	0.159	0.634	0.662	0.645	0.663	0.663	0.663	0.674	0.664	0.675	0.675	0.675
BIC	-45807	-50930	-51421	-51105	-51412	-51398	-51395	-51605	-51382	-51592	-51593	-51579
LR	5955***	780***	263***	578***	246***	233***	236***	26***	223***	13***	12***	
PDC	62%	12%	4%	9%	4%	4%	4%	0%	4%	0%	0%	
***F*-test**			180***	68***	93***	63***	63***	89***	48***	68***	68***	55***

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Table 3. Out-of-sample results for daily US realized volatility

The table reports the out-of-sample forecasting ability of various HARQ-RV-X models for the daily US realized volatility (*RV*). The analysis is based on a rolling window of 250 days which gives 5977 out-of-sample observations. The random-walk model uses the first lagged *RV* as the predicted value. The constant model uses the average of the *RV* observations over a rolling window of 250 days. The HARQ-RV model includes only lagged *RV* and *RQ*. The B (benchmark) HARQ-RV-X model includes lagged *RV*, *RA*, and *EU*. The benchmark + *EPU* extends the benchmark model with *EPU*, etc. The full HARQ-RV-X model includes all the available variables. The first three columns report the mean squared error (MSE) compare the predicted volatility with the realized volatility for horizons of a day, week, and month. The model with the lowest MSE is indicated by boldface. Based on the Diebold and Mariano (1995) test, asterisks indicate if the MSE of the model is significantly different from the MSE of the model with the lowest MSE. The last three columns report the corresponding mean absolute error (MAE). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on Newey and West (1987) standard errors.

	MSE			**MAE**		
	1 day	**1 week**	**1 month**	**1 day**	**1 week**	**1 month**
Random walk	0.247*	0.191***	0.247***	0.282	0.252	0.286
Constant volatility	0.395***	0.288***	0.237***	0.364	0.313	0.288
HARQ-RV (RV)	**0.191**	**0.119**	**0.171**	**0.242**	**0.196**	**0.222**
RV* + *RA	0.192	0.132	0.192*	0.247	0.202	0.230
***RV* + EU**	0.195	0.124	0.177	0.245	0.199	0.225
B (benchmark)	0.200	0.141	0.196	0.249	0.207	0.234
B + *EPU*	0.203	0.143*	0.201*	0.252	0.211	0.238
B + *TED*	0.203	0.144*	0.197	0.255	0.215	0.239
B + *VIX*	0.203	0.142*	0.195	0.255	0.215	0.245
B + *EPU* + *TED*	0.207	0.148**	0.203*	0.260	0.219	0.245
B + *EPU* + *VIX*	0.206	0.143**	0.197*	0.259	0.219	0.249
B + *TED* + *VIX*	0.208	0.145**	0.195	0.261	0.222	0.250
Full HARQ-RV-X	0.210	0.147**	0.199*	0.264	0.225	0.253

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Table 4. Extreme-bound analysis for monthly US realized volatility

The table reports Leamer's (1983) extreme-bound analysis for the monthly US realized volatility (*RV*). The benchmark HAR-RV-X model consists of lagged *RV*, *RA*, and *EU*. All possible combinations of adding the other exogenous variables (*EPU*, *MAC*, *FIN*, *IP*, *TED*, *VIX*, and *CLI*) to the benchmark model are estimated. The first and second columns report the minimum and maximum parameter estimates from all the models including the variable, and the third column reports the number of models that include variable. The last two columns report the number of models where the variable is significantly positive and negative at the 10% level of significance. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on Newey and West (1987) standard errors. The estimations are based on 355 monthly observations.

	Min	**Max**	**# of models**	**# pos sig at 10%**	**# neg sig at 10%**
Recession	0.002	0.013*	128	19	0
***RV* 1m**	-0.174	0.311***	128	16	0
***RV* 3m**	-0.055	0.324***	128	22	0
***RA* 1m**	0.176***	0.459***	128	128	0
***RA* 3m**	-0.405***	-0.107***	128	0	128
***EU* 1m**	-0.034	0.052***	128	22	0
***EU* 3m**	-0.035	0.040	128	5	0
***EPU* 1m**	-0.009	-0.002	64	0	0
***EPU* 3m**	-0.004	0.006	64	0	0
***MAC* 1m**	0.177	0.547***	64	44	0
***MAC* 3m**	-0.453***	-0.107	64	0	34
***FIN* 1m**	0.400***	0.501***	64	64	0
***FIN* 3m**	-0.424***	-0.327***	64	0	64
***IP* 1m**	-0.190	0.089	64	0	0
***IP* 3m**	-0.095	0.207	64	0	0
***TED* 1m**	0.000	0.017	64	0	0
***TED* 3m**	-0.015	0.000	64	0	0
***VIX* 1m**	0.036**	0.053***	64	64	0
***VIX* 3m**	-0.044***	-0.013	64	0	40
***CLI* 1m**	-2.641*	-0.136	64	0	1
***CLI* 3m**	0.196	2.785*	64	6	0

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Table 5. In-sample HAR-RV-X models for monthly US realized volatility

The table reports the estimated parameters for selected HAR-RV-X models for the monthly US realized volatility (*RV*). The right-side variables are the 1-month and 3-month lags of the natural logarithms of the exogenous variables and the lagged NBER recession indicator. The exogenous variables are *RV*, the risk-aversion (*RA*) index, the economic-uncertainty (*EU*) index, the economic-policy-uncertainty (*EPU*) index, the macroeconomic-uncertainty (*MAC*) index, financial-uncertainty (*FIN*) index, the *TED* spread, industrial-production (*IP*) growth, the volatility index (*VIX*), and the composite leading indicator (*CLI*). The table reports the adjusted R^2, the Bayesian information criterion (BIC), the likelihood ratio (LR) test statistics compared to model (13), the partial determination coefficient (PDC), compared to model (13), and the *F*-test compared to model (1). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on Newey and West (1987) standard errors. The estimations are based on 355 monthly observations.

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Intercept	0.015***	-0.064**	0.012***	−0.064**	−0.061*	−0.068***	−0.060**	−0.066**	−0.074***	−0.073***	-0.068**	-0.058**	-0.057**
Recession	0.017*	0.013*	0.016*	0.012*	0.013*	0.004	0.007	0.013*	0.011	0.013*	0.013*	0.002	0.003
***RV* 1m**	0.523***	0.270***	0.437***	0.298***	0.300***	0.159	0.090	0.306***	0.282***	0.126	0.296***	-0.151	-0.144
***RV* 3m**	0.082	0.072	0.135	0.049	0.064	0.155	0.069	0.005	0.027	0.118	-0.044	0.292**	0.264*
***RA* 1m**		0.170***		0.176***	0.176***	0.247***	0.388***	0.185***	0.182***	0.219***	0.212***	0.447***	0.457***
***RA* 3m**		-0.100***		−0.109***	−0.111***	−0.178***	−0.330***	−0.115***	−0.107***	−0.145***	-0.140***	-0.392***	-0.403***
***EU* 1m**			0.044**	−0.018	−0.020	0.029	0.022	−0.016	−0.021	−0.010	-0.026	0.052***	0.042
***EU* 3m**			-0.039**	0.021	0.023	−0.023	−0.003	0.019	0.025	0.016	0.030*	-0.029	-0.019
***EPU* 1m**					−0.002								-0.007
***EPU* 3m**					−0.004								0.002
***MAC* 1m**						0.506***						0.293*	0.250
***MAC* 3m**						−0.427***						-0.223	-0.189
***FIN* 1m**							0.501***					0.428***	0.412***
***FIN* 3m**							−0.424***					-0.360***	-0.337***
***IP* 1m**								−0.098					-0.034
***IP* 3m**								0.139					0.054
***TED* 1m**									0.010				0.013
***TED* 3m**									−0.003				-0.013
***VIX* 1m**										0.039**		0.044***	0.045***
***VIX* 3m**										−0.020		-0.041**	-0.042**
***CLI* 1m**											-1.367		-0.476
***CLI* 3m**											1.669		0.386
Adj R^2	0.477	0.590	0.478	0.586	0.586	0.611	0.661	0.585	0.584	0.597	0.592	0.673	0.662
BIC	-1782	-1861	-1775	-1850	-1843	-1864	-1913	-1842	-1840	-1851	-1847	-1910	-1868
LR	192***	101***	187***	100***	96***	75***	25**	97***	98***	87***	92***	5	
PDC	42%	25%	41%	25%	24%	19%	7%	24%	24%	22%	23%	1%	
***F*-test**		51***	4**	25***	18***	22***	34***	18***	17***	20***	19***	24***	13***

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Table 6. Out-of-sample results for monthly US realized volatility

The table reports the out-of-sample forecasting ability of various HAR-RV-X models for the monthly US realized volatility (*RV*). The random-walk model uses the first lag of *RV* as the predicted value. The constant model uses the average of the observations over a rolling 10-year window of monthly *RV*s. The HAR-RV model from Corsi (2009) includes only lagged *RV*. The B (benchmark) HAR-RV-X model includes lagged *RV*, *RA*, and *EU*. Benchmark + *EPU* extends the benchmark model with *EPU*, etc. The Full HAR-RV-X model includes all the available variables. The first four columns report the mean squared error (MSE) comparing the predicted volatility with the realized volatility for 1-month, 3-month, 6-month, and 12-month horizons. The model with the lowest MSE is indicated by boldface. Based on Diebold and Mariano's (1995) test, asterisks indicate if the MSE of the model is significantly different from the MSE of the model with the lowest MSE. The last four columns report the corresponding mean absolute error (MAE). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on Newey and West (1987) standard errors.

	MSE				MAE			
	1 month	**3 months**	**6 months**	**12 months**	**1 month**	**3 months**	**6 months**	**12 months**
Random walk	4.413	5.017**	5.951***	7.152*	1.45	1.47	1.63	1.83
Constant volatility	8.835***	7.035***	5.721	**4.511**	2.10	1.93	1.78	1.66
HAR-RV	4.192	4.274	4.634	5.311	1.35	1.31	1.41	1.57
RV* + *RA	4.801**	5.113**	5.558**	6.277	1.43	1.38	1.46	1.59
RV* + *EU	4.418	4.520	5.021	5.707	1.43	1.37	1.50	1.67
B (benchmark)	4.840***	5.150***	5.708**	6.447	1.45	1.42	1.54	1.69
B + *EPU*	4.804**	5.124**	5.742***	6.626	1.46	1.42	1.54	1.72
B + *MAC*	4.758*	5.138*	5.670*	6.396	1.44	1.37	1.45	1.57
B + *FIN*	**4.117**	**3.944**	**4.260**	4.943	**1.32**	**1.23**	**1.35**	**1.51**
B + *IP*	4.892**	5.321**	5.975**	6.878	1.46	1.44	1.54	1.72
B + *TED*	4.892***	5.200***	5.689***	6.388	1.46	1.42	1.53	1.67
B + *VIX*	5.221***	5.401***	5.713***	6.087	1.48	1.47	1.57	1.69
B + *CLI*	4.558*	4.555*	5.148*	5.954	1.44	1.39	1.53	1.65
B + *MAC* + *FIN* + *VIX*	4.776*	4.867**	5.243**	5.961	1.41	1.38	1.50	1.63
Full	4.693**	4.619**	4.966**	5.842	1.42	1.38	1.53	1.69

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Table 7. In-sample models for international realized volatility and correlation

The table reports selected estimated parameters for the full HAR-RV-X (Panel A) and HAR-RC-X (Panel B) model for the monthly realized volatility (*RV*) for international stock markets (Canada CA, France FR, Germany GE, Hong Kong HK, Japan JP, Switzerland SW, and the UK), the world (excluding US), and the US. The table leaves out intercept as well as variables that are not significant for any countries. The dependent variables are the 1-month and 3-month lags of the natural logarithms of the lagged exogenous variables: Local *RV*/local-US *RC*, the risk-aversion (*RA*) index, the economic-uncertainty (*EU*) index, the economic-policy-uncertainty (*EPU*) index, the macroeconomic-uncertainty (*MAC*) index, financial-uncertainty (*FIN*) index, the *TED* spread, industrial-production (*IP*) growth, the volatility index (*VIX*) volatility index, and the composite leading indicator (*CLI*). The table reports the adjusted R^2 and *F*-test to compare the full model with the HAR-RV and HAR-RC models. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on Newey and West (1987) standard errors. The estimations are based on 355 monthly observations.

Panel A. Realized volatility

	CA	FR	GE	HK	JP	SW	UK	World	US
***RV* 1m**	-0.090	0.144	0.103	0.110	0.232***	0.110	0.097	0.182**	-0.144
***RV* 3m**	0.412***	0.358***	0.456***	0.407**	0.060	0.266**	0.283**	0.204*	0.266*
***RA* 1m**	0.297***	0.305***	0.317***	0.235***	0.135**	0.282***	0.270***	0.216***	0.456***
***RA* 3m**	-0.261***	-0.298***	-0.306***	-0.204***	-0.118*	-0.268***	-0.251***	-0.186***	-0.402***
***MAC* 1m**	0.424**	0.107	0.194	0.084	0.003	0.158	0.188	0.070	0.250
***MAC* 3m**	-0.349*	-0.138	-0.271*	-0.136	-0.004	-0.226	-0.204	-0.001	-0.189
***FIN* 1m**	0.183**	0.219**	0.228**	0.237**	0.077	0.230**	0.200**	0.143*	0.412***
***FIN* 3m**	-0.097	-0.154	-0.160	-0.170	-0.057	-0.190*	-0.138	-0.116	-0.338***
***VIX* 1m**	0.022*	0.014	0.013	0.014	0.025*	0.017	0.018	0.012	0.045***
***VIX* 3m**	-0.040**	-0.021	-0.023	-0.021	-0.017	-0.019	-0.021	-0.012	-0.042**
Adj R^2	0.630	0.546	0.590	0.503	0.331	0.450	0.574	0.546	0.682
***F*-test**	10***	6***	6***	4***	3***	5***	6***	6***	13***

Panel B. Realized correlation

	CA	FR	GE	HK	JP	SW	UK	World
***RC* 1m**	-0.017	0.026	-0.040	-0.101*	0.011	-0.061	-0.073	-0.041
***RC* 3m**	0.358***	0.224**	0.341***	0.257**	0.184*	0.351***	0.243**	0.224**
***EU* 1m**	0.112	0.062	-0.089	-1.075***	-0.534	-0.172	0.187	0.038
***EU* 3m**	0.003	0.353	0.617**	1.093***	0.951***	0.459	0.083	0.510
***MAC* 3m**	-0.667	0.569	1.343	2.267*	1.608	0.850	0.288	2.313*
***IP* 1m**	-0.499	1.355	1.907	4.488***	3.369*	2.672*	0.632	0.940
***IP* 3m**	-0.161	-1.093	-1.236	-3.959**	-2.852	-2.544	-0.668	-0.259
***TED* 3m**	-0.049	-0.103	-0.389**	-0.021	-0.117	0.147	-0.172	-0.368**
***VIX* 1m**	0.227**	0.147	0.079	0.213	0.205	0.016	-0.006	0.177
***CLI* 1m**	5.042	-1.003	-2.661	-14.916***	-6.302	2.358	-0.545	0.289
***CLI* 3m**	-3.401	3.676	4.746	16.668***	8.573	0.438	3.691	0.677
Adj R^2	0.205	0.292	0.448	0.068	0.154	0.206	0.163	0.331
***F*-test**	2**	3***	3***	2**	2**	2***	2***	3***

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Table 8. Out-of-sample results for monthly world realized volatility and world-US realized correlation

The table reports the out-of-sample forecasting ability of various HAR-RV-X models for the monthly world (excluding US) realized volatility (*RV*) and HAR-RC-X models for the world-US realized correlation (*RC*). The random-walk model uses the first lag of *RV*/*RC* as the predicted value. The constant model uses the average of the observations over a rolling 10-year window of monthly *RV*s/*RC*s. The HAR-RV/HAR-RC model from Corsi (2009) includes only lagged *RV*/*RC*. The B (benchmark) HAR-RV-X/HAR-RC-X model includes lagged *RV*/*RC*, *RA*, and *EU*. Benchmark + *EPU* extends the benchmark model with *EPU*, etc. The Full HAR-RV-X model includes all the available variables. The mean squared error (MSE) compares the predicted volatility with the realized volatility for 1-month, 3-month, 6-month, and 12-month horizons. The model with the lowest MSE is indicated by boldface. Based on Diebold and Mariano's (1995) test, asterisks indicate if the MSE of the model is significantly different from the MSE of the model with the lowest MSE. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on Newey and West (1987) standard errors.

	MSE *RV*				**MSE *RC***			
	1 month	**3 months**	**6 months**	**12 months**	**1 month**	**3 months**	**6 months**	**12 months**
Random walk	3.967	4.412*	4.732***	5.088*	0.059***	0.039***	0.034***	0.034***
Constant volatility	6.566***	4.952***	3.953**	**3.177**	0.047***	0.028***	0.023***	0.021***
HAR-RV/RC	3.672	3.386	3.203	3.225	0.037	0.017*	0.014**	0.013***
RV*/*RC* + *RA	3.985*	3.774**	3.607**	3.694	0.036	0.016	0.012**	0.012***
RV*/*RC* + *EU	3.732	3.341	3.233	3.221	0.036	0.015	0.011	0.010
B (benchmark)	3.933*	3.607**	3.502**	3.587	0.036	**0.015**	**0.011**	**0.010**
B + *EPU*	3.906*	3.662**	3.584**	3.759	0.037*	0.016*	0.013***	0.012***
B + *MAC*	3.825	3.530	3.402	3.515	0.037	0.016	0.012**	0.010
B + *FIN*	**3.663**	**3.295**	**3.167**	3.299	0.036	0.015	0.011	0.010
B + *IP*	4.153**	3.887***	3.792**	3.939	0.036	0.015	0.011	0.010
B + *TED*	3.968**	3.635**	3.446*	3.467	**0.035**	0.015	0.012*	0.012***
B + *VIX*	4.000**	3.683***	3.538**	3.611	0.038**	0.017***	0.012***	0.011***
B + *CLI*	3.901*	3.460	3.363	3.482	0.037**	0.017***	0.013***	0.012***
Full	4.013	3.899*	3.840**	4.146	0.042***	0.022***	0.019***	0.018***

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Table 9. Out-of-sample results for international-portfolio analysis

The table reports out-of-sample portfolio analysis of various HAR-RV-X/HAR-RC-X models for the world (excluding US), Canada, France, Germany, Hong Kong, Japan, Switzerland, UK, and the US. The random-walk model uses the first lag of *RV*/*RC* as the predicted value. The constant model uses the average of the observations over a rolling 10-year window of monthly *RV*s. The HAR-RV/HAR-RC model includes only lagged *RV*/*RC*. The B (benchmark) HAR-RV-X/HAR-RC-X model includes lagged *RV*, *RA*, and *EU*. The benchmark + *EPU* extends the benchmark model with *EPU*, etc. The Full HAR-RV-X/HAR-RC-X model includes all the available variables. The last row is for an equally weighted portfolio. Column 1 shows the yearly standard deviations of the minimum variance portfolios (MVP), where the model with the lowest standard deviation is shown in boldface. Colum 2 shows the Engle and Colacito (2006) test (EC) for comparison with the best model. Column 3 shows the economic value (Delta) compared to the best model. Column 4 show the means of the estimated realized betas from the Cosemans et al. (2019) market-neutral minimum-variance portfolio, where the model with the lowest beta is shown in boldface. ***, **, and * indicate that EC/Beta is significantly different from the best model at the 1%, 5%, and 10% levels, respectively, based on Newey and West (1987) standard errors.

	HAR-RV-X & HAR-RC-X				**HAR-RV-X & HAR-RC**			
	MVP	**EC**	**Delta**	**Beta**	**MVP**	**EC**	**Delta**	**Beta**
Random walk	13.586	5.760***	3.171	0.349***	13.586	4.958**	2.668	0.349***
Constant volatility/corr.	11.566	1.569	1.060	0.114	11.566	0.768**	0.557	0.114
HAR-RV/RC	11.198	0.864	0.522	0.131	11.198	0.063	0.019	0.131
RV*/*RC* + *RA	10.890	0.329		0.110	11.668	0.879***	0.297	0.107
RV*/*RC* + *EU	**10.739**		0.007	0.104	**11.168**			0.102
B (benchmark)	10.902	0.334*	0.081	**0.102**	11.764	1.070	0.409	**0.083**
B + *EPU*	11.060	0.650**	0.221	0.153	11.530	0.637*	0.210	0.114
B + *MAC*	11.143	0.783	0.463	0.154	11.903	1.392**	0.624	0.141
B + *FIN*	11.219	0.891	0.331	0.136	12.010	1.555**	1.037	0.103
B + *IP*	11.307	1.118*	0.483	0.113	11.953	1.420	0.546	0.090
B + *TED*	11.375	1.300	0.926	0.131	11.940	1.496*	0.774	0.104
B + *VIX*	11.031	0.618	0.243	0.106	11.741	1.069**	0.414	0.085
B + *CLI*	11.380	1.163**	0.602	0.131	11.926	1.270**	0.554	0.103
B + *MAC* + *FIN* + *VIX*	11.269	1.054	0.494	0.204**	12.074	1.727	0.874	0.166**
Full HAR-RV/RC-X	11.768	1.897	1.932	0.223***	11.969	1.422	0.693	0.188***
Equally weighted	113.023	-	-	0.623***	113.023	-	-	0.623***

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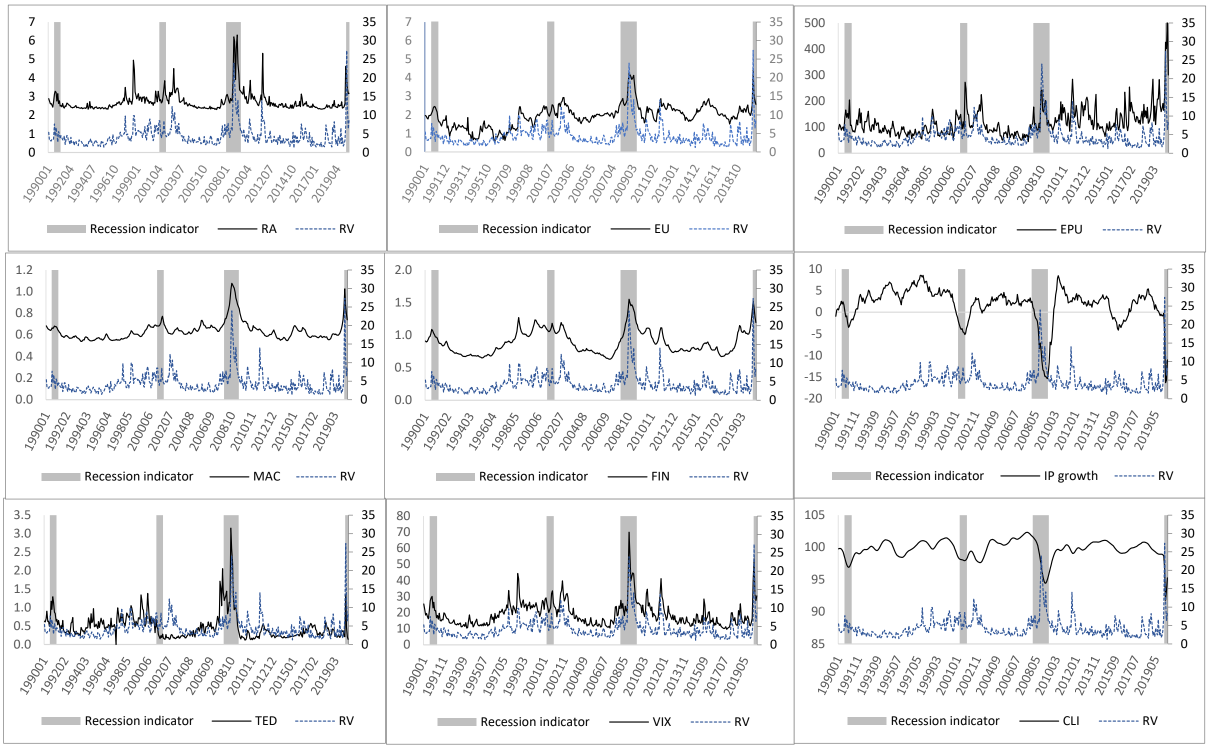
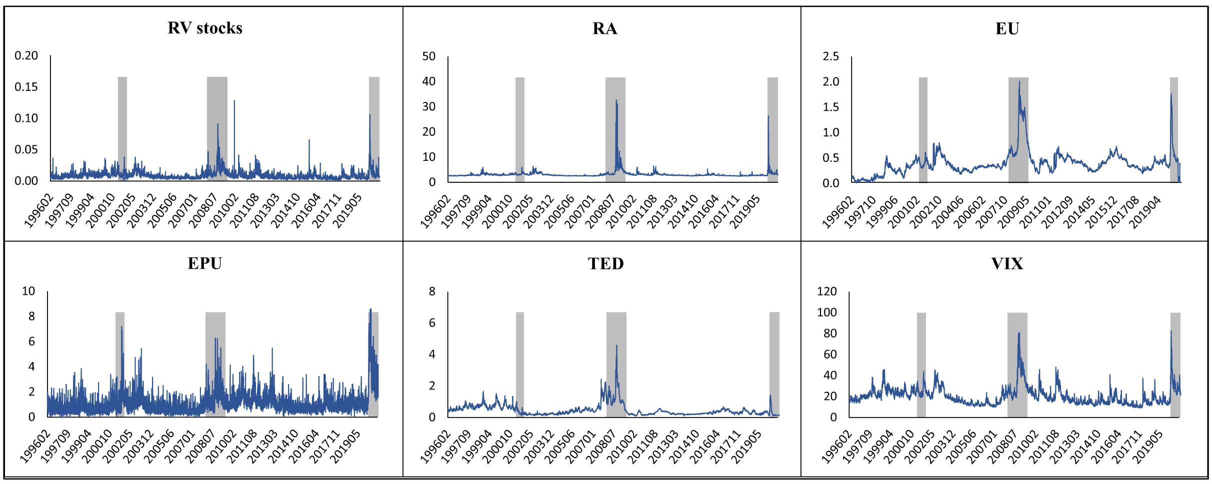
Figure 1. Time series of uncertainty variables

The figure shows the time series of each uncertainty variable: The US stock realized volatility (*RV*), the risk-aversion (*RA*) index, the economic-uncertainty (*EU*) index, the economic-policy-uncertainty (*EPU*) index, the macroeconomic-uncertainty (*MAC*) index, the financial-uncertainty (*FIN*) index, the *TED* spread, the industrial-production (*IP*) growth, the volatility index (*VIX*) volatility index, and the composite leading indicator (*CLI*). Panel A (B) is for the monthly (daily) frequency and each graph shows the *RV* (left axis), an uncertainty variable (right axis), and the NBER recession periods in shaded areas.

Panel A. Monthly frequency



Panel B. Daily frequency



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