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# The effect of uncertainty on stock market volatility and correlation

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A B S T R A C T

In this study, we use an extension of the heterogeneous autoregressive model to investigate the influence of time-varying risk aversion and macroeconomic, financial, and economic policy uncertainty measures on stock market volatility and correlation. Based on the findings, there is a stronger predictive ability of these variables at the monthly frequency than at the daily frequency. We also highlight the importance of risk aversion, which, alongside fundamental factors, reflects investor sentiment in predicting stock market volatility. Meanwhile, although uncertainty variables, such as economic uncertainty and financial uncertainty, are important, the widely used variable, economic policy uncertainty, is not helpful for predicting stock market volatility. Moreover, there is evidence of higher economic value and reduced portfolio risk when including risk aversion and economic uncertainty in international portfolio analysis.



## 1. Introduction

Understanding how uncertainty and risk aversion affect the volatility and correlation of financial markets is important for investors when planning their risk management and portfolio selection strategies as well as for policymakers when devising their economic policies.[1] Thus, we conduct an empirical study on the relative importance of time-varying risk aversion and different sources of uncertainty in order to predict stock market volatility and correlation as well as determine whether this information is useful for international portfolio analysis.

As emphasized in previous research, risk aversion and economic uncertainty are key determinants of financial returns and risk premiums. Many studies have assumed constant risk aversion and focused on the time variation in economic uncertainty (e.g., Kandel and Stambaugh, 1990; Bansal et al., 2005, 2014). The importance of time variation in risk aversion has been highlighted in Campbell and Cochrane's (1999) consumption-based asset pricing model. Recently, Bekaert et al. (2022) suggested an asset pricing model in which conditional volatility is driven by variation in both risk aversion and economic uncertainty.[2] Economic uncertainty is primarily related to shocks from fundamental factors (e.g., consumption shocks in Bansal and Yaron, 2004), while risk aversion is driven by shocks from both fundamental and non-fundamental factors such as investor sentiment (e.g., Baker and Wurgler, 2006).[3]

In the present study, we compare the relative importance of time-varying risk aversion and economic uncertainty on stock market volatility and correlation. To measure risk aversion, we use the time-varying risk aversion index (*RA*) constructed by Bekaert et al. (2022). This index relates several observable financial variables to preferences, macroeconomic fundamentals, and cash flow dynamics in a dynamic no-arbitrage asset pricing model. Empirically, this index is highly correlated with measures of

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[1] We use the following abbreviations in the following: RA: risk aversion index. EU: economic uncertainty index. FIN: financial uncertainty index. MAC: macroeconomic uncertainty index. EPU: economic policy uncertainty index. TED: Treasury-EuroDollar spread. VIX: Chicago Board of Options Exchange (CBOE) volatility index. IP: industrial production growth. CLI: OECD composite leading indicator. HAR: heterogenous autoregressive. RV: realized volatility. RC: realized correlation. RQ: realized quarticity.

[2] For time-varying risk aversion, see also Bekaert et al. (2009) and Bekaert and Hoerova (2016).

[3] Bekaert et al. (2009) showed that accounting for changes in risk aversion that are not driven by fundamental factors is essential for capturing asset price dynamics.

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sentiment/confidence, especially those related to consumer confidence. As for uncertainty, it can originate from various sources. Previous empirical studies have generally focused on the impact of one or several sources of uncertainty on stock market volatility such as economic policy uncertainty (Liu and Zhang, 2015; Baker et al., 2016) and macroeconomic uncertainty (Engle et al., 2013; Asgharian et al., 2015). The present study contributes to the literature by focusing on the relative importance of different sources of uncertainty, while accounting for risk aversion, to predict stock market volatility and correlation.

Specifically, we consider several types of uncertainty from the existing literature, primarily macroeconomic, financial, and economic policy uncertainty. Bekaert et al. (2022) constructed an economic uncertainty index (*EU*), which reflects the part of industrial production volatility that is explained by financial variables. Empirically, *EU* is highly correlated with corporate bond volatility and credit spread. Ludvigson et al. (2021) constructed two measures of uncertainty that gage the time-varying volatility of forecast errors in the prediction of future macroeconomic and financial conditions. They showed that the financial uncertainty measure (*FIN*) is more important than the macroeconomic uncertainty measure (*MAC*) in explaining economic fluctuations. Economic policy uncertainty is also different from but related to general economic uncertainty (Brogaard and Detzel, 2015). A well-known representative for economic policy uncertainty is the news-based economic policy uncertainty index (*EPU*) of Baker et al. (2016). They showed that a greater *EPU* causes higher stock market volatility and reduces investment in policy-sensitive sectors. For comparison, in addition to the aforementioned uncertainty measures, we consider several macroeconomic and financial variables such as the Treasury-EuroDollar spread (*TED*), the Chicago Board Options Exchange (CBOE) volatility index (*VIX*), industrial production growth (*IP*), and the OECD composite leading indicator (*CLI*).

Since most of the variables are only available for the United States, our primary analysis concerns U.S. stock market volatility. We further extend our analysis to seven large international stock markets as well as the world stock market. In this regard, we use an extended version of Corsi's (2009) heterogeneous autoregressive (*HAR*) model to describe realized stock market volatility (*RV*) and Audrino and Corsi's (2010) parallel extension to describe the realized correlation (*RC*) among international stock markets. The *HAR* model is a state-of-the-art model that can be easily extended to include *RA* and uncertainty measures as exogenous predictor variables. Due to the predictive ability of different measures and the fact that sources of uncertainty may change across horizons, we study the U.S. stock market at both daily and monthly frequencies. Additionally, because of data availability and differences in opening hours, we only study international stock markets at the monthly frequency.

We contribute to the existing literature by performing a comparative analysis of the ability of *RA* and various uncertainty measures to predict stock market volatility and correlation. Hence, we provide new insights into the relative importance of these variables for stock market movement and co-movement. First, we find stronger predictive ability of the models for the stock market *RV* at the monthly frequency than at the daily frequency, which indicates that the fluctuations in uncertainty variables are smoother than the variations in stock market volatility. This result aligns with Chiu et al. (2018), who found that only the persistent component of asset return volatility is linked to fundamental factors. Second, we provide empirical evidence on the importance of using *RA* for stock market volatility, which highlights the role of non-fundamental factors such as investor sentiment on stock market volatility. Both in- and out-of-sample analyses show that, among the uncertainty variables, *FIN* effectively predicts monthly stock market volatility. More importantly, we show that, in contrast to previous research (e.g., Liu and Zhang, 2015; Baker et al., 2016), *EPU* does not provide useful information for predicting monthly stock market volatility once we account for *RA* and *EU*. Similar results were obtained for *IP* and *CLI*.

Overall, our international analysis is closely related to that of Xu (2019), who developed a dynamic no-arbitrage asset pricing model that includes time-varying risk aversion and economic uncertainty variables (related to output growth, inflation, and the real interest rate) and indicates that *RA* can explain a large part of global stock market co-movements.[4] We also contribute by investigating other sources of uncertainty and demonstrating the practical benefits of using *RA* and uncertainty variables for international portfolio analysis. We found that models that only include *EU* and/or *RA* as predictor variables can result in lower portfolio risk and higher utility than alternative models.

The remainder of this study is organized as follows. Section 2 introduces the data, while the econometric framework is presented in Section 3. Section 4 discusses the in- and out-of-sample analyses of U.S. volatility, while Section 5 conducts an international portfolio analysis. Finally, Section 6 presents the conclusion.

## 2. Data

In this section, we present the data used to calculate *RV* and *RC* (Section 2.1) as well as the predictor variables (Section 2.2). The sample period is from January 1990 to July 2020 for monthly frequency and from February 1996 to November 2020 for daily frequency.[5]

### 2.1. Realized volatility and correlation

In this study, we include both daily and monthly *RV* when studying the U.S. market. Due to the unavailability of intraday data for all countries and because international stock markets do not have identical opening hours, we only consider monthly *RV* and *RC* in our international portfolio analysis.[6] Similar to Corsi (2009), we define *RV* as the square root of the realized variance. The daily *RV* is calculated as the square root of the sum of the squared five-minute intraday returns of the S&P 500 price index within a day, while the monthly *RV* is calculated as the square root of the sum of the squared daily returns within a month. Additionally, the monthly *RC* is calculated as the monthly realized covariance divided by the product of the monthly *RV*s, where the monthly realized covariance is the sum of the cross-products of the daily returns within the month. In order to calculate the monthly *RV* and *RC*, we use the daily total return index for the S&P 500 (U.S.) and seven international stock indices based on their market capitalizations, i.e., the S&P/TSX composite index (Canada), the CAC 40 (France), the DAX 30 (Germany), the

[4] Demirer et al. (2018) also showed that global risk aversion is a significant determinant of emerging stock market correlations.

[5] For the monthly frequency, the beginning of the sample period is determined by the availability of *VIX*, while the end of the sample period is determined by the availability of *MAC* and *FIN*. For the daily frequency, the sample period is determined by the availability of the intraday stock returns.

[6] The North American and European stock markets have partially overlapping opening hours, while the Asian markets do not have overlapping opening hours with the U.S. In order to accommodate this, we follow Jondeau and Rockinger (2006) and use one-day leading returns for the Asian countries. The unconditional correlations of the U.S.-Asian stock returns are higher for the one-day leading Asian stock returns than for the same-day closing returns and the one-day leading opening prices for the Asian markets. Meanwhile, the unconditional correlations between the U.S. and European markets are higher when using the same-day closing price returns than using the one-day leading prices of the European markets.

SMI (Switzerland), the TOPIX (Japan), the Hang Sang index (Hong Kong), and the FTSE 100 (United Kingdom), as well as the MSCI World, excluding the U.S. (henceforth, the world). Finally, stock returns are calculated as the log first differences of the total return indices.[7]

### 2.2. Predictor variables

In our benchmark model, we include the time-varying risk aversion and economic uncertainty measures from Bekaert et al. (2022), i.e., *RA* and *EU*, as exogenous variables. Bekaert et al. (2022) proposed a generalized habit model with a time-varying relative risk-aversion parameter for a representative agent. This model relates the prices of corporate bonds and equity to preferences, consumption growth, and cash-flow dynamics, while using industrial production data to define macro uncertainty. This model also spans risk aversion with several observable financial variables, such as credit and term spreads and realized equity and bond return variances, which simultaneously solve for the model parameters to obtain *RA*. In addition to fundamental factors, *RA* captures non-fundamental factors such as consumer sentiment.[8] Similarly, *EU* is the fitted value from the projection of the monthly conditional variance of industrial production growth onto the same set of financial variables used to span *RA*.

We also augment the benchmark model by using different combinations of other measures of uncertainty and economic indicators. Following the approach of Jurado et al. (2015), Ludvigson et al. (2021) defined the one-month macroeconomic and financial uncertainty indices, *MAC* and *FIN*, which measure the level of uncertainty regarding future macroeconomic and financial conditions. More specifically, *MAC* and *FIN* are defined as the common components in the time-varying volatilities of forecast errors obtained from a vector autoregressive model with 134 macroeconomic variables and 148 financial market variables, respectively. We also employ the *EPU* index of Baker et al. (2016), a news-based uncertainty measure that quantifies newspaper coverage of policy-related economic uncertainty in 10 major U.S. newspapers.

For comparison, we apply several macroeconomic and financial variables as predictor variables. Specifically, we use two financial indicators, i.e., *TED* and *VIX*, which reflect uncertainty in credit and stock markets. *TED* is the difference between the three-month LIBOR and the three-month T-bill rate, and measures the default risk on interbank loans, which is commonly used as a proxy for credit risk in the general economy (e.g., Cornett et al., 2011). *VIX* 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 (e.g., Whaley, 2000). *VIX* has also been used in many previous studies as a predictor of future volatility (e.g., Lamoureux and Lastrapes, 1993; Chernov, 2007; Bekaert and Hoerova, 2014; Mittnik et al., 2015). As macroeconomic variables, we include *IP* and *CLI*. We calculate *IP* as the log first difference of U.S. industrial production. *IP* is a popular variable for modeling business cycles and is widely used to forecast stock return volatility (e.g., Schwert, 1989; Hamilton and Lin, 1996; Engle et al., 2013). Regarding *CLI*, it predicts economic activity relative to its trend and is commonly used as another business cycle indicator.[9]

Overall, five predictor variables are available at the daily frequency: *RA, EU, EPU, TED*, and *VIX*. We plot the predictor variables and U.S. *RV* in Fig. 1 (monthly *RV* in Panel A and daily *RV* in Panel B). The predictor variables are all highly volatile, with peaks during the 2007–2008 financial crisis and the recent COVID-19 pandemic, which is similar to the pattern of the U.S. daily *RV*. All of the predictor variables follow *RV*'s pattern, except for *IP* and *CLI*, which mirror *RV* (as expected). Panel A of Table 1 presents the correlation matrix of the monthly *RV* and predictor variables. As anticipated, the uncertainty measures are significantly and positively correlated with one another and with the U.S. *RV*, whereas they are negatively and significantly correlated with the two measures of economic activity, i.e., *IP* and *CLI*. Moreover, the U.S. *RV* has the highest correlation with the *VIX, RA*, and *FIN*, which is natural, since these variables are constructed from financial data. In fact, the correlations between the *VIX* and *RA* (0.915) and *FIN* (0.816) are higher than those between *RV* and these two variables (0.880 and 0.735, respectively), which indicates the forward-looking nature of *RA* and *FIN*. Panel B of Table 1 shows the correlation matrix for the daily *RV* and the available daily predictors in which all of the correlations are positive. As with the monthly data, the daily *RV* is highly correlated with the *VIX* and *RA*.

## 3. Econometric methodology

In this section, we present the models used to predict *RV* and *RC*. First, we present the model for daily *RV* prediction (Section 3.1), followed by the models for monthly *RV* and *RC* prediction (Section 3.2). We conclude this section by discussing the estimation approach and evaluation metrics (Section 3.3).

### 3.1. Daily rv models

In Corsi's (2009) HAR-RV model, the dependent variable is the daily *RV*, while the independent variables are lagged daily, weekly, and monthly *RV*s. Haugom et al. (2011) and Haugom et al. (2014) augmented the HAR-RV model by adding one-day lagged exogenous variables to the models for electricity and oil volatility, respectively. Bekaert and Hoerova (2014) and Liu and Zhang (2015) used the same extended HAR-RV model for stock volatility, incorporating exogenous variables *VIX* and *EPU*, respectively. Since *RV* may be measured with errors, Bollerslev et al. (2016) proposed an HARQ model that augments the HAR-RV model by including integrated realized quarticity (*RQ*) for different horizons (see also Bollerslev et al., 2018; Clements and Preve, 2021). We extend the HARQ-RV model by including exogenous predictive variables for different horizons, which we call the HARQ-RV-X model. We also include the lagged *RV* and exogenous variables at the same horizons because this allows the lagged exogenous variables and the *RV* to have equal bearing on predicting the current *RV*.

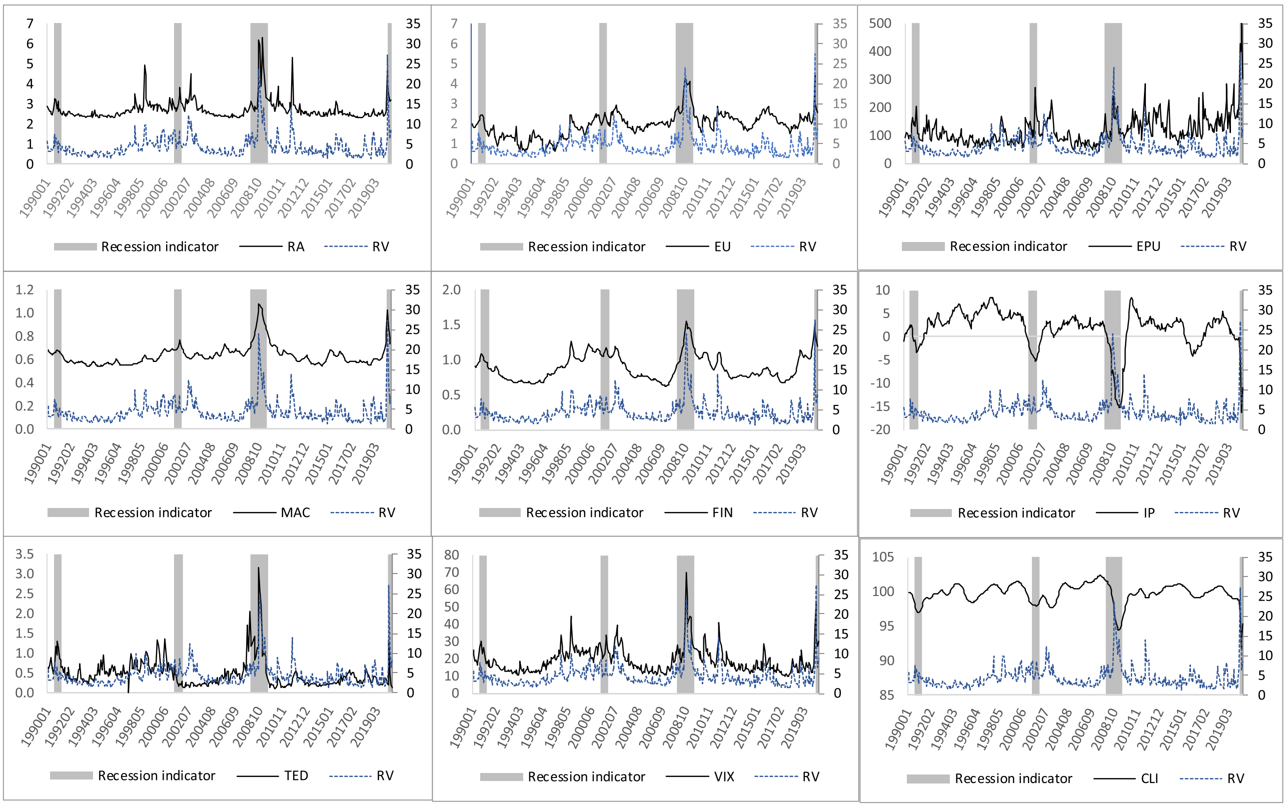
Since most of the daily variables are only available for the U.S., the daily *RV* model is only estimated for the U.S. stock market. We denote the daily *RV* for the U.S. stock market on day *t* as $RV_t^{1d}$. The first set of independent variables in the HARQ-RV-X model follows Corsi (2009), i.e., the lagged daily five-day (i.e., weekly), and 22-day (i.e., monthly) *RV*s. Following Corsi (2009), the five-day and 22-day *RVs* are calculated as the rolling average of the lagged daily *RV*s over the corresponding number of days, denoted by $RV_t^{5d}$ and

[7] Daily indices are collected from DataStream, while intraday data are collected from Refinitiv Datascope.

[8] Bekaert et al. (2022) performed external validation by relating *RA* to seven macro news announcements and found low explanatory power in general, whereas the industrial production shock was the most important determinant of variations in *RA* among the macro shocks. Comparing *RA* with a large number of sentiment/confidence measures showed that *RA* is highly correlated with these measures, especially with those related to consumer confidence.

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

**Panel A. Monthly frequency**




**Panel B. Daily frequency**

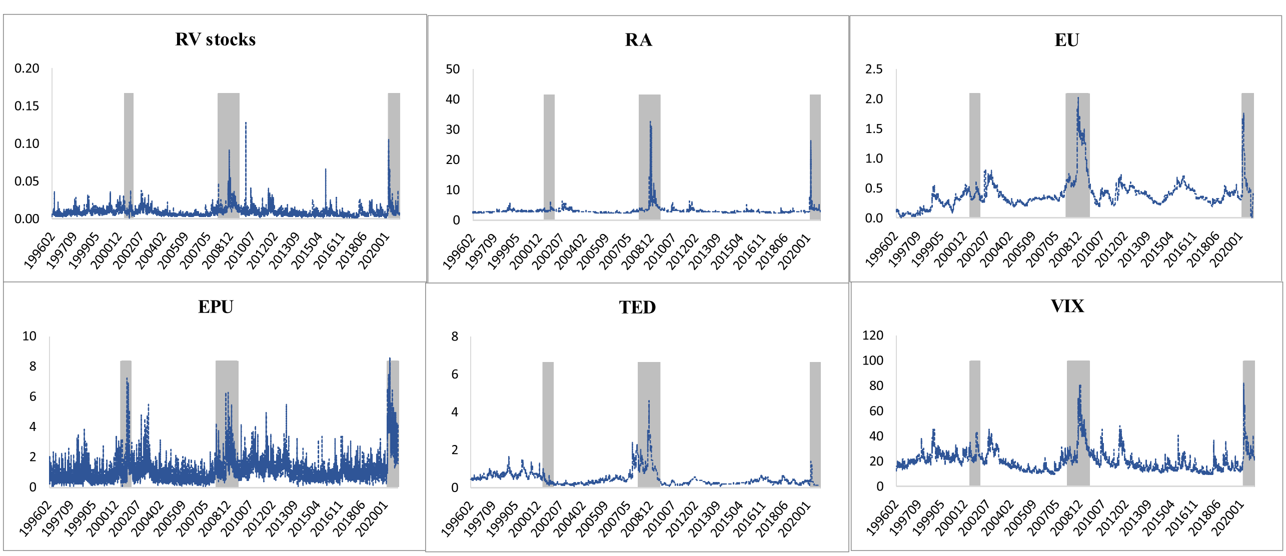



**Fig. 1.** Time series of uncertainty variables.
This figure shows the time series of each uncertainty variable: The U.S. stock realized volatility (*RV*), *RA*, *EU*, *EPU*, *MAC*, *FIN*, *TED*, *IP*, *VIX*, and *CLI*. Panel A shows the monthly *RV* (left axis), an uncertainty variable (right axis), and the NBER recession periods in the shaded areas. Similarly, Panel B shows the daily uncertainty variables. For the monthly (daily) frequency, the number of observations is 367 (6219). For the monthly (daily) frequency, the sample period is January 1990 to July 2020 (February 1996 to November 2020).

$RV_t^{22d}$, respectively. For instance, the five-day *RV* is defined as follows:

$$RV_t^{5d} = \frac{1}{5}\left(RV_t^{1d} + RV_{t-1}^{1d} + RV_{t-2}^{1d} + RV_{t-3}^{1d} + RV_{t-4}^{1d}\right). \quad (1)$$

The second set of independent variables in the HARQ-RV-X model includes the lagged *RQ*s, which are included in the same horizons as the lagged *RV*s. The daily *RQ* is calculated as the sum of the power-four of *N* intraday returns on day *t*: $RQ_t^{1d} = \frac{N}{3}\sum_{l=1}^{N} r_{t,l}^4$,

**Table 1**
Correlation matrix of the variables.

| Panel A. Monthly frequency | *RV* | *RA* | *EU* | *EPU* | *MAC* | *FIN* | *IP* | *TED* | *VIX* | *CLI* |
|---|---|---|---|---|---|---|---|---|---|---|
| *RV* | 1.000 | | | | | | | | | |
| *RA* | 0.748*** | 1.000 | | | | | | | | |
| *EU* | 0.624*** | 0.614*** | 1.000 | | | | | | | |
| *EPU* | 0.467*** | 0.374*** | 0.525*** | 1.000 | | | | | | |
| *MAC* | 0.649*** | 0.655*** | 0.731*** | 0.327*** | 1.000 | | | | | |
| *FIN* | 0.735*** | 0.734*** | 0.609*** | 0.449*** | 0.685*** | 1.000 | | | | |
| *IP* | −0.384*** | −0.432*** | −0.656*** | −0.402*** | −0.710*** | −0.472*** | 1.000 | | | |
| *TED* | 0.481*** | 0.377*** | 0.221*** | 0.004 | 0.428*** | 0.333*** | −0.102* | 1.000 | | |
| *VIX* | 0.880*** | 0.915*** | 0.586*** | 0.415*** | 0.629*** | 0.816*** | −0.360*** | 0.443*** | 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 |

This table reports the correlation coefficients for the variables. The set of variables include the U.S. realized volatility (*RV*) and the predictor variables *RA, EU, EPU, MAC, FIN, TED, IP, VIX*, and *CLI*. Panel A includes the monthly frequency and Panel B includes the daily frequency. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. For the monthly (daily) frequency, the number of observations is 367 (6219), while the sample period is January 1990 to July 2020 (February 1996 to November 2020).

where $l$ is the intraday interval. $RQ_t^{5d}$ and $RQ_t^{22d}$ are calculated in a similar manner to the five-day and 22-day *RV*s.[10]

The third set of independent variables in the HARQ-RV-X model is the corresponding lagged exogenous variables. Similar to the five-day and 22-day *RV*s, we use the rolling average of the lagged daily values of the $k$th exogenous variable at day $t$ and $X_{k,t}^{1d}$ over five and 22 days to calculate $X_{k,t}^{5d}$ and $X_{k,t}^{22d}$.

The HARQ-RV-X model is given as follows :[11]

$$RV_t^{1d} = \alpha + \beta^{1d} RV_{t-1}^{1d} + \beta^{5d} RV_{t-1}^{5d} + \beta^{22d} RV_{t-1}^{22d} + \delta^{1d} RQ_{t-1}^{1d} + \delta^{5d} RQ_{t-1}^{5d} + \delta^{22d} RQ_{t-1}^{22d} + \sum_k \left(\gamma_k^{1d} X_{k,t-1}^{1d} + \gamma_k^{5d} X_{k,t-1}^{5d} + \gamma_k^{22d} X_{k,t-1}^{22d}\right) + \varepsilon_t \tag{2}$$

where $\varepsilon_t$ is the error term on day $t$. Meanwhile, the set of daily exogenous predictor variables consists of *RA, EU, EPU, TED*, and *VIX*.

### 3.2. Monthly rv and rc models

Since the estimation error of *RV* only has a substantial impact at the daily frequency (see Bollerslev et al., 2016), we estimate the monthly HAR-RV-X model without the *RQ*s. In addition, the monthly model is estimated for both the U.S. and international stock markets. The monthly *RV* for market $i$ in month $t$ is denoted by $RV_{i,t}^{1m}$, while the independent variables are lagged monthly three-month *RV*s, and exogenous variables.[12] The three-month *RV* is calculated as the rolling average of the monthly *RV*s, while the other variables are defined as follows:

$$RV_{i,t}^{3m} = \frac{1}{3}\left(RV_{i,t}^{1m} + RV_{i,t-1}^{1m} + RV_{i,t-2}^{1m}\right). \tag{3}$$

The monthly HAR-RV-X model is as follows:

$$RV_{i,t}^{1m} = \alpha_i + \beta_i^{1m} RV_{i,t-1}^{1m} + \beta_i^{3m} RV_{i,t-1}^{3m} + \sum_k (\gamma_{i,k}^{1m} X_{k,t-1}^{1m} + \gamma_{i,k}^{3m} X_{k,t-1}^{3m}) + \varepsilon_{i,t} \tag{4}$$

where the set of exogenous predictor variables comprises *RA, EU, EPU, MAC, FIN, IP, TED, VIX*, and *CLI*. Meanwhile, $\varepsilon_{i,t}$ is the error term for stock market $i$ at month $t$.[13]

In order to estimate the monthly *RC* model, we use an extended version of Audrino and Corsi's (2010) model, where the monthly HAR-RC-X model is defined parallel to the monthly HAR-RV-X model in Eq. (4). The dependent variable is the monthly *RC* for markets $i$ and $j$ in month $t$, denoted as $RC_{ij,t}^{1m}$, while the independent variables are the lagged monthly three-month *RC* and exogenous variables. The three-month *RC* is calculated as the rolling averages of the monthly *RC*s, while the other predictor variables are calculated in a similar manner.

The monthly *RC* model is as follows:

$$RC_{ij,t}^{1m} = \alpha_{ij} + \beta_{ij}^{1m} RC_{ij,t-1}^{1m} + \beta_{ij}^{3m} RC_{ij,t-1}^{3m} + \sum_k (\gamma_{i,j,k}^{1m} X_{k,t-1}^{1m} + \gamma_{ij,k}^{3m} X_{k,t-1}^{3m}) + \varepsilon_{ij,t} \tag{5}$$

where the predictor variables are identical to those in Eq. (4) and $\varepsilon_{ij,t}$ is the error term for stock markets $i$ and $j$ at month $t$.

[10] The standard deviation of the realized volatility error is $\sqrt{\frac{1}{2N}\frac{RQ_{it}^1}{(RV_{it}^1)^2}}$, cf. Corsi et al. (2008).

[11] To ensure that the predicted *RV* is always positive, we consider the logarithmic version of the HARQ-RV-X model (without changing notation), taking the natural logs of the *RV* and the predictor variables. Previous studies have also used the logarithmic version of the HAR-RV model (Corsi et al., 2008; Tian et al., 2017; Buccheri and Corsi, 2019). We use the natural log of one plus the variables' value, since some variables can have zero or negative values in certain periods.

[12] We also include the six-month and 12-month horizons. However, they are not significant. The results are available upon request (see further discussions in Section 4.2).

[13] In order to account for the leverage effect and greater volatility in the periods with negative returns, we also estimate an extension of Corsi and Renò's (2012) HAR-RV model by including the lagged negative stock returns (results not tabulated). In addition, we extend 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 it has low explanatory power and does not improve the predictive ability out-of-sample. Additionally, we do not find any asymmetric effect from the predictors.

### 3.3. Estimation and evaluation

The benchmark model for *RV* (*RC*) uses lagged *RV* (*RC*) in combination with *RA* and *EU*. In the other models, we include additional uncertainty variables. To identify the incremental contribution from the additional predictors, we use orthogonalized (residuals from univariate regressions of the variable on *RA* and *EU* of the same horizon) and standardized (divided by the standard deviation) variables to make the estimated coefficients comparable.[14] We estimate all of the models by using OLS regressions with heteroskedasticity-consistent standard errors, following Newey and West (1987).[15] Moreover, we include the one-period lagged National Bureau of Economic Research (NBER) recession indicator in all of the in-sample analyses to account for potential level shifts during recessions, whereas it is not included in the out-of-sample analysis.

We report a number of metrics for a comparison of the in-sample predictions of the models, including: adjusted $R^2$, the Bayesian information criterion (BIC), the likelihood ratio test (LR), the partial determinant coefficient (PDC), and the *F*-test.[16] The PDC is the percentage difference between the sum of the squared residuals of the two models and it measures the proportion of the variation explained by the general model that cannot be explained by the nested model. Furthermore, we use the LR test and the PDC to compare the full model (which includes all of the predictors with different nested models) and use the *F*-test to analyze the contribution of exogenous predictors, compared with only including *RV*/*RC*.[17]

The out-of-sample forecasts of the various models for *RV* and *RC* are based on a rolling estimation window of 1250 days (120 months) for the daily (monthly) frequency.[18] We also compare the out-of-sample predictions of the models with those from the simple random walk and constant volatility/correlation models. The random walk model uses the one-day (one-month) lag of *RV* and *RC* as the predicted values at the one-day (one-month) horizon, while the constant volatility/correlation model is based on the 1250-day (120-month) rolling average of the historical daily (monthly) *RV* and *RC* values.

We also perform an out-of-sample analysis of the multi-period horizons. More specifically, for the daily frequency (in addition to the one-day forecasts), we calculate the forecasts at the five-day and 22-day horizons by recursively updating daily predictions of *RV* over the corresponding horizon, while the parameter estimates are from the estimation window using available information on the exogenous variables before the start of the forecast period. Moreover, the multi-period forecasts are evaluated by comparing the average *RV* and predicted *RV* over the multi-period horizons. Similar to Corsi (2009), the multi-period daily *RV*s are the averages of the one-day *RV*s. Formally, *h*-day forecast at time *t* is $\widehat{RV}_t^h = \frac{1}{h}\sum_{j=1}^{h}\widehat{RV}_{t+j}^{1d}$, where $\widehat{RV}_{t+j}^{1d} = E_t[RV_{t+j}^{1d}]$, indicating that $\widehat{RV}_{t+j}^{1d}$ is based on the information available at time *t*.

As for the exogenous variables, we use autoregressive moving average (ARMA) model forecasts, which are based on the best univariate ARMA (*p, q*) model for each variable. In this case, the best model is determined by using the entire sample period. We choose the model with the minimum number of parameters that results in the insignificant Ljung and Box (1978) test of residual autocorrelation of up to 10 lags. The resulting ARMA (*p, q*) model is then estimated for each window to obtain the forecasts of each variable. For the monthly frequency, we consider the one-, three-, six-, and 12-month forecast horizons. Monthly multi-period forecasts are obtained in a similar manner to the daily frequency.[19] Finally, for each model and horizon, we report the root mean squared error (RMSE) obtained by comparing the predictions with future values of *RV*/*RC*. We also use the Diebold and Mariano (1995) test to compare the mean squared errors (MSE) with the lowest MSE.

## 4. Analysis of U.S. volatility

In this section, we discuss the estimation results for the U.S. *RV*. First, we present the in- and out-of-sample results of the daily *RV* (Section 4.1) and then the monthly *RV* (Section 4.2).

### 4.1. Daily volatility

Table 2 presents the in-sample results for the U.S. daily *RV* obtained from the different specifications of the HARQ-RV-X model given in Eq. (2). Model (1) only includes the recession indicator. The coefficient for the recession indicator is equal to the intercept, implying that *RV* is twice as large in recessions than in expansions. Model (2) presents the HAR-RV model, while Model (3) shows the HARQ-RV model with no exogenous predictor variables. Similar to the findings of Corsi (2009), the daily *RV* positively and significantly depends on the lagged daily *RV* and the lagged five-day *RV*.

Models (4) and (5) individually show the HARQ-RV-X model extended with *RA* and *EU*, whereas Model (6) shows the benchmark HARQ-RV-X model with both *RA* and *EU*. Although both *RA* and *EU* significantly enter with positive effects of their one-day horizons, we observe a reversion for the five-day and 22-day horizons. Meanwhile, *RA* is more important than *EU*, as judged from the model metrics (the adjusted $R^2$, PDC, and *F*-test are all in favor of adding *RA*, rather than *EU*).

Models (7) to (13) show the results with all possible combinations of the last three daily uncertainty variables (*EPU, TED*, and *VIX*). Adding these variables changes neither the sign of the coefficients for *RA* nor its significance for the one-day and 22-day horizons. However, it does improve its effect for the five-day horizon. Additionally, *EU* becomes insignificant in all specifications that include *VIX*. Although most predictor variables show positive effects on *RV* with a one-day lag, the effect turns negative at the five-day or 22-day horizons. Meanwhile, the recession indicator is insignificant in Models (6) to (13), suggesting that a major part of the additional volatility during recession periods is captured by the exogenous variables. As for *RQ*, it is mainly significant for the one-day horizon, which shows that the measurement error variance for longer horizons is negligible (see Bollerslev et al., 2016).

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[14] We also estimate all of the models without orthogonalization. In this case, the results are qualitatively similar.

[15] For the daily analysis, we use 22 lags for the Newey and West (1987) standard errors, while we use 12 (6) lags for the monthly in-sample (out-of-sample) analysis. In general, the results are robust to the choice of lags.

[16] Since the BIC and Akaike information criterion (AIC) rank the models identically, we do not report AIC.

[17] The F-test for comparing two models is $F = \frac{(SS_1 - SS_2)/(df_1 - df_2)}{SS_2/df_2} \sim F(df_1 - df_2, df_2)$, where $SS_i$ and $df_i$ are the residual sum of squares and the degrees of freedom of model *i*, with $i = 1$ being the restricted model. The degree of freedom for each model is the difference between the number of observations and the number of parameters.

[18] For the out-of-sample evaluations of *RC*, we consider the Fischer transformation of the *RC* and the predicted *RC* to ensure that the correlations are within the [−1; 1] interval. Audrino and Corsi (2010) applied the same transformation for the same reason. They found qualitatively identical results for the two methods.

[19] For the monthly frequency, we have $\widehat{RV}_{t+j}^{1m} = \hat{\alpha} + \hat{\beta}^{1m}\widehat{RV}_{t+j-1}^{1m} + \hat{\beta}^{3m}\widehat{RV}_{t+j-1}^{3m} + \sum_k(\hat{\gamma}_k^{1m}\hat{X}_{k,t+j-1}^{1m} + \hat{\gamma}_k^{3m}\hat{X}_{k,t+j-1}^{3m})$, where $\widehat{RV}_{t+j-1}^{3m} = \frac{1}{3}(\widehat{RV}_{t+j-1}^{1m} + \widehat{RV}_{t+j-2}^{1m} + \widehat{RV}_{t+j-3}^{1m})$, $\hat{X}_{k,t+j-1}^{1m}$ is the ARMA model forecast for $j-1$ periods ahead, and $\hat{X}_{k,t+j-1}^{3m}$ is calculated in a similar manner to $\widehat{RV}_{t+j-1}^{3m}$, by taking the average of the ARMA model forecasts for the corresponding periods, i.e., $t+j-1$, $t+j-2$, and $t+j-3$. The equation for the daily frequency is similarly written, but is longer due to the larger number of variables.

**Table 2**
In-sample HARQ-RV-X models for daily U.S. realized volatility.

| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.081*** | 0.129*** | 0.043* | −0.564*** | 0.030 | −0.668*** | −0.670*** | −0.673*** | −0.562** | −0.665** | −0.567** | −0.575** | −0.578** |
| Recession | 0.082*** | 0.112*** | 0.105*** | 0.065** | 0.106*** | 0.074 | 0.078* | 0.077 | 0.072 | 0.083 | 0.073 | 0.074 | 0.073 |
| *RV* 1 d | | 0.273*** | 0.414*** | 0.286*** | 0.350*** | 0.281*** | 0.279*** | 0.278*** | 0.170*** | 0.276*** | 0.168*** | 0.166*** | 0.163*** |
| *RV* 5 d | | 0.441*** | 0.464*** | 0.347*** | 0.442*** | 0.342*** | 0.336*** | 0.339*** | 0.283*** | 0.333*** | 0.283*** | 0.277*** | 0.278*** |
| *RV* 22 d | | 0.094* | 0.037 | 0.179*** | 0.085** | 0.170*** | 0.174*** | 0.169*** | 0.265*** | 0.175*** | 0.266*** | 0.264*** | 0.266*** |
| *RQ* 1 d | | | −0.129*** | −0.119*** | −0.112*** | −0.115*** | −0.114*** | −0.114*** | −0.062*** | −0.113*** | −0.061*** | −0.060*** | −0.060*** |
| *RQ* 5 d | | | −0.053 | −0.056*** | −0.062 | −0.057** | −0.055** | −0.058** | −0.034 | −0.057** | −0.034 | −0.035 | −0.035 |
| *RQ* 22 d | | | 0.007 | 0.013 | −0.003 | 0.009 | 0.007 | 0.010 | −0.016 | 0.007 | −0.019 | −0.015 | −0.019 |
| *RA* 1 d | | | | 0.510*** | | 0.462*** | 0.474*** | 0.519*** | 0.863*** | 0.528*** | 0.877*** | 0.933*** | 0.945*** |
| *RA* 5 d | | | | −0.160*** | | −0.139** | −0.138** | −0.197** | −0.337*** | −0.195** | −0.351*** | −0.407*** | −0.421*** |
| *RA* 22 d | | | | −0.250*** | | −0.205*** | −0.216*** | −0.203*** | −0.416*** | −0.214*** | −0.414*** | −0.413*** | −0.410*** |
| *EU* 1 d | | | | | 0.851*** | 0.248** | 0.253** | 0.240* | −0.035 | 0.244** | −0.034 | −0.045 | −0.043 |
| *EU* 5 d | | | | | −0.773*** | −0.204 | −0.210 | −0.202 | 0.043 | −0.207 | 0.050 | 0.046 | 0.053 |
| *EU* 22 d | | | | | −0.050 | −0.054 | −0.051 | −0.042 | 0.018 | −0.041 | 0.010 | 0.031 | 0.021 |
| *EPU* 1 d | | | | | | | 0.030*** | | | 0.029*** | 0.028** | | 0.027** |
| *EPU* 5 d | | | | | | | 0.011 | | | 0.011 | 0.018 | | 0.017 |
| *EPU* 22 d | | | | | | | −0.034*** | | | −0.034** | −0.034*** | | −0.033** |
| *TED* 1 d | | | | | | | | 0.134 | | 0.129 | | 0.160* | 0.157* |
| *TED* 5 d | | | | | | | | −0.119 | | −0.118 | | −0.151 | −0.151 |
| *TED* 22 d | | | | | | | | −0.014 | | −0.013 | | −0.007 | −0.004 |
| *VIX* 1 d | | | | | | | | | 0.321*** | | 0.324*** | 0.324*** | 0.326*** |
| *VIX* 5 d | | | | | | | | | −0.169*** | | −0.180*** | −0.169*** | −0.179*** |
| *VIX* 22 d | | | | | | | | | −0.108*** | | −0.101*** | −0.110*** | −0.103*** |
| Adj $R^2$ | 0.159 | 0.622 | 0.634 | 0.662 | 0.645 | 0.663 | 0.663 | 0.663 | 0.674 | 0.664 | 0.675 | 0.675 | 0.675 |
| BIC | −45,807 | −50,758 | −50,930 | −51,421 | −51,105 | −51,412 | −51,398 | −51,395 | −51,605 | −51,382 | −51,592 | −51,593 | −51,579 |
| LR | 5955*** | 978*** | 780*** | 263*** | 578*** | 246*** | 233*** | 236*** | 26*** | 223*** | 13*** | 12*** | |
| PDC | 62% | 15% | 12% | 4% | 9% | 4% | 4% | 4% | 0% | 4% | 0% | 0% | |
| *F*-test | | | | 180*** | 68*** | 93*** | 63*** | 63*** | 89*** | 48*** | 68*** | 68*** | 55*** |

This table reports the estimated parameters for the various HARQ-RV-X models for the daily U.S. realized volatility (*RV*). The independent variables are the recession indicator and the lagged *RV, RQ, RA, EU, EPU, TED*, and *VIX*, over one-, five-, and 22-day horizons. This table also 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 (13), and the *F*-test compared to Model (3). The highest adjusted $R^2$, lowest BIC, and lowest PDC are marked in bold. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on the Newey and West (1987) standard errors. The estimations are based on 6219 daily observations. The sample period is February 1996 to November 2020.

**Table 3**
Out-of-sample results for daily U.S. realized volatility.

| | One-day | Five-day | 22-day |
|---|---|---|---|
| Random walk | 0.516*** | 0.452** | 0.519* |
| Constant volatility | 0.746*** | 0.662*** | 0.607*** |
| HARQ-RV (*RV*) | 0.431 | 0.374 | 0.485 |
| *RV* + *RA* | 0.438 | 0.382 | 0.499 |
| *RV* + *EU* | **0.428** | **0.355** | **0.443** |
| B (benchmark) | 0.440 | 0.379 | 0.509 |
| *B* + *EPU* | 0.442 | 0.381 | 0.511 |
| *B* + *TED* | 0.444 | 0.381 | 0.509 |
| *B* + *VIX* | 0.439 | 0.373 | 0.552 |
| *B* + *EPU* + *TED* | 0.445 | 0.383 | 0.506 |
| *B* + *EPU* + *VIX* | 0.440 | 0.374 | 0.551 |
| *B* + *TED* + *VIX* | 0.442 | 0.373 | 0.537 |
| Full model | 0.443 | 0.374 | 0.533 |

This table reports the out-of-sample forecasting ability of the various HARQ-RV-X models, the random walk, and the constant volatility models for the daily U.S. realized volatility (*RV*). The HARQ-RV model only includes lagged *RV* and *RQ* over one-, five-, and 22-day horizons. The benchmark (B) model includes lagged *RV*, *RA*, and *EU*. *B*+ denotes the benchmark model extended with one or more of the predictor variables, *EPU*, *TED*, and *VIX*. The full HARQ-RV-X model is the benchmark model with all of the predictor variables. We use the root mean squared error (RMSE) to compare the predicted volatility with the realized volatility for one-, five-, and 22-day horizons. The lowest RMSE values are marked in bold. According to the Diebold and Mariano (1995) test ***, **, and * indicate if the mean squared error (MSE) of the model is significantly different from the lowest MSE at the 1%, 5%, and 10% levels, respectively, based on the Newey and West (1987) standard errors. The estimations are based on a 1250-day rolling window with 4977 out-of-sample observations. The sample period is February 1996 to November 2020.

Although the *F*-test rejects the HARQ-RV model against all HARQ-RV-X models, augmenting the HARQ-RV model with additional variables does not considerably enhance the explanatory power. Specifically, the adjusted $R^2$ of the HARQ-RV-X model with all of the predictor variables is 0.675 (Model 13), compared with 0.634 for the HARQ-RV model (Model 3). Moreover, *TED* and *EPU* add no explanatory power, since Model (10) gives almost the same adjusted $R^2$ as the benchmark model. Interestingly, the benchmark model augmented with *VIX* (Model 9) has the best fit according to the BIC metric.

Table 3 presents the out-of-sample results for the various HARQ-RV-X models for daily *RV* at the one-, five-, and 22-day forecast horizons. At all of the horizons, the HARQ-RV model, including *EU*, has the lowest RMSE. However, the RMSE is only significantly different from the random walk and constant volatility models. For instance, for the one-day horizon, the RMSE of the constant volatility model is almost twice as large as the lowest RMSE. Overall, for daily frequency, the exogenous predictor variables (despite their in-sample significance) neither considerably improve the in-sample explanatory power of the HARQ-RV model nor significantly improve its out-of-sample predictive ability.

### 4.2. Monthly volatility

The daily volatility results in Table 2 show that lagged *RQ* is not significant for the monthly horizon, which implies that uncertainty regarding *RV* can be disregarded at longer horizons. Thus, we do not include lagged *RQ*s in any of the monthly *RV* models. First, we estimate the monthly HAR-RV-X model for each predictor variable one at a time, with lags of four horizons of the variable (one-, three-, six-, and 12-month) to determine how many horizons are included in the subsequent analysis. Since the parameters of the six- and 12-month horizons for all of the variables are insignificant, we only include the one- and three-month lags in the subsequent analyses, which is consistent with Eq. (4).[20]

We use Leamer's (1983) extreme-bound analysis to assess the robustness of the variables. More specifically, we consider the variables in the benchmark model as “important” ones to be included in all specifications, with the other variables as “doubtful” ones to be either included or omitted. Additionally, we estimate all of the models that include the important variables and all possible combinations of the doubtful variables. The extreme bounds of each coefficient are defined as the lowest and highest estimated values resulting from all of the estimated regressions. In this case, we define a coefficient as sensitive or fragile if it changes signs or becomes insignificant at extreme bounds (Levine and Renelt, 1992). The results are summarized in Table 4.

In addition to the benchmark variables, we add seven exogenous variables. Hence, the number of possible specifications is $2^7 = 128$. The benchmark variables are in all of these specifications, whereas each of the additional predictor variables is only included in $2^6 = 64$ combinations. Meanwhile, the coefficients for *RA* and *FIN* at both horizons, along with the coefficient for *VIX* at the one-month horizon, are all robust and significant in all possible combinations (128 for *RA* and 64 for *FIN* and *VIX*). All of the other coefficients can be considered as fragile.

Regarding *EPU* and *TED*, they are not significant in any combination, whereas *IP* and *CLI* are only significant in a few instances. The insignificance of *EPU* does not support the previous findings in, e.g., Liu and Zhang (2015) and Baker et al. (2016). We find that *EPU* is significant in the univariate model (the results are available upon request), but insignificant when added to the benchmark model. Thus, we can conclude that *EPU* does not provide information beyond that communicated by *RA* and *EU*.

Table 5 shows the in-sample estimation results of the selected models from the extreme-bound analysis for the monthly *RV*, in addition to the two specifications that only include one of the benchmark predictors (*RA* or *EU*) at a time. The selected models clearly illustrate the importance of including the exogenous predictor variables. The remaining models are not tabulated, but they lead to the same conclusions. Specifically, Model (1) shows that the monthly *RV* is almost twice as large in recessions as in expansions. Models (2) and (3) show the HAR-RV-X model with either *RA* or *EU*, whereas Model (4) presents the benchmark HAR-RV-X model with both *RA* and *EU*. Similar to the daily *RV*, the *RA* is more important than *EU*.

Models (5) to (11) include one additional uncertainty variable at a time, while Model (12) (extending the benchmark with *MAC*, *FIN*, and *VIX*) is the most parsimonious model that is not rejected by the LR test against the full model with all of the predictor variables (Model 13) and has almost the same explanatory power as the full model (1% PDC). Meanwhile, the one-month horizon *RV* becomes insignificant when *FIN*, *MAC*, or *VIX* is included in the model, which may be due to the relatively high correlation between *RV* and these variables (see Panel A in Table 1). In contrast, *RA*, *VIX*, and *FIN* remain highly significant in the full model, despite their high pairwise correlations. As for the benchmark model augmented with *FIN* (Model 7), it has the lowest BIC. Similar to the daily volatility results, the recession indicator is insignificant when we include several exogenous predictor variables.

Based on the findings, including exogenous predictor variables increases the explanatory power. This can be seen from the adjusted $R^2$, which is 0.477 for the HAR-RV model and 0.587 for the benchmark HAR-RV-X model, compared to 0.673 for Model (12).

[20] The HAR-RV-X model in Eq. (4) only includes the variables at the one- and three-month horizons. The six- and 12-month horizons are added in a straightforward manner. The results including the six- and 12-month lags are not reported, but are available upon request. The LR test that compares the model, including all four lags of the model with only the first two lags, supports this exclusion. Furthermore, the one-month lags of all of the variables are significant with the expected sign (except for *TED* and *CLI*), whereas the parameters of the three-month lags are only significant for *MAC* and *FIN*.

**Table 4**
Extreme-bound analysis for monthly U.S. realized volatility.

| | Min | Max | # of models | # pos sig at 10% | # neg sig at 10% |
|---|---|---|---|---|---|
| Recession | 0.079 | 0.505* | 128 | 17 | 0 |
| *RV* 1 m | −0.175 | 0.310*** | 128 | 16 | 0 |
| *RV* 3 m | −0.046 | 0.284*** | 128 | 34 | 0 |
| *RA* 1 m | 0.812*** | 2.113*** | 128 | 128 | 0 |
| *RA* 3 m | −1.731*** | −0.459*** | 128 | 0 | 128 |
| *EU* 1 m | −0.276 | 0.423*** | 128 | 19 | 1 |
| *EU* 3 m | −0.278 | 0.314 | 128 | 8 | 0 |
| *EPU* 1 m | −0.105* | −0.022 | 64 | 0 | 4 |
| *EPU* 3 m | −0.045 | 0.062 | 64 | 0 | 0 |
| *MAC* 1 m | 0.226 | 0.699*** | 64 | 55 | 0 |
| *MAC* 3 m | −0.540*** | −0.127 | 64 | 0 | 44 |
| *FIN* 1 m | 0.924*** | 1.156*** | 64 | 64 | 0 |
| *FIN* 3 m | −0.874*** | −0.676*** | 64 | 0 | 64 |
| *IP* 1 m | −0.241 | 0.114 | 64 | 0 | 0 |
| *IP* 3 m | −0.112 | 0.243 | 64 | 1 | 0 |
| *TED* 1 m | −0.002 | 0.120 | 64 | 0 | 0 |
| *TED* 3 m | −0.099 | −0.002 | 64 | 0 | 0 |
| *VIX* 1 m | 0.211** | 0.311** | 64 | 64 | 0 |
| *VIX* 3 m | −0.208*** | −0.064 | 64 | 0 | 32 |
| *CLI* 1 m | −0.608* | −0.031 | 64 | 0 | 8 |
| *CLI* 3 m | 0.041 | 0.595** | 64 | 12 | 0 |

This table reports Leamer's (1983) extreme-bound analysis for the monthly U.S. realized volatility (*RV*). The benchmark HAR-RV-X model includes the lagged *RV, RA*, and *EU* over one- and three-month horizons. We estimate all possible combinations of the benchmark model with the other predictor variables *EPU, MAC, FIN, IP, TED, VIX*, and *CLI*. The first and second columns report the minimum and maximum parameter estimate from all possible combinations, while the third column reports the number of estimated models. The last two columns report the number of models in which the variable is significantly positive and negative at the 10% level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on the Newey and West (1987) standard errors. The estimations are based on 355 monthly observations. The sample period is January 1990 to July 2020.

Hence, even when we have already accounted for *RA* and *EU*, there is room for further improvement by including additional predictor variables. In this case, the additional explanatory power is mainly due to *FIN* (seen from the *F*-test and adjusted $R^2$). In the full model (Model 13), the coefficients for the one-month horizons of *RA*, *FIN*, and *VIX* are all positive and highly significant. However, we observe a reversal in the effect of these variables for the three-month horizons.

By comparing the adjusted $R^2$ values in the in-sample estimations, we can conclude that adding exogenous predictor variables to the HAR model is more beneficial at the monthly frequency than at the daily frequency. For example, the adjusted $R^2$ of daily *RV* increases from 0.634 for the HARQ-RV model (Model 3 in Table 2) to 0.663 for the benchmark model (Model 6 in Table 2), whereas the adjusted $R^2$ of the monthly *RV* increases from 0.477 for the HAR-RV model (Model 1 in Table 5) to 0.587 for the benchmark model (Model 4 in Table 5).

Table 6 presents the out-of-sample results for predicting monthly *RV* at the one-, three-, six-, and 12-month forecast horizons. For the one-month horizon, the results indicate that the benchmark model extended with *FIN* has the lowest RMSE. In addition, Diebold and Mariano's (1995) test shows that this model outperforms all other models, except for the HAR-RV and the benchmark models extended with *MAC, FIN*, and *VIX*. Similarly, at all the longer forecast horizons, the benchmark model extended with *FIN* has the lowest RMSE, which is significantly lower than most of the other models. For all of the four horizons, this model significantly outperforms the random walk and constant volatility model, which confirms the results of the daily frequency and underscores the advantages of employing HAR-RV-X models for volatility forecasting.

While the difference in performance between the best-performing HAR-RV-X and HAR-RV models is not statistically significant, even for the monthly frequency, the relative improvement in RMSE is greater for the monthly frequency than for the daily frequency. For instance, the RMSE is 4% lower for one-period-ahead forecasts for the monthly frequency, compared to 0.7% for the daily frequency. Moreover, the differences between the benchmark model extended with *FIN* and the HAR-RV model for the three- and six-month-ahead forecasts are approximately 10% and statistically significant at the 10% and 5% levels, respectively, especially when using conventional, instead of Newey and West (1987) standard errors (the results are available upon request). In sum, both the in- and out-of-sample analyses show that risk aversion and uncertainty variables are more helpful for predicting U.S. stock market *RV* at the monthly frequency than at the daily frequency.

## 5. International portfolio analysis

In this section, we analyze the world market as well as seven international stock markets (i.e., Canada, France, Germany, Hong Kong, Japan, Sweden, and the U.K.; see Section 2.1) to obtain an overall assessment of the predictive ability of U.S. risk aversion and uncertainty measures for international stock markets and their usefulness for portfolio analysis.[21] First, we illustrate the in- and out-of-sample results for international stock markets *RV* and *RC* (Section 5.1). Subsequently, we conduct an international portfolio analysis (Section 5.2).

[21] 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 can lead to worse performance, both in- and out-of-sample, in international portfolio analysis, compared to using the U.S. exogenous variable. The results are available upon request.

**Table 5**
In-sample HAR-RV-X models for monthly U.S. realized volatility.

| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.580$^{***}$ | −2.421$^{*}$ | 0.449$^{**}$ | −2.420$^{*}$ | −2.299$^{*}$ | −2.550$^{***}$ | −2.248$^{**}$ | −2.489$^{**}$ | −2.770$^{**}$ | −2.738$^{**}$ | −2.553$^{**}$ | −2.182$^{**}$ | −2.133$^{***}$ |
| Recession | 0.623$^{**}$ | 0.483$^{*}$ | 0.610$^{**}$ | 0.464$^{*}$ | 0.470$^{*}$ | 0.156 | 0.270 | 0.488$^{*}$ | 0.410 | 0.500$^{*}$ | 0.470$^{*}$ | 0.081 | 0.124 |
| *RV* 1 m | 0.523$^{***}$ | 0.270$^{**}$ | 0.436$^{***}$ | 0.298$^{***}$ | 0.300$^{***}$ | 0.158 | 0.089 | 0.306$^{***}$ | 0.281$^{***}$ | 0.126 | 0.296$^{***}$ | −0.151 | −0.145 |
| *RV* 3 m | 0.072 | 0.063 | 0.118 | 0.043 | 0.056 | 0.136 | 0.062 | 0.005 | 0.024 | 0.103 | −0.037 | 0.256$^{***}$ | 0.231$^{*}$ |
| *RA* 1 m | | 0.784$^{***}$ | | 0.813$^{***}$ | 0.812$^{***}$ | 1.140$^{***}$ | 1.788$^{***}$ | 0.853$^{***}$ | 0.839$^{***}$ | 1.010$^{***}$ | 0.979$^{***}$ | 2.057$^{***}$ | 2.104$^{***}$ |
| *RA* 3 m | | −0.429$^{***}$ | | −0.466$^{***}$ | −0.478$^{***}$ | −0.763$^{***}$ | −1.414$^{***}$ | −0.491$^{***}$ | −0.459$^{***}$ | −0.620$^{***}$ | −0.601$^{***}$ | −1.677$^{***}$ | −1.723$^{***}$ |
| *EU* 1 m | | | 0.363$^{*}$ | −0.143 | −0.165 | 0.242 | 0.184 | −0.132 | −0.170 | −0.077 | −0.207 | 0.423$^{***}$ | 0.346 |
| *EU* 3 m | | | −0.315$^{*}$ | 0.162 | 0.182 | −0.183 | −0.026 | 0.148 | 0.199 | 0.128 | 0.237$^{*}$ | −0.230 | −0.152 |
| *EPU* 1 m | | | | | −0.025 | | | | | | | | −0.080 |
| *EPU* 3 m | | | | | −0.045 | | | | | | | | 0.024 |
| *MAC* 1 m | | | | | | 0.648$^{***}$ | | | | | | 0.374$^{**}$ | 0.319$^{**}$ |
| *MAC* 3 m | | | | | | −0.510$^{***}$ | | | | | | −0.266$^{*}$ | −0.224 |
| *FIN* 1 m | | | | | | | 1.156$^{***}$ | | | | | 0.988$^{***}$ | 0.950$^{***}$ |
| *FIN* 3 m | | | | | | | −0.874$^{***}$ | | | | | −0.742$^{***}$ | −0.696$^{***}$ |
| *IP* 1 m | | | | | | | | −0.125 | | | | | −0.043 |
| *IP* 3 m | | | | | | | | 0.163 | | | | | 0.063 |
| *TED* 1 m | | | | | | | | | 0.070 | | | | 0.090 |
| *TED* 3 m | | | | | | | | | −0.018 | | | | −0.088 |
| *VIX* 1 m | | | | | | | | | | 0.230$^{*}$ | | 0.258$^{**}$ | 0.265$^{**}$ |
| *VIX* 3 m | | | | | | | | | | −0.098 | | −0.194$^{**}$ | −0.198$^{**}$ |
| *CLI* 1 m | | | | | | | | | | | −0.315 | | −0.109 |
| *CLI* 3 m | | | | | | | | | | | 0.357$^{*}$ | | 0.082 |
| Adj $R^2$ | 0.477 | 0.596 | 0.478 | 0.587 | *0.587* | 0.611 | 0.662 | 0.586 | 0.584 | 0.597 | 0.592 | 0.673 | 0.662 |
| BIC | 793 | 714 | 800 | 725 | 732 | 711 | 661 | 733 | 734 | 723 | 727 | 664 | 706 |
| LR | 192$^{***}$ | 101$^{***}$ | 188$^{***}$ | 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$^{***}$ | 3$^{**}$ | 35$^{***}$ | 18$^{***}$ | 27$^{***}$ | 44$^{***}$ | 23$^{***}$ | 23$^{***}$ | 27$^{***}$ | 26$^{***}$ | 29$^{***}$ | 14$^{***}$ |

This table reports the estimated parameters for the selected HAR-RV-X models for the monthly U.S. realized volatility (*RV*). The independent variables are the recession indicator and the lagged predictor variables over one- and three-month horizons. The predictor variables are: *RV, RA, EU, EPU, MAC, FIN, IP, VIX*, and *CLI*. This table also 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). The highest adjusted $R^2$, lowest BIC, and lowest PDC are marked in bold. $^{***}$, $^{**}$, and $^{*}$ indicate significance at the 1%, 5%, and 10% levels, respectively, based on the Newey and West (1987) parameter standard errors. The estimations are based on 355 monthly observations. The sample period is January 1990 to July 2020.

**Table 6**
Out-of-sample results for monthly U.S. realized volatility.

| | One-month | Three-month | Six-month | 12-month |
|---|---|---|---|---|
| Random walk | 2.151*** | 2.334*** | 2.528*** | 2.677** |
| Constant volatility | 2.685*** | 2.580** | 2.407*** | 2.234* |
| HAR-RV | 1.977 | 2.076 | 2.093 | 2.079 |
| *RV* + *RA* | 2.104* | 2.277* | 2.208 | 2.122 |
| *RV* + *EU* | 2.023** | 2.202** | 2.311** | 2.334*** |
| B (benchmark) | 2.117** | 2.300** | 2.328** | 2.311*** |
| *B* + *EPU* | 2.144** | 2.326** | 2.364** | 2.361*** |
| *B* + *MAC* | 2.130* | 2.292* | 2.236 | 2.156 |
| *B* + *FIN* | **1.897** | **1.887** | **1.880** | **2.000** |
| *B* + *IP* | 2.130** | 2.324** | 2.283** | 2.252*** |
| *B* + *TED* | 2.137** | 2.299** | 2.299** | 2.224** |
| *B* + *VIX* | 2.127*** | 2.264*** | 2.248** | 2.180*** |
| B + *CLI* | 2.058** | 2.144* | 2.132* | 2.148*** |
| *B* + *MAC* + *FIN* + *VIX* | 1.988 | 2.023 | 2.007 | 2.133*** |
| Full | 2.001*** | 1.965 | 1.951 | 2.069 |

This table reports the out-of-sample forecasting ability of the various HAR-RV-X models, the random walk, and the constant volatility model for the monthly U.S. realized volatility (*RV*). The HAR-RV model only includes lagged *RV* over the one- and three-month horizons. The benchmark (B) HAR-RV-X model includes lagged *RV*, *RA*, and *EU*. *B*+ denotes the benchmark model extended with one or more of the predictor variables: *EPU*, *MAC*, *FIN*, *IP*, *TED*, *VIX*, and *CLI*. The full HAR-RV-X model includes all of the predictor variables. We use the root mean squared error (RMSE) to compare the predicted volatility with the realized volatility for one-, three-, six-, and 12-month horizons. The lowest RMSE values are marked in bold. According to Diebold and Mariano's (1995) test, ***, **, and * indicate if the mean square error (MSE) is significantly different from the lowest MSE at the 1%, 5%, and 10% levels, respectively, based on the Newey and West (1987) standard errors. The estimations are based on a 120-month rolling window with 223 out-of-sample observations. The sample period is January 1990 to July 2020.

### 5.1. International volatility and correlation

In this section, we estimate the monthly HAR-RV-X model by using Eq. (4) for the *RV*s of the international stock markets, the world stock market, and the U.S. We also estimate the HAR-RC-X model in Eq. (5) for the *RC*s of all stock market pairs. For the *RV* models, the predictor variables are the lagged one- and three-month horizon local *RV*s of each stock market and the lagged one- and three-month horizons of the U.S. predictor variables. For the *RC* models, the predictor variables are the lagged one-and three-month horizon *RC*s as well as the lagged one-and three-month horizons of the U.S. predictor variables.

Table 7 reports the in-sample results for the world *RV* and the world–U.S. *RC* models. The results for the individual international stock market *RV*s and the international-U.S. *RC*s are reported in Table A1 in the Appendix.[22] The explanatory power of the included variables is higher for the U.S. *RV* than for the world *RV*, i.e., the adjusted $R^2$ is 0.546 for the world, compared to 0.662 for the U.S. Similar to the U.S. results, the one-and three-month lagged *RA* are significant for the world (this is also the case for all international stock markets; see Panel A in Table A1). The one-month lagged *FIN* is also marginally significant for the world market.

Regarding the in-sample estimations of the world–U.S. *RC* model, they have much lower explanatory power (adjusted *R*-square of 0.332) than those of the world *RV* model. The only significant variables are the lagged three-month *RC*, *MAC* (at the 10% level), and *TED*. The insignificance of the variables at the one-month lag indicates that the movement of the *RC* is more persistent than the *RV*. Meanwhile, the *F*-test is significant for both the world *RV* and the world–U.S. *RC* models, implying that the augmented models with *RA* and the uncertainty variables (i.e., the HAR-RV-X and HAR-RC-X models) outperform the HAR-RV and HAR-RC models, respectively (this is

[22] To save space, we only tabulate the full models with all of the predictor variables, and we only tabulate the *RC* models for the U.S. with another stock market.

**Table 7**
In-sample models for world realized volatility and world–U.S. realized correlation.

| | RV World | US | RC World–US |
|---|---|---|---|
| Intercept | −1.297* | −2.133*** | −1.503*** |
| Recession | 0.077 | 0.124 | −0.447** |
| *RV*/*RC* 1 m | 0.182** | −0.145 | −0.042 |
| *RV*/*RC* 3 m | 0.175* | 0.231* | 0.175** |
| *RA* 1 m | 1.221*** | 2.104*** | 0.150 |
| *RA* 3 m | −0.976*** | −1.723*** | −0.091 |
| *EU* 1 m | 0.163 | 0.346 | 0.037 |
| *EU* 3 m | −0.031 | −0.152 | 0.431 |
| *EPU* 1 m | −0.039 | −0.080 | −0.038 |
| *EPU* 3 m | 0.009 | 0.024 | 0.140 |
| *MAC* 1 m | 0.109 | 0.319** | −0.180 |
| *MAC* 3 m | −0.001 | −0.224 | 0.299* |
| *FIN* 1 m | 0.406* | 0.950*** | 0.173 |
| *FIN* 3 m | −0.292 | −0.696*** | −0.109 |
| *IP* 1 m | −0.045 | −0.043 | 0.127 |
| *IP* 3 m | 0.060 | 0.063 | −0.031 |
| *TED* 1 m | 0.105 | 0.090 | 0.110 |
| *TED* 3 m | −0.101 | −0.088 | −0.261** |
| *VIX* 1 m | 0.083 | 0.265** | 0.110 |
| *VIX* 3 m | −0.072 | −0.198** | −0.042 |
| *CLI* 1 m | −0.064 | −0.109 | 0.016 |
| *CLI* 3 m | 0.045 | 0.082 | 0.028 |
| Adj $R^2$ | 0.546 | 0.662 | 0.332 |
| *F*-test | 6*** | 14*** | 3*** |

This table reports the estimated parameters for the full HAR-RV-X (Panel A) and the HAR-RC-X (Panel B) models for the world and the U.S. The independent variables are the lagged variables over the one- and three-month horizons: World *RV*/world–US *RC*, *RA*, *EU*, *EPU*, *MAC*, *FIN*, *TED*, *IP*, *VIX*, and *CLI*. This table also reports the adjusted $R^2$ and *F*-test that compares the full model with the HAR-RV and HAR-RC models. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on the Newey and West (1987) standard errors. The estimations are based on 355 monthly observations. The sample period is from January 1990 to July 2020.

also the case for all of the international stock markets; see Table A1).

The results of the international out-of-sample analysis are reported in Table 8, in which we again focus on the world *RV* and the

**Table 8**
Out-of-sample results for monthly world realized volatility and world–U.S. realized correlation.

| | *RV* | *RC* |
|---|---|---|
| Random walk | 1.992 | 0.242*** |
| Constant vol./corr. | 2.562*** | 0.216*** |
| HAR-RV/RC | 1.916 | 0.194 |
| *RV*/*RC* + *RA* | 1.996* | 0.190 |
| *RV*/*RC* + *EU* | 1.932 | 0.190 |
| B (benchmark) | 1.983* | 0.189 |
| *B* + *EPU* | 1.976* | 0.193* |
| *B* + *MAC* | 1.956 | 0.191 |
| *B* + *FIN* | **1.914** | 0.190 |
| *B* + *IP* | 2.038** | 0.189 |
| *B* + *TED* | 1.992** | **0.188** |
| *B* + *VIX* | 2.000** | 0.195** |
| B + *CLI* | 1.975* | 0.194** |
| Full | 1.938 | 0.198*** |

This table reports the out-of-sample forecast results of various HAR-RV-X models, the random walk, and the constant volatility/correlation model for the monthly world realized volatility (*RV*) and the HAR-RC-X models for the world–U.S. realized correlation (*RC*). The HAR-RV/HAR-RC model only includes lagged *RV*/*RC* over the one- and three-month horizons. The benchmark (B) HAR-RV-X/HAR-RC-X model includes lagged *RV*/*RC*, *RA*, and *EU*. *B*+ denotes the benchmark model extended with one or more of the predictor variables: *EPU, MAC, FIN, IP, TED, VIX*, and *CLI*. The full HAR-RV-X model includes all of the available variables. We use the root mean squared error (RMSE) to compare the predicted volatility (correlation) with the *RV* (*RC*). The model with the lowest RMSE is indicated by boldface. According to Diebold and Mariano's (1995) test ***, **, and * indicate if the mean squared error (MSE) of the model is significantly different from the lowest MSE at the 1%, 5%, and 10% levels, based on the Newey and West (1987) standard errors. The estimations are based on a 120-month rolling window with 223 out-of-sample observations. The sample period is January 1990 to July 2020.

world–U.S. *RC*.[23] The results for the world *RV* are similar to those for the U.S. *RV* (see Table 6). Meanwhile, the benchmark model extended with *FIN* has the lowest RMSE and significantly outperforms most of the other models.

For the world–U.S. *RC*, the benchmark model extended with *TED* yields the lowest RMSE, which is consistent with the in-sample results in Table 7. Interestingly, the worst-performing models are the simple approaches (random walk and constant correlation) as well as the full model that includes all of the exogenous predictor variables. This reconfirms the benefits of our models for predicting volatility and correlation, while also suggesting that we should avoid using a richer model than necessary.

### 5.2. International portfolio analysis

In this section, we determine whether exogenous predictor variables are useful for international portfolio analysis, from the perspective of U.S. investors. For each month, we use the out-of-sample predicted *RV*s and *RC*s of all stock market pairs to form the predicted covariance matrix for each model.[24] In this case, we use two approaches to evaluate international portfolio performance across various models. The first approach assesses the economic value of different models, whereas the second approach investigates the differences in portfolio risk across the models.

We use the frameworks of Fleming et al. (2001), Fleming et al. (2003), and Bollerslev et al. (2018) to analyze the economic value of the different models. This approach provides the economic value of choosing the model with the highest utility, rather than an alternative model for an investor with quadratic utility for a given level of risk aversion. In this case, the economic value is denoted as *delta* and measures the maximum return an investor would be willing to give up to capture the performance gains associated with switching to the best (highest utility) model from an alternative model. Here, we follow Rapach et al. (2016) and use a risk aversion parameter equal to three.[25]

To assess the usefulness of the models in reducing portfolio risk, we use the market-neutral minimum-variance portfolio approach (e.g., Cosemans et al., 2016). We not only assume a single-factor model in which the factor is the U.S. stock market, but we also use all of the stock markets' predicted *RV*s and the international stock markets' *RC*s with the U.S. to estimate the predicted *betas* against the U.S. market. Following Cosemans et al. (2016), we use the predicted *beta* of the markets to forecast the covariance matrix implied by the single-factor model. Moreover, we construct a market-neutral, minimum-variance portfolio by minimizing the portfolio variance with the additional constraint that the ex-ante *beta* of the portfolio equals zero.[26]

Table 9 presents the results of the out-of-sample portfolio analysis for each model. For comparison, we report the results for an equally weighted portfolio (the last row). Panel A uses exogenous predictor variables in both the *RV* and *RC* models, whereas Panel B only uses exogenous predictor variables in the *RV* model. Since the results are qualitatively similar for the two sets of estimations, we mainly concentrate our discussion on the former. The similarity of the results of the two panels implies that the use of exogenous predictor variables is more important for volatility than for correlation models. This is consistent with the lower in-sample adjusted $R^2$ of the *RC* models, compared with the *RV* models for all international stock markets (see Tables 7 and A1).

The first column in Table 9 shows the economic value, i.e., the *delta*. Although the HAR-RV-X model with *RA* as the exogenous predictor variable has the highest utility, the difference in economic value from the HAR-RV-X model that includes *EU* is small (less than a 0.05% yearly return). Similarly, when exogenous variables are used to predict *RV* (Panel B), the HAR-RV-X model with *EU* has the highest utility. Meanwhile, the difference in economic value is large across some models. For instance, the *delta* is 2.967%, 0.856%, and 1.646% for the random walk, constant volatility/correlation, and full models, respectively. This indicates that investors are willing to sacrifice a 2.967% yearly return to invest in a portfolio based on the HAR-RV-X with *RA* model, instead of a portfolio based on the random walk approach. This also shows that investors are willing to give up a 0.318% yearly return for not switching to the HAR-RV/RC model from the HAR-RV-X model with *RA*.

The second column presents the means of the estimated realized *betas* from the market-neutral, minimum-variance portfolio for each model, which should be close to zero if the model successfully predicts volatility and correlation. Here, the lowest mean realized *beta* value is obtained for the benchmark model. The mean realized *beta* of the benchmark model is significantly lower than that of the random walk and benchmark models extended with *MAC, FIN*, and *VIX* as well as the full and equally weighted models. The *beta* of the equally weighted portfolio is approximately six times that of the benchmark model, which shows the degree of risk reduction when applying the optimization algorithm with a proper model.[27]

[23] The results for individual international stock markets and for longer forecasting horizons are available upon request.

[24] To ensure that the covariance matrices are positive definite, as in Voev (2008), we first use Cholesky decompositions of the *RC* matrices and predict the Cholesky series. Then, we reconstruct the variance and covariance forecasts.

[25] For robustness, we also use a risk aversion coefficient equal to 1 and 5, and the results remain qualitatively the same.

[26] We would like to thank the anonymous referee for this helpful suggestion.

[27] We also compare the yearly standard deviation for the minimum variance portfolios (MVPs) from different models and use Engle and Colacito's (2006) test to

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

| | Panel A | | Panel B | |
|---|---|---|---|---|
| Random walk | Delta | Beta | Delta | Beta |
| Random walk | 2.967 | 0.352*** | 2.714 | 0.352*** |
| Constant volatility/corr. | 0.856 | 0.115 | 0.604 | 0.115 |
| HAR-RV/RC | 0.318 | 0.132 | 0.066 | 0.132 |
| *RV/RC + RA* | | 0.108 | 0.208 | 0.107 |
| *RV/RC + EU* | 0.046 | 0.103 | | 0.101 |
| B (benchmark) | 0.082 | **0.099** | 0.112 | **0.079** |
| *B + EPU* | 0.156 | 0.152 | 0.102 | 0.111 |
| *B + MAC* | 0.323 | 0.153 | 0.218 | 0.139 |
| *B + FIN* | 0.115 | 0.135 | 0.449 | 0.101 |
| *B + IP* | 0.168 | 0.112 | 0.208 | 0.086 |
| *B + TED* | 0.721 | 0.130 | 0.464 | 0.104 |
| *B + VIX* | 0.213 | 0.104 | 0.157 | 0.082 |
| B + *CLI* | 0.164 | 0.129 | 0.190 | 0.100 |
| *B + MAC + FIN + VIX* | 0.439 | 0.204* | 0.311 | 0.165 |
| Full HAR-RV/RC-X | 1.646 | 0.223** | 0.982 | 0.187* |
| Equally weighted | | 0.623*** | | 0.623*** |

This table reports the out-of-sample portfolio analysis of the various HAR-RV-X/HAR-RC-X models, the HAR-RV-X/HAR-RC models, the random walk, and the constant volatility/correlation model using data for Canada, France, Germany, Hong Kong, Japan, Switzerland, the U.K., and the U.S. 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 10-year window of monthly *RV*s. The HAR-RV/HAR-RC models only include lagged *RV*/*RC* over the one- and three-month horizons. The benchmark (B) model includes lagged *RV*/*RC*, *RA*, and *EU*. *B*+ denotes the benchmark model extended with one or more of the predictor variables: *EPU, MAC, FIN, IP, TED, VIX*, and *CLI*. The full HAR-RV-X/HAR-RC-X model includes all of the predictor variables. The last row is for an equally weighted portfolio. In Panel A, we use exogenous predictor variables in both the *RV* and *RC* models, whereas in Panel B, we exclude the exogenous predictor variables in the *RC* models. Columns 1 and 3 give the economic value (*delta*) of each model compared to the best (highest utility) model, while Columns 2 and 4 show the averages of the estimated realized *betas* from market-neutral minimum-variance portfolio, in which the model with the lowest *beta* is indicated in boldface. ***, **, and * indicate that *beta* is significantly different from the best model at the 1%, 5%, and 10% levels, respectively, based on the Newey and West (1987) standard errors. The estimations are based on a 120-month rolling window with 223 out-of-sample observations. The sample period is January 1990 to July 2020.

In sum, our international portfolio analysis documents the importance for U.S. investors of considering the influence of *RA* and *EU* when estimating second-order moments. However, including too many exogenous predictor variables can lead to overfitting and sub-optimal portfolio compositions.

## 6. Conclusion

This study contributes to the existing literature by comparing the predictive ability of risk aversion and various sources of economic uncertainty (macroeconomic, financial, and economic policy measures) for stock market volatility and correlation. Our results provide new insights into the relative importance of these predictor variables in stock market volatility and correlation.

In order to examine the influence of risk aversion and various uncertainty predictor variables on U.S. stock market volatility, we use the HAR model extended with exogenous predictor variables of Corsi (2009). As a benchmark model, we use the HAR model extended with the risk aversion and economic uncertainty measures of Bekaert et al. (2022). Our analysis shows the importance of the risk-aversion measure proposed by Bekaert et al. (2022). The results may indicate that non-fundamental factors, such as sentiment, are important for predicting variations in realized volatility. In addition, we find that the financial market uncertainty index from Ludvigson et al. (2021) is beneficial for predicting monthly realized volatility when added to the benchmark model.

In this study, the financial market uncertainty index is constructed from a large number of financial market variables, enabling it to capture the overall uncertainty of financial markets. In contrast to previous research, we find that *EPU* does not provide useful information for predicting stock market volatility once we account for *RA* and *EU*. Similar results are obtained for *IP* and *CLI*. Our analyses also show that exogenous predictor variables are more useful for modeling *RV* at the monthly frequency than at the daily frequency. This is partly because fluctuations in uncertainty follow a much smoother path than changes in stock market volatility, and partly because some of the predictor variables are not available at the daily frequency.

Moreover, we analyze international stock market *RV* by using the same model. The empirical findings are largely identical to the U.S. findings, while the explanatory power of the predictor variables is much lower for predicting the *RC* between the U.S. and international stock markets than for predicting the stock market *RV*s. Finally, we conduct an international portfolio analysis by assessing the economic value of using different *RV* and *RC* models as well as investigating the models' risk reduction ability. We find that U.S. investors benefit from accounting for the risk aversion and economic uncertainty measures of Bekaert et al. (2022) when deciding on their portfolio composition, whereas overfitting the model with additional predictor variables worsens portfolio performance.

### Declaration of Competing Interest

None.

### Data availability

The authors do not have permission to share data.

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examine the relative performance of the various models. The model with *RV*/*RC* augmented with *EU* has the lowest standard deviation for the MVPs. The results are available upon request.

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## Appendix

Table A1

**Table A1**
In-sample models for international realized volatility and correlation.

| Panel A. Realized volatility | CA | FR | GE | HK | JP | SW | U.K. |
|---|---|---|---|---|---|---|---|
| Intercept | −1.486** | 0.350 | 0.021 | 0.157 | 0.144 | 0.248 | −0.506 |
| Recession | 0.140 | 0.369* | 0.303 | 0.183 | 0.329* | 0.451** | 0.317 |
| *RV* 1 m | −0.092 | 0.152 | 0.103 | 0.110 | 0.231*** | 0.104 | 0.085 |
| *RV* 3 m | 0.358*** | 0.297*** | 0.396*** | 0.351*** | 0.051 | 0.217*** | 0.253** |
| *RA* 1 m | 1.435*** | 1.404*** | 1.356*** | 0.914*** | 0.697*** | 1.457*** | 1.420*** |
| *RA* 3 m | −1.171*** | −1.272*** | −1.213*** | −0.736*** | −0.565** | −1.283*** | −1.225*** |
| *EU* 1 m | 0.396* | 0.133 | 0.269 | 0.123 | 0.635 | 0.273 | 0.277 |
| *EU* 3 m | −0.258 | −0.069 | −0.204 | −0.226 | −0.530 | −0.248 | −0.154 |
| *EPU* 1 m | −0.057 | −0.059 | 0.027 | −0.040 | −0.050 | −0.007 | 0.006 |
| *EPU* 3 m | −0.030 | −0.050 | −0.148** | −0.003 | −0.007 | −0.103 | −0.075 |
| *MAC* 1 m | 0.571*** | 0.138 | 0.230 | 0.091 | 0.001 | 0.221 | 0.273* |
| *MAC* 3 m | −0.439** | −0.166 | −0.300** | −0.137 | −0.003 | −0.298* | −0.276** |
| *FIN* 1 m | 0.443*** | 0.505** | 0.488** | 0.461** | 0.206 | 0.586*** | 0.517** |
| *FIN* 3 m | −0.213 | −0.319 | −0.305 | −0.295 | −0.138 | −0.433** | −0.322* |
| *IP* 1 m | 0.016 | 0.069 | −0.111 | −0.454 | −0.387 | −0.243 | −0.017 |
| *IP* 3 m | −0.040 | −0.050 | 0.095 | 0.304 | 0.250 | 0.211 | −0.023 |
| *TED* 1 m | 0.097 | 0.048 | −0.025 | 0.174 | 0.027 | −0.043 | 0.051 |
| *TED* 3 m | −0.051 | −0.132 | −0.080 | −0.059 | −0.007 | −0.010 | −0.083 |
| *VIX* 1 m | 0.133 | 0.083 | 0.073 | 0.069 | 0.159 | 0.119 | 0.129 |
| *VIX* 3 m | −0.199*** | −0.099 | −0.101 | −0.084 | −0.093 | −0.107 | −0.117* |
| *CLI* 1 m | 0.107 | −0.281 | −0.070 | 0.319 | 0.298 | 0.120 | −0.090 |
| *CLI* 3 m | −0.003 | 0.226 | 0.046 | −0.184 | −0.186 | −0.125 | 0.117 |
| Adj $R^2$ | 0.631 | 0.548 | 0.590 | 0.503 | 0.330 | 0.449 | 0.575 |
| *F*-test | 10*** | 6*** | 6*** | 4*** | 3*** | 5*** | 6*** |

| Panel B. Realized correlations with the U.S. market | CA | FR | GE | HK | JP | SW | U.K. |
|---|---|---|---|---|---|---|---|
| Intercept | −0.566 | −1.025* | −1.345** | 0.725 | 1.109* | −1.628*** | −1.163* |
| Recession | −0.338 | −0.342 | −0.141 | −0.065 | 0.181 | −0.195 | −0.404* |
| *RC* 1 m | −0.024 | 0.024 | −0.039 | −0.101** | 0.003 | −0.067 | −0.076 |
| *RC* 3 m | 0.261*** | 0.171** | 0.280*** | 0.159** | 0.128* | 0.261*** | 0.176** |
| *RA* 1 m | 0.335** | −0.108 | −0.094 | 0.372 | 0.380* | −0.192 | −0.290 |
| *RA* 3 m | −0.107 | 0.162 | 0.127 | −0.287 | −0.500** | 0.313 | 0.413 |
| *EU* 1 m | 0.133 | 0.078 | −0.075 | −1.054*** | −0.489 | −0.174 | 0.180 |
| *EU* 3 m | 0.009 | 0.308 | 0.504** | 1.041*** | 0.853*** | 0.439 | 0.084 |
| *EPU* 1 m | 0.023 | 0.086 | 0.121 | −0.084 | −0.013 | 0.098 | 0.088 |
| *EPU* 3 m | 0.023 | 0.008 | −0.113 | 0.043 | 0.059 | 0.034 | 0.032 |
| *MAC* 1 m | 0.078 | 0.022 | −0.070 | −0.224 | −0.216 | −0.041 | 0.153 |
| *MAC* 3 m | −0.105 | 0.078 | 0.166 | 0.329* | 0.231 | 0.113 | 0.052 |
| *FIN* 1 m | 0.108 | −0.123 | −0.105 | 0.154 | 0.472** | −0.072 | −0.320 |
| *FIN* 3 m | −0.013 | 0.173 | 0.183 | −0.233 | −0.320 | 0.115 | 0.304 |
| *IP* 1 m | −0.079 | 0.195 | 0.244 | 0.689*** | 0.479* | 0.369 | 0.095 |
| *IP* 3 m | −0.043 | −0.151 | −0.143 | −0.561** | −0.370 | −0.315 | −0.092 |
| *TED* 1 m | 0.016 | −0.049 | 0.113 | −0.003 | 0.088 | −0.158 | −0.026 |
| *TED* 3 m | −0.052 | −0.077 | −0.264** | −0.015 | −0.084 | 0.109 | −0.115 |
| *VIX* 1 m | 0.201** | 0.098 | 0.049 | 0.150* | 0.131 | 0.021 | 0.018 |
| *VIX* 3 m | −0.140 | −0.117 | −0.030 | 0.023 | −0.134 | −0.024 | 0.006 |
| *CLI* 1 m | 0.326 | −0.058 | −0.123 | −0.823*** | −0.320 | 0.131 | −0.042 |
| *CLI* 3 m | −0.195 | 0.188 | 0.204 | 0.852*** | 0.404 | 0.009 | 0.198 |
| Adj $R^2$ | 0.204 | 0.290 | 0.447 | 0.068 | 0.154 | 0.209 | 0.162 |
| *F*-test | 2** | 3*** | 3*** | 2** | 2** | 2** | 2** |

Panel A reports the estimated parameters regarding the full HAR-RV-X model for seven international stock market *RVs* (Canada [CA], France [FR], Germany [GE], Hong Kong [HK], Japan [JP], Switzerland [SW], and the U.K.). Panel B reports the estimated parameters regarding the full HAR-RC-X model for the local-U.S. *RCs*. The independent variables are the lagged variables over the one- and three-month horizons: Local *RV* or local-U.S. *RC, RA, EU, EPU, MAC, FIN, TED, IP, VIX,* and *CLI*. This table also reports the adjusted $R^2$ and *F*-test that compares the full model with the HAR-RV and HAR-RC models. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on the Newey and West (1987) standard errors. The estimations are based on 355 monthly observations. The sample period is January 1990 to July 2020.

## References

Asgharian, H., Christiansen, C., Hou, A.J., 2015. Effects of macroeconomic uncertainty on the stock and bond markets. Finance Res. Lett. 13, 10–16.
Audrino, F., Corsi, F., 2010. Modeling tick-by-tick realized correlations. Comput. Stat. Data Anal. 54, 2372–2382.
Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61, 1645–1680.
Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131, 1593–1636.
Bansal, R., Yaron, A., 2004. Risks for the long run: a potential resolution of asset pricing puzzles. J. Finance 59, 1481–1509.
Bansal, R., Khatchatrian, V., Yaron, A., 2005. Interpretable asset markets? Eur. Econ. Rev. 49, 531–560.
Bansal, R., Kiku, D., Shaliastovich, I., Yaron, A., 2014. Volatility, the macroeconomy, and asset prices. J. Finance 69, 2471–2511.
Bekaert, G., Hoerova, M., 2014. The VIX, the variance premium and stock market volatility. J. Econom. 183, 181–192.
Bekaert, G., Hoerova, M., 2016. What do asset prices have to say about risk appetite and uncertainty? J. Bank Financ. 67, 103–118.
Bekaert, G., Engstrom, E.C., Xing, Y., 2009. Risk, Uncertainty, and Asset Prices. J. financ. econ. 91, 59–82.
Bekaert, G., Engstrom, E.C., Xu, N.R., 2022. The time variation in risk appetite and uncertainty. Manage. Sci. 68, 3975–4004.
Bollerslev, T., Patton, A.J., Quaedvlieg, R., 2016. Exploiting the errors: a simple approach for improved volatility forecasting. J. Econom. 192, 1–18.
Bollerslev, T., Patton, A.J., Quaedvlieg, R., 2018. Modeling and forecasting (un)reliable realized covariances for more reliable financial decisions. J. Econom. 207, 71–91.
Brogaard, J., Detzel, A., 2015. The asset-pricing implications of government economic policy uncertainty. Manage Sci 61, 3–18.
Buccheri, G., Corsi, F., 2019. HARK the SHARK: realized volatility modeling with measurement errors and nonlinear dependencies. J. Financ. Econometrics 1–36.
Campbell, J.Y., Cochrane, J.H., 1999. By force of habit: a consumption-based explanation of aggregate stock market behavior. J. Polit. Econ. 107, 205–251.
Chernov, M., 2007. On the role of risk premia in volatility forecasting. J. Bus. Econ. Stat. 25, 411–426.
Chiu, C.W., Harris, R.D.F., Stoja, E., Chin, M., 2018. Financial market volatility, macroeconomic fundamentals and investor sentiment. J. Bank Financ. 92, 130–145.
Clements, A., Preve, D.P.A., 2021. A practical guide to harnessing the har volatility model. J. Bank Financ. 133.
Cornett, M.M., McNutt, J.J., Strahan, P.E., Tehranian, H., 2011. Liquidity risk management and credit supply in the financial crisis. J. financ. econ. 101, 297–312.
Corsi, F., 2009. A simple approximate long-memory model of realized volatility. J. Financ. Econometrics 7, 174–196.
Corsi, F., Renò, R., 2012. Discrete-time volatility forecasting with persistent leverage effect and the link with continuous-time volatility modeling. J. Bus. Econ. Stat. 30, 368–380.
Corsi, F., Mittnik, S., Pigorsch, C., Pigorsch, U., 2008. The volatility of realized volatility. Econom. Rev. 27, 46–78.
Cosemans, M., Frehen, R., Schotman, P.C., Bauer, R., 2016. Estimating security betas using prior information based on firm fundamentals. Rev. Financial Stud. 29, 1072–1112.
Demirer, R., Omay, T., Yuksel, A., Yuksel, A., 2018. Global risk aversion and emerging market return comovements. Econ. Lett. 173, 118–121.
Diebold, F.X., Mariano, R.S., 1995. Comparing predictive accuracy. J. Bus. Econ. Stat. 13, 253–263.
Engle, R.F., Colacito, R., 2006. Testing and valuing dynamic correlations for asset allocation. J. Bus. Econ. Stat. 24, 238–253.
Engle, R.F., Ghysels, E., Sohn, B., 2013. Stock market volatility and macroeconomic fundamentals. Rev. Econ. Stat. 95, 776–797.
Tian, F., Yang, K., Chen, L., 2017. Realized volatility forecasting of agricultural commodity futures using the HAR model with time-varying sparsity. Int. J. Forecast. 33, 132–152.
Fleming, J., Kirby, C., Ostdiek, B., 2001. The Economic Value of Volatility Timing. J. Finance 56, 329–352.
Fleming, J., Kirby, C., Ostdiek, B., 2003. The economic value of volatility timing using "realized" volatility. J. financ. econ. 67, 473–509.
Hamilton, J.D., Lin, G., 1996. Stock market volatility and the business cycle. J. Appl. Econ. 11, 573–593.
Haugom, E., Langeland, H., Molnár, P., Westgaard, S., 2014. Forecasting volatility of the US oil market. J Bank Financ 47, 1–14.
Haugom, E., Westgaard, S., Solibakke, P.B., Lien, G., 2011. Realized volatility and the influence of market measures on predictability: analysis of nord pool forward electricity data. Energy Econ. 33, 1206–1215.
Jondeau, E., Rockinger, M., 2006. The Copula-GARCH model of conditional dependencies: an international stock market application. J. Int. Money Financ. 25, 827–853.
Jurado, K., Ludvigson, S.C., Ng, S., 2015. Measuring uncertainty. Am. Econ. Rev. 105, 1177–1216.
Kandel, S., Stambaugh, R.F., 1990. Expectations and volatility of consumption and asset returns. Rev. Financ. Stud. 3, 207–232.
Lamoureux, C.G., Lastrapes, W.D., 1993. Forecasting stock-return variance: toward an understanding of stochastic implied volatilities. Rev. Financ. Stud. 6, 293–326.
Leamer, E., 1983. Let's take the con out of econometric. Am. Econ. Rev. 73, 1–43.
Levine, R., Renelt, D., 1992. A sensitivity analysis of cross-country growth regressions. Am. Econ. Rev. 82, 942–963.
Liu, L., Zhang, T., 2015. Economic Policy Uncertainty and Stock Market Volatility. Financ. Res. Lett. 15, 99–105.
Ljung, G.M., Box, G.E.P., 1978. On a measure of lack of fit in time series models. Biometrika 65, 297–303.
Ludvigson, S.C., Ma, S., Ng, S., 2021. Uncertainty and business cycles: exogenous impulse or endogenous response? Am. Econ. J.: Macroeconomics 13, 369–410.
Mittnik, S., Robinzonov, N., Spindler, M., 2015. Stock market volatility: identifying major drivers and the nature of their impact. J. Bank Financ. 58, 1–14.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Rapach, D.E., Ringgenberg, M.C., Zhou, G., 2016. Short interest and aggregate stock returns. J. financ. econ. 121, 46–65.
Schwert, G.W., 1989. Why does stock market volatility change over time? J. Finance 44, 1115–1153.
HD Voev, V., 2008. Dynamic modelling of large-dimensional covariance matrices. In: Bauwens, L., Pohlmeier, W., Veredas, D. (Eds.), High Frequency Financial Econometrics. Studies in Empirical Economics, p. 293 –231.
Whaley, R.E., 2000. The investor fear gauge. J. Portfolio Manage. 26, 12–17.
Xu, N.R., 2019. Global risk aversion and international return comovements. Working paper. SSRN Electr. J..