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Global equity market volatility spillovers: A broader role for the United States

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ABSTRACT

Rapach et al. (2013) recently showed that U.S. equity market returns contain valuable information for improving return forecasts in global equity markets. In this study, we extend the work of Rapach et al. (2013) and examine whether U.S.-based equity market information can be used to improve realized volatility forecasts in a large cross-section of international equity markets. We use volatility data for the U.S. and 17 foreign equity markets from the Oxford Man Institute's realized library, and augment our benchmark HAR model with U.S. equity market volatility information for each foreign equity market. We show that U.S. equity market volatility information improves the out-of-sample forecasts of realized volatility substantially in all 17 foreign equity markets that we consider. Not only are these forecast gains highly significant, they also produce out-of-sample R^2 values of between 4.56% and 14.48%, with 9 being greater than 10%. The improvements in out-of-sample forecasts remain statistically significant for horizons up to one month ahead. A substantial part of these predictive gains is driven by forward-looking volatility, as captured by the VIX.

' *…since the US equity market is the world's largest, investors likely focus more intently on this market, so that information on macroeconomic fundamentals relevant for equity markets worldwide diffuses gradually from the US market to other countries' markets.*'

[Rapach, Strauss, & Zhou, 2013, p. 1635]

1. Introduction

In a recent influential paper, Rapach et al. (2013) showed that the equity market returns of the United States (US) have significant predictive power for forecasting equity returns in a large cross-section of international equity markets. This predictive power is attributed to the leading role played by the US in generating relevant macroeconomic and financial information for both US and non-US investors. Rapach et al. (2013) argue that information frictions cause information to diffuse only gradually from the US to other equity markets around the world, leading to lagged US returns having predictive content. The US is the world's largest economy, is a large and important trading partner for many countries, and has the world's largest equity market in terms of market capitalization. Thus, when forming investment decisions, investors who take a global investment perspective are focused intently on not only developments in macroeconomic and financial fundamentals in the

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US, but also the formation of expectations and risk premia that arise from this process.[1]

The objective of this study is to provide a first comprehensive analysis of the predictive content of US-based equity market volatility information for volatility forecasts in a large cross-section of 17 international (non-US) equity markets. For this purpose, we use daily realized volatility data from the Oxford Man Institute's realized library and augment the well-known and widely used heterogeneous autoregressive (HAR) model of Corsi (2009) with (lagged) daily, weekly and monthly US realized volatility and VIX HAR components. We utilize the HAR model of Corsi (2009) as our benchmark realized volatility model for measuring the contribution of US-based volatility information to realized volatility forecasts in international equity markets, employing standard in-sample and out-of-sample evaluation criteria. In this context, our study can be viewed as an extension of the work of Rapach et al. (2013), but with our analysis focussing on the role of the US as a source of relevant volatility information. We find US-based volatility information to play an overwhelmingly strong role for all 17 international equity markets that we consider.

Our study is related to a growing body of volatility spillover literature. The literature on spillovers in international equity markets goes back to the research of Eun and Shim (1989), Hamao et al. (1990) and Lin et al. (1994). More recent studies include those of Baur and Jung (2006) and Savva, Osborn, and Gill (2009), among others. The contributions to this body of literature typically differ in their definitions of the interdependence measure adopted and the modelling approaches used. For example, Hamao et al. (1990) use a generalized autoregressive conditional heteroscedastic (GARCH) type of model to analyze spillovers across three major equity markets. They define spillovers as impacts from foreign stock markets on the conditional mean and variance of daytime returns in the subsequently traded markets. Their results show evidence of volatility spillovers across these markets. Similarly, Lin et al. (1994) employ a signal extraction model with GARCH innovations in order to analyze spillover effects between two major equity markets. In contrast to Hamao et al. (1990), Lin et al. (1994) do not find any evidence of spillover effects between the two stock markets, but rather attribute their contradictory results to non-synchronous trading and stale quotes at opening time. On the other hand, Eun and Shim (1989) apply a vector autoregressive model (VAR) to stock market returns from nine international markets, and use simulated responses to trace the spillover effects of international stock market shocks. They find that US stock market shocks are transmitted to the other markets quickly, but not vice versa, highlighting the dominant role of the US. More recently, Savva et al. (2009) use a dynamic conditional correlation (DCC) model to analyze return and volatility spillovers across four major stock markets. Their results show that both domestic stock prices and volatilities are subject to spillover effects. In fact, they find more evidence of spillovers from Europe to the US than the other way around. However, this finding might be attributable to the pseudo-closing approach that they use in order to avoid synchronous trading.

With the increasing availability of high-frequency data, the literature on volatility spillovers has again gained momentum (see Bonato, Caporin, & Ranaldo, 2013; Diebold & Yilmaz, 2014, 2016; Dimpfl & Jung, 2012; Fengler & Gisler, 2015, among others). Diebold and Yilmaz (2014) model realized volatility as a vector autoregressive process and define volatility spillovers based on a multiple-step-ahead forecast-error variance decomposition. Their results suggest that there are strong realized volatility spillovers across financial institutions, particularly during crises. Using a similar approach, Fengler and Gisler (2015) extend the results of Diebold and Yilmaz (2012, 2014) by including realized covariances in the spillover transmission mechanism. They show that realized covariance spillovers are substantial, and allow for an earlier detection of the recent financial and debt-ceiling crises that are attributable to a flight-to-quality phenomenon. Bonato et al. (2013), on the other hand, define spillovers as the dependence of realized covariance on cross-lag realized covariances. They model realized covariance matrix as a Wishart autoregressive process, and find that sector and currency covariance spillovers improve the forecasting performance. Similarly, Dimpfl and Jung (2012) model realized volatility and return spillovers around the globe in a structural VAR framework. They find significant return and realized volatility spillovers that also result in forecast improvements.[2] In summary, the spillover literature has analyzed return and volatility spillovers in international stock markets extensively. However, the literature to date has not analyzed the predictive content of US realized volatility information for realised volatility forecasts in a large cross-section of international equity markets. Our study aims to fill this gap.

Although our study is related to the volatility spillover literature, we intentionally avoid the use of (structural) VAR approaches for modelling the information flow from the US to international equity markets. Standard structural VAR models require assumptions on the causal ordering

[1] The New York Stock Exchange (NYSE) is by far the largest equity market in the world, with a market capitalization of over 21 Trillion US Dollars (as of the end of 2014). The second is the NASDAQ, with a market capitalization of around 7 Trillion. Tokyo and London are the next biggest, with market capitalizations of around 4 Trillion. Moreover, an abundance of economic and financial data are released every day. These range from soft survey data related to durable goods, inventories, employment reports, the ISM (manufacturing) index, PMIs (purchasing manager indices) and the like, to hard data releases related to jobless claims, home sales, residential construction, personal income and outlays, PPI, CPI, employment and GDP figures. International financial agents and the financial media focus on these releases intently. Also, in terms of a calender (or trading) day timeline, it is the last (or one of the last) equity markets to close. As market participants begin work on a given day, they naturally look at important financial and economic developments in the US first. The dominant role of the US market as a source of both return and volatility transmission in international equity markets has been documented in numerous multi-country studies (see for example Becker, Finnerty, & Friedman, 1995; Engle, 1990; Hamao, Masulis, & Ng, 1990; King & Wadhwani, 1990; Lin, Engle, & Ito, 1994, and others).

[2] The modelling of spillover effects also plays a much broader role in the financial stability literature. For instance, given the role of US volatility and an interconnected world, it may be important to account for US-based information when designing macro-prudential stress tests, especially for Eastern European countries. See for instance Buncic and Melecky (2013) for a recent study as to how this could be implemented.

if impulse responses or forecast error variance decompositions are used as measures of spillovers. This may not be a problem for smaller VARs, where the causal ordering is known from the underlying assumption as to which equity market generates the most important information (i.e., the US), for instance, or in cases where the causal ordering is based on the chronological structure of the markets that are analysed (see for example Dimpfl & Jung, 2012; Knaus, 2014). Nevertheless, since we are considering realized volatility data for 17 international equity markets, it becomes much more difficult to justify the ordering of the countries in a structural VAR. Also, overlapping trading hours mean that one can only analyze up to three different international stock markets (i.e., over three different trading/time zones). Moreover, estimating unrestricted VARs with large numbers of variables is highly inefficient, leading to poor out-of-sample forecast performances. Thus, we prefer to examine the role of the US as a source of volatility information within our proposed simple augmented HAR modelling framework.

Using daily realized volatility data for the US and 17 international equity markets, covering the period from January 3, 2000, to November 13, 2015, we find the US equity market to play a strong role internationally as a source of volatility information. Our in-sample results show that US-based volatility information is jointly highly significant. The daily and weekly HAR components of the log VIX, together with the daily and monthly HAR components of the US realized volatility, are the most important sources of volatility information from the US. For some equity markets, such as the All Ordinaries and the EURO STOXX 50, the parameter estimate on the daily US HAR component has a larger magnitude than its own daily HAR component, suggesting that the previous day's high frequency volatility information from the US is more important than its own lagged volatility. Moreover, our in-sample analysis shows that the low frequency volatility component from the US has a negative effect on the realized volatility in non-US equity markets. This finding is consistent across all 17 of the international equity markets that we consider.

Our out-of-sample analysis shows that one-step-ahead forecasts from the augmented HAR model with US volatility information are highly significant, yielding Clark and West (2007) adjusted t-statistics of at least 8.4 and as high as 15.7, indicating rather strong rejections of the null hypothesis of no forecast improvement. The one-step-ahead out-of-sample R^2 values range from 4.56% (Hang Seng) to 14.84% (All Ordinaries), and are above 10% for nine of the 17 equity markets that we analyse. Thus, the forecast improvements are not only highly statistically significant, but also sizeable economically. To put these magnitudes into perspective, Patton and Sheppard (2015) recently documented improvements in out-of-sample R^2 values of in the order of 2.5%–3% by splitting the volatility into bad and good volatility states (in addition to various other considerations related to leverage and signed jumps). Thus, improvements in excess of 10% are substantial. Our out-of-sample analysis also shows that forecast improvements are experienced consistently over the full out-of-sample period, and are not driven purely by individual episodes. The forecast improvements for the multiple-step-ahead horizon remain highly significant (at the 1% level) for all 17 international equity markets at the five-day-ahead (one week) and 10-day-ahead (two week) horizons, and start to deteriorate at the 22-day-ahead (one month) horizon. The improvements in the 22-day-ahead forecasts remain significant and produce positive out-of-sample R^2 values for 12 of the 17 equity markets that we analyse. Overall, our results show that US-based volatility data are most informative for forecasts of realized volatility for the All Ordinaries index and all of the European equity markets that are included in our comparison.

The remainder of the paper is organised as follows. In Section 2, we outline how realized volatility is modelled and how we extend the standard HAR model of Corsi (2009) by augmenting it with US-based information about equity market volatility. The data that we use in the study are described in detail in Section 3. In Section 4, we evaluate the importance of US-based volatility information for the determination of volatility in 17 international (non-US) equity markets, by means of in-sample and out-of-sample evaluations. In Section 5, we provide an analysis of the robustness of our findings. Lastly, we conclude the study.

2. Modelling the volatility

This section outlines the modelling approach that we use to assess the role played by US equity market volatility information in improving realized volatility forecasts in a large cross-section of international equity markets. Before describing the empirical model that we employ for modelling and forecasting realized volatility in international equity markets, we first briefly describe the background that links empirical realized volatility to its theoretical counterpart, integrated volatility.

2.1. Theoretical framework

Let p_t denote the logarithm (log) of an asset price at time t. The log asset price is assumed to be a continuous-time diffusion process that is driven by Brownian motion, with the dynamics described by the following stochastic differential equation:

$$dp_t = \mu_t dt + \sigma_t dW_t, \tag{1}$$

where μ_t is a predictable and locally bounded drift term, σ_t is a càdlàg volatility process that is bounded away from zero, and W_t is a standard Brownian motion. The quadratic variation (QV) process of p_t is given by[3]:

$$\mathrm{QV}_t = \int_0^t \sigma_s^2 ds. \tag{2}$$

In the absence of jumps, as is the case in our setting in Eq. (1), the term $\int_0^t \sigma_s^2 ds$ in Eq. (2) is known as the integrated variance (IV) of the process p_t.

[3] The quadratic variation process of p_t is defined as $[p_t] = \mathrm{plim}_{m\to\infty} \sum_{k=1}^{m}(p(t_k) - p(t_{k-1}))^2$, where plim denotes convergence in probability, and $0 = t_0 \le t_1 < \cdots < t_m = t$ is a partition such that $\sup_k\{t_{k+1} - t_k\} \to 0$ as $m \to \infty$ (Jacod & Shiryaev, 1987).

By definition, the simplest consistent estimator of QV in Eq. (2) is the realized variance (RV), which is computed as the sum of discretely-observed squared intraday log returns. More formally, let $r_{t,i}$ be the log return observed at time t in the ith interval of an equidistant grid with a total of m intervals. Then, the classical RV estimator of QV in Eq. (2) is defined as:

$$\mathrm{RV}_t = \sum_{i=1}^{m} r_{t,i}^2, \tag{3}$$

and its square root $\sqrt{\mathrm{RV}_t}$ is known as the *realized volatility*. The general properties of the estimator in Eq. (3) are summarised by Andersen, Bollerslev, Diebold, and Labys (2003).

2.2. Empirical volatility model

There exist three broad classes of empirical models for RV. The first belongs to the traditional ARMA and fractionally integrated ARMA (ARFIMA) classes of long-memory time series models for RV (see Andersen et al., 2003; Baillie, 1996; Baillie, Bollerslev, & Mikkelsen, 1996; Comte & Renault, 1996, 1998, among many others). The second class considers nonlinear time series models, where long-memory patterns in RV are generated spuriously from nonlinear short-memory models with structural breaks or regime switches (see for instance the papers by Chen, Härdle, & Pigorsch, 2010; Fengler, Mammen, & Vogt, 2015; McAleer & Medeiros, 2008, and others). The third belongs to the class of heterogeneous autoregressive (HAR) models for RV, as initially introduced into the realized variance modelling literature by Corsi (2009).

We use the HAR model of Corsi (2009) as our benchmark RV model for each of the foreign equity markets that we consider. The HAR model has a cascade-type structure, where the volatility at any point in time is constructed as a linear combination of daily, weekly and monthly volatility components. This temporal cascade structure is motivated by the so-called heterogeneous market hypothesis (HMH) of Müller et al. (1993), where it is assumed that financial markets are populated by heterogeneous agents, each with different endowments, risk profiles, institutional constraints and information processing capabilities, as well as various other characteristics (see Corsi, 2009, for a more detailed discussion). The defining feature of the HAR model is that each agent has a different time horizon for trading. The intuition is that the short-term volatility does not matter to a long-term investor, whereas the long-term volatility is still of importance to short-term investors because of its impact on the investment opportunity set.

To formalise the structure of the HAR model for RV, let $\log \mathrm{RV}_t^{(d)} = \log \mathrm{RV}_t$, $\log \mathrm{RV}_t^{(w)} = \frac{1}{5}\sum_{i=1}^{5} \log \mathrm{RV}_{t+1-i}$ and $\log \mathrm{RV}_t^{(m)} = \frac{1}{22}\sum_{i=1}^{22} \log \mathrm{RV}_{t+1-i}$ be the daily, weekly, and monthly HAR components. The HAR model is then defined as[4]:

$$\begin{aligned}\log \mathrm{RV}_{t+1} &= b_0 + b^{(d)} \log \mathrm{RV}_t^{(d)} + b^{(w)} \log \mathrm{RV}_t^{(w)} \\ &\quad + b^{(m)} \log \mathrm{RV}_t^{(m)} + \epsilon_{t+1},\end{aligned} \tag{4}$$

where ϵ_{t+1} is an innovation term. One of the main attractions of the HAR model in Eq. (4) is its simplicity. Once the daily, weekly, and monthly volatility components have been constructed, the HAR model can be estimated by ordinary least squares (OLS) regression. Moreover, the HAR model is an extremely difficult benchmark model to beat in out-of-sample forecast evaluations, due to its parsimonious setup (see Corsi, Audrino, & Renó, 2012, for a recent survey of different types of models for RV that have been evaluated against the HAR model). Since we are interested primarily in a real time out-of-sample comparison of the predictive content of US equity market volatility information on the volatility in other global equity markets, it is necessary to update the model parameters of interest recursively when constructing the forecasts. Unlike AR(FI)MA and other more general nonlinear time series models, which require a numerical optimisation of the likelihood function, and therefore are time consuming to estimate, as well as frequently being numerically unstable, the HAR model in Eq. (4) can be estimated efficiently and accurately by standard OLS procedures.

At this point, we should also highlight the fact that the HAR model of Corsi (2009) has undergone numerous refinements since its initial introduction. For instance, some recent evidence suggests that separating the quadratic variation process in Eq. (2) into continuous and jump component parts can lead to better out-of-sample forecasts (see for instance Andersen et al., 2007; Corsi et al., 2010; Corsi & Renó, 2012). Moreover, allowing for nonlinear and asymmetric effects in the HAR model, such as the leverage effect, also seems to be beneficial for out-of-sample forecasting (see Bollerslev, Litvinova, & Tauchen, 2006; Chen & Ghysels, 2011; Corsi & Renó, 2012; Patton & Sheppard, 2015, among others). Nevertheless, in spite of these findings, we want to abstract from the inclusion of such refinements of the HAR model in this study, and instead focus our attention solely on the role of the US as a source of information in relation to international asset price volatility, and, most importantly, on the question of whether this information can be exploited in order to improve forecasts of the realized volatility in other global equity markets.[5] In studies using S&P 500 RV data, the improvements

[4] Note here that the original formulation of the HAR model by Corsi (2009) used RV instead of log RV in the HAR specification in Eq. (4). Nevertheless, there has been a shift toward modelling the log RV series. In the words of Andersen, Bollerslev, and Diebold (2007, p. 704): '*from a modeling perspective, the logarithmic realized volatilities are more amenable to the use of standard time series procedures*'. Moreover, log transformed RV data are much closer to being normally distributed, and there is also no need to impose any non-negativity restrictions on the fitted and forecasted volatilities. We will therefore follow Corsi, Pirino, and Renó (2010), Corsi and Renó (2012) and many others in the empirical RV literature and use log RV in the HAR model.

[5] Evidently, as the number of regressors grows, one could also make the modelling of the HAR more flexible by using either a time-varying parameter model, like those that were used by Buncic and Moretto (2015), Buncic and Piras (2016) and Grassi, Nonejad, and de Magistritis (2014), or a shrinkage estimator such as the lasso for variable selection, as was done by Buncic and Melecky (2014) in a cross-sectional setting. Nevertheless, despite the fact that our econometric modelling could be extended to address additional, potentially important features in the data, this would abstract further from our consideration of the information contained in US volatility data for forecasting the volatility in international equity markets.

in out-of-sample forecast performances seem to be rather marginal relative to the magnitudes that we find at the international level. For instance, the models considered by Patton and Sheppard (2015), which allow the volatility to be split into bad and good volatility components (in addition to various other considerations related to leverage and signed jumps), lead to improvements in the out-of-sample R^2 values of around 2.5%–3% points at best (see Table 6 of Patton & Sheppard, 2015). Another recent study by Prokopczuk, Symeonidis, and Wese Simen (in press), which analysed the impacts of jumps on energy-related asset prices, found that jumps do not improve the out-of-sample forecasts of the volatility. Their findings are robust to a number of different jump detection procedures, and also to varying the size of the estimation window.

We assess the value of US equity market volatility data for forecasts of the log RV in other equity markets around the world by augmenting each individual foreign (local) equity market's benchmark HAR model with US volatility information. This is achieved by adding the log RV and log VIX HAR components from the US as predictor variables. Since the VIX displays a rather strong long-range dependence, it appears to be desirable to apply a HAR-type structure. In fact, Fernandes, Medeiros, and Scharth (2014) recently assessed the success of different HAR type models in forecasting the VIX, and found that a pure HAR specification as per Corsi (2009) is very difficult to beat out-of-sample.[6] We specify the following *augmented* HAR model for each of the 17 international equity markets that we consider:

$$\begin{aligned}
&\log \mathrm{RV}_{t+1} \\
&= \overbrace{\beta_0 + \beta^{(d)} \log \mathrm{RV}_t^{(d)} + \beta^{(w)} \log \mathrm{RV}_t^{(w)} + \beta^{(m)} \log \mathrm{RV}_t^{(m)}}^{\text{benchmark (local) HAR components of each foreign equity market}} \\
&\quad + \underbrace{\beta_{\mathrm{VIX}}^{(d)} \log \mathrm{VIX}_t^{(d)} + \beta_{\mathrm{VIX}}^{(w)} \log \mathrm{VIX}_t^{(w)} + \beta_{\mathrm{VIX}}^{(m)} \log \mathrm{VIX}_t^{(m)}}_{\text{US volatility information: VIX HAR components}} \\
&\quad + \underbrace{\beta_{\mathrm{US}}^{(d)} \log \mathrm{RV}_{t,\mathrm{US}}^{(d)} + \beta_{\mathrm{US}}^{(w)} \log \mathrm{RV}_{t,\mathrm{US}}^{(w)} + \beta_{\mathrm{US}}^{(m)} \log \mathrm{RV}_{t,\mathrm{US}}^{(m)}}_{\text{US volatility information: RV HAR components}} \\
&\quad + \epsilon_{t+1}^{\mathrm{US}}, \qquad (5)
\end{aligned}$$

where the daily, weekly, and monthly HAR components for US log RV and log VIX, denoted by $\log \mathrm{RV}_{t,\mathrm{US}}^{(\cdot)}$ and $\log \mathrm{VIX}_t^{(\cdot)}$, are defined analogously to the local HAR components used above in Eq. (4). The $\log \mathrm{VIX}_t$ series is the log of the Chicago Board Options Exchange (CBOE) volatility index (henceforth, VIX for short), β_0 is a standard regression intercept, and $\epsilon_{t+1}^{\mathrm{US}}$ is again a random disturbance term.

Our motivation for including the VIX as an additional source of volatility information in the augmented HAR model in Eq. (5) is as follows. Recall that the VIX measures the volatility implied by option prices on the S&P 500, thus reflecting investors' expectations about the stock market volatility over the next month.[7] Thus, the VIX is meant to provide not only a forward looking view on *expected* US equity market volatility, but also a general sense of the risk aversion in the market. A higher value in the VIX is generally taken as an indication that market participants anticipate an overall negative economic or financial outlook, and hence have an increased aversion to risk (see Brunnermeier, Nagel, & Pedersen, 2009, for a discussion). This increased risk aversion is likely to spill over into other international equity markets, given the dominant position of the US in the world economy as a source of economic and financial information. Moreover, in a recent study, Grassi et al. (2014) documented that the VIX has some predictive power for S&P 500 realized volatility forecasts. We therefore expect the VIX likewise to contain predictive information that can be exploited to improve the realized volatility forecasts in other international equity markets.

3. Data

We obtain daily volatility data from the publicly-available Oxford-Man Institute's Quantitative Finance Realized Library of Heber, Lunde, Shephard, and Sheppard (2009). The Oxford-Man Realized Library uses high-frequency tick data from Reuters DataScope Tick History[8] to construct a whole suite of daily realized measures of the asset price variability, as well as providing the number of transactions, the time span between the first and last observations, the close-to-open return, the local opening time, the high–low range, the high–open range, and the opening and closing prices for each series.[9] The library contains realized measures for four US and 17 foreign (non-US) equity price indices from January 3, 2000, to the present. Our sample ends on November 13, 2015.

As our preferred estimator of asset price variation, we use the realized variance sampled at equally-spaced five minute intervals (simply 'five minute RV' henceforth). This is the estimator given under the heading '`*.rv`' in the

6 We thank an anonymous referee for suggesting that we also use a HAR structure for the log VIX process. In an earlier version of the paper, we used only $\log \mathrm{VIX}_t^{(d)} = \log \mathrm{VIX}_t$ as an additional control variable in the augmented HAR specification in Eq. (5). Adding the weekly and monthly HAR VIX components improved both the overall in-sample fit and the out-of-sample forecast performance of the augmented HAR model in Eq. (5).

7 The VIX is computed as the weighted average of the implied volatilities of options on the S&P 500 index for a wide range of strikes, and mainly first and second month expirations. Note here that Chow, Jiang, and Li (2014) recently showed the VIX to be a biased measure of market expectations about the future volatility. Nevertheless, we include the VIX as a regressor in the HAR model in order to account for the potential predictive information that it may have for the volatility in other global equity markets, rather than trying to gauge whether it is an appropriate measure of volatility expectations in the US.

8 http://www2.reuters.com/productinfo/tickhistory/material/DataScopeTickHistoryBrochure_260707.pdf.

9 The term 'realized measures' was coined by Liu, Patton, and Sheppard (2015). The various types of realized measures that are included in the library are listed at http://realized.oxford-man.ox.ac.uk/documentation/estimators. With regard to the quality of the tick data, Heber et al. (2009) point out that the raw data from Reuters DataScope Tick History are already of a high quality. Nevertheless, Heber et al. (2009) still employ the high frequency data cleaning procedure described in detail at http://realized.oxford-man.ox.ac.uk/documentation/data-cleaning and in the references therein, in order to make the data suitable for econometric analysis. Also, our data are from Library Version 0.2. The url link to the data source is http://realized.oxford-man.ox.ac.uk/media/1366/oxfordmanrealizedvolatilityindices.zip.

Oxford-Man Realized Library for each equity market data block. The choice of the five minute RV is due partly to simplicity and partly to robustness. In a recent extensive study of realized measures, Liu et al. (2015) highlighted the fact that there is little evidence to suggest that the five minute RV is outperformed significantly by any of the other realized measures that are considered in the benchmark comparison. In particular, when working with international equity market data, Liu et al. (2015, p. 294) pointed out that "*more sophisticated realized measures generally perform significantly worse*" than the five minute RV. We therefore use the five minute RV estimator of Heber et al. (2009) – henceforth simply 'RV', to avoid cumbersome and repetitive language – throughout this study. Moreover, to make the magnitudes of the RV measure comparable to those of the VIX, we transform all RV series to annualised volatilities.[10]

In total, we have access to realized measures data for 17 international equity markets that are included in the Oxford-Man Realized Library. These are the FTSE 100 (United Kingdom), the Nikkei 225 (Japan), the DAX (Germany), the All Ordinaries (Australia), the CAC 40 (France), the Hang Seng (Hong Kong), the KOSPI (South Korea), the AEX (The Netherlands), the Swiss Market Index (Switzerland), the IBEX 35 (Spain), the S&P CNX Nifty (India), the IPC Mexico (Mexico), the Bovespa (Brazil), the S&P TSX (Canada), the Euro STOXX 50 (Euro area), the FT Straits Times (Singapore), and the FTSE MIB (Italy).

For the US, the library contains realized measures for four different equity market indices. These are the Dow Jones Industrial Average (DJIA), the Russel 2000, the Nasdaq 100 and the S&P 500. We use the S&P 500 as our key headline US equity market index. The Nasdaq 100 is a specialized technology industry index, and thus is defined too narrowly to be considered as a valid headline US equity market index. The Russel 2000, on the other hand, is likely to be too sensitive to volatility movements induced by the small cap nature of the index. From our point of view, only the DJIA qualifies as a viable alternative to the S&P 500, as it is an index that is focused on widely by the financial media, thus providing broad headline information about the performance of US equities. Nevertheless, one evident shortcoming of the DJIA is that it is composed of only 30 blue chip stocks, and we therefore find it to be too narrowly focused as well. Thus, our preference is to use the S&P 500 as our key equity market index for the US.[11] The VIX data that we include in the augmented HAR model in Eq. (5) are obtained from the St. Louis Fed FRED2 database.[12]

Table 1 provides standard summary statistics on all of the (log transformed) RV and VIX data that are used in our study. In addition to the summary statistics in Table 1, we also show time series and autocorrelation function (ACF) and partial ACF (PACF) plots in Figs. 1 and 2, to provide further information about the data series that we use. The first to fifth columns of Table 1 show the equity index, the corresponding country, the full sample period, the number of observations T, and the percentage of missing entries (%Miss). The percentages of missing entries were obtained by matching the dates from the Oxford-Man Realized Library to official trading dates data from Bloomberg. In columns six to twelve, we list standard sample statistics such as the mean, median (Med), standard deviation (Std.dev), skewness (Skew) and kurtosis (Kurt), as well as the minimum (Min) and maximum (Max) of each series. The last six columns (grouped in threes) provide the first to third order ACF and PACF (ACF(1–3) and PACF(1–3), respectively). We can see from the third column of Table 1 that there are some differences with respect to the actual first data points across the various equity markets that are available. For all but two series, the first data point is on either the 3rd or the 4th of January 2000. For the S&P TSX (Canada), the sample starts on May 2, 2002, and for the S&P CNX Nifty (India) it starts on July 8, 2002.[13] The end of the sample is either the 12th or 13th of November 2015 for all series except for FT Straits Times (Singapore), which ends on the 18th of September 2015, due to data availability in the Oxford-Man Realized Library.

Looking over the summary statistics in Table 1, one sees that the log RV data are distributed fairly symmetrically, with the means and medians lining up reasonably closely, the skewness being between 0 and 1, and the kurtosis being around 3 for all but four markets.[14] Interestingly, Bovespa and FT Straits Times have the lowest variations, with the standard deviations of log RV being only around 0.37, while those for the remaining series are closer to 0.5. The ACF and PACF entries in Table 1 highlight the well-known long-memory property of volatility data. The most persistent log RV series are the KOSPI (South Korea) and the Swiss Market Index, with first order ACFs of 0.86 and 0.85, respectively, while the least persistent ones are the All Ordinaries and the Bovespa, with values of around 0.67. The VIX is the most persistent series overall, with an ACF(1) of 0.98. The long-memory property of realized volatility

[10] This is done by taking the five minute RV series, re-scaling it by $100^2 \times 252$, and taking the square root to be interpreted as the annualised volatility (in percentage terms). That is, the annualized realized volatility is equal to: $(`*.\texttt{rv}' \times 100^2 \times 252)^{1/2}$.

[11] However, we would like to stress that, while we have chosen the S&P 500 here, the results that we obtain change very little if we use the DJIA as the US headline index instead. The results based on the DJIA are available from the authors upon request.

[12] The url of the database is http://research.stlouisfed.org/fred2/. The FRED mnemonic for the VIX is VIXCLS, and it contains daily closing prices (16:15 EST) of the Chicago Board Options Exchanges (CBOEs) volatility index.

[13] Before July 8, 2002, the availability of realized measures data for the S&P CNX Nifty was extremely sparse. That is, only 100 data entries were available for the 653 entries before July 8, 2002 (553 missing entries). We therefore decided to delete all entries before July 8, 2002, and start the effective sample for the S&P CNX Nifty from July 8, 2002. There are three other equity markets with unusual missing data patterns that deserve mentioning: (1) the All Ordinaries (Australia), where data are missing for 15 consecutive days from July 4, 2014, to July 25, 2014; (2) the FT Straits Times (Singapore), where 43 consecutive entries are missing from January 2, 2008, to March 3, 2008; and (3) the Hang Seng (Hong Kong), which had 168 entries missing out of 300 between September 5, 2008 to November 3, 2009. All missing entries were deleted from the final data set used in the analysis.

[14] These exceptions are the log RV series of Bovespa (Brazil) and Euro STOXX 50, which are close to 5, and S&P CNX Nifty (India) and IPC Mexico (Mexico), with kurtosis values of 4.1 and 3.6, respectively, thus showing somewhat heavier tails than a Gaussian random variable.

Table 1
Summary statistics of (log) RV and (log) VIX data.

Equity index	Country	Full sample period	T	%Miss	Mean	Med	Std.dev	Skew	Kurt	Min	Max	ACF(1–3)			PACF(1–3)		
FTSE 100	United Kingdom	04.01.2000–13.11.2015	3986	0.63	2.41	2.37	0.51	0.47	3.14	1.13	4.68	0.84	0.81	0.79	0.84	0.34	0.21
Nikkei 225	Japan	04.01.2000–13.11.2015	3844	1.38	2.61	2.60	0.43	0.30	3.53	1.29	4.50	0.78	0.72	0.69	0.78	0.30	0.17
DAX	Germany	03.01.2000–13.11.2015	4017	0.47	2.78	2.75	0.51	0.36	3.13	1.27	4.80	0.84	0.80	0.77	0.84	0.33	0.20
All Ordinaries	Australia	04.01.2000–13.11.2015	3966	1.29	2.13	2.09	0.48	0.51	3.51	0.57	4.13	0.67	0.66	0.64	0.68	0.38	0.23
CAC 40	France	03.01.2000–13.11.2015	4040	0.45	2.70	2.70	0.48	0.31	3.18	1.16	4.73	0.83	0.79	0.77	0.83	0.33	0.19
Hang Seng	Hong Kong	03.01.2000–13.11.2015	3643	7.47	2.54	2.51	0.41	0.60	3.88	1.27	4.65	0.72	0.70	0.68	0.72	0.38	0.23
KOSPI	South Korea	04.01.2000–13.11.2015	3907	0.46	2.65	2.63	0.51	0.32	2.93	1.33	4.81	0.86	0.83	0.81	0.86	0.35	0.19
AEX	The Netherlands	03.01.2000–13.11.2015	4039	0.50	2.60	2.55	0.50	0.48	3.18	0.87	4.56	0.84	0.81	0.78	0.84	0.33	0.19
Swiss Market Index	Switzerland	04.01.2000–13.11.2015	3972	0.48	2.45	2.36	0.46	0.89	3.82	1.45	4.63	0.85	0.82	0.80	0.85	0.34	0.20
IBEX 35	Spain	03.01.2000–13.11.2015	4005	0.47	2.74	2.78	0.49	−0.04	2.88	1.17	4.61	0.84	0.80	0.78	0.84	0.32	0.21
S&P CNX Nifty	India	08.07.2002–13.11.2015	3295	0.97	2.73	2.67	0.48	0.75	4.09	1.20	5.38	0.75	0.70	0.67	0.75	0.31	0.19
IPC Mexico	Mexico	03.01.2000–13.11.2015	3967	0.76	2.42	2.36	0.49	0.62	3.58	1.07	4.74	0.68	0.64	0.61	0.68	0.33	0.20
Bovespa	Brazil	03.01.2000–12.11.2015	3879	1.31	3.01	2.98	0.37	0.70	4.92	1.61	4.87	0.67	0.61	0.56	0.67	0.29	0.15
S&P TSX	Canada	02.05.2002–13.11.2015	3379	0.68	2.15	2.08	0.52	0.84	4.07	0.75	4.56	0.79	0.76	0.73	0.79	0.35	0.20
Euro STOXX 50	Euro Area	03.01.2000–13.11.2015	4017	1.27	2.76	2.73	0.50	0.10	5.09	−1.07	5.11	0.77	0.72	0.70	0.77	0.32	0.21
FT Straits Times	Singapore	03.01.2000–18.09.2015	3839	2.71	2.33	2.30	0.38	0.60	3.70	1.45	4.29	0.81	0.77	0.75	0.81	0.33	0.22
FTSE MIB	Italy	03.01.2000–12.11.2015	4000	0.68	2.65	2.63	0.49	0.30	2.97	1.42	4.75	0.83	0.79	0.76	0.83	0.33	0.19
S&P 500	United States	03.01.2000–13.11.2015	3964	0.73	2.53	2.50	0.53	0.47	3.36	1.02	4.94	0.80	0.76	0.73	0.80	0.34	0.18
VIX (log)	United States	03.01.2000–13.11.2015	3992	0.00	2.96	2.92	0.37	0.65	3.30	2.29	4.39	0.98	0.97	0.96	0.98	0.08	0.08

Notes: The table reports standard summary statistics of the 18 annualised (log) realized volatility series of the various equity markets and the (log) VIX. Columns one to five show the equity index, the corresponding country, the full sample period, the sample size T, and the percentage of missing trading days (%Miss). Columns six to twelve show common sample statistics, namely the mean, median (Med), standard deviation (Std.dev), skewness (Skew) and kurtosis (Kurt), as well as the minimum (Min) and maximum (Max) of the series. The last six columns (grouped into blocks of three) provide the first- to third-order autocorrelation function (ACF) and partial ACF (PACF). The full available sample is from January 3, 2000, to November 13, 2015.

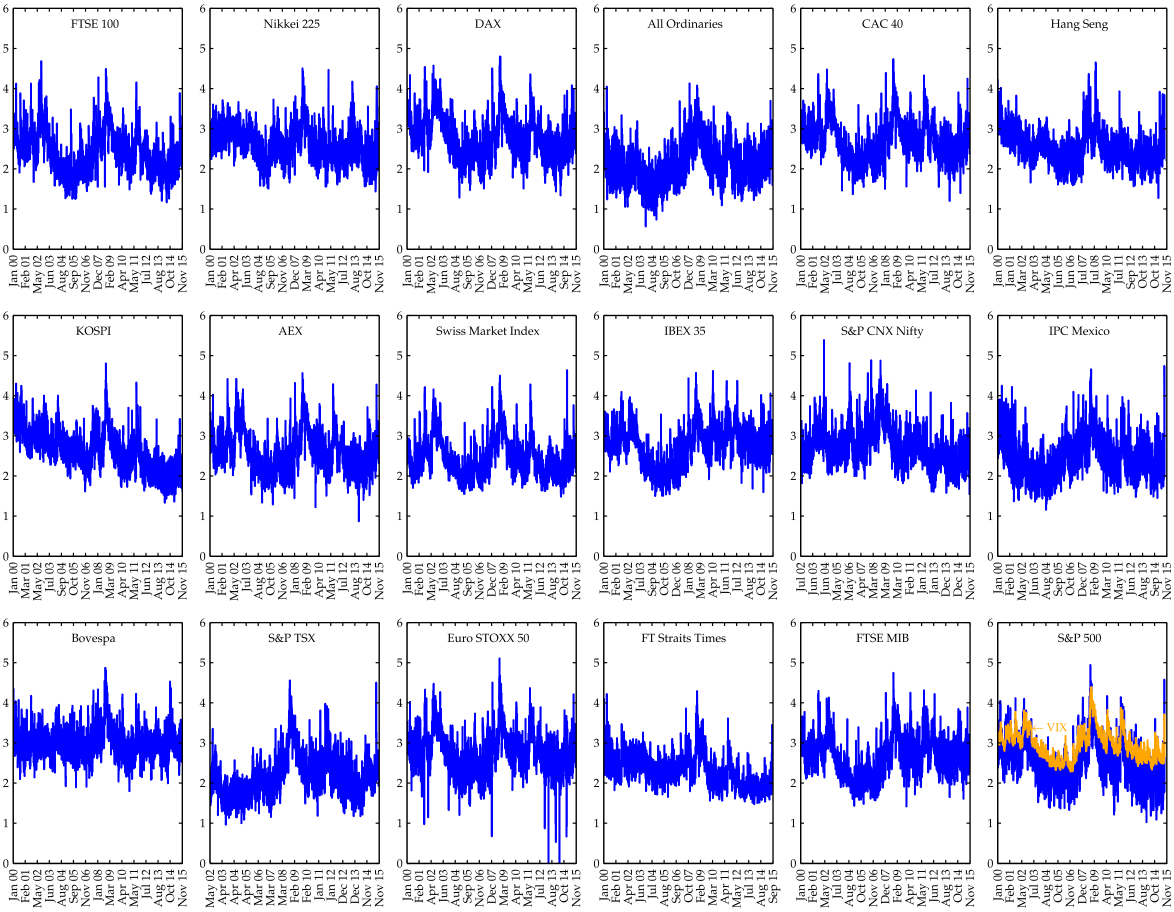

Fig. 1. Time series evolution of (log) RV and (log) VIX over the full available sample period for each series.

data is also visible from the ACF and PACF plots in Fig. 2. For instance, it is evident that the log RV series of Bovespa displays the shortest memory, while the Nikkei 225 has the most hyperbolic-looking ACF decay pattern. Finally, the time series plots of the log RV and log VIX in Fig. 1 show that the movement in volatility across equity markets is rather homogenous for major events such as the Lehman Brothers collapse in September 2008.

One last, and potentially important, point that we would like to stress here is that the Oxford-Man Realized Library only uses intraday data collected over the official (local) trading hours of the respective equity markets of interest. That is, no variation due to overnight price changes is considered in the construction of the realized measures. Since we are using information from the US at time t to forecast the (log) realized volatility in all other foreign equity markets at time $t+1$ (and further ahead), there is no overlap in the official trading hours between the US market's previous day closing and the foreign market's current day opening.[15]

4. Assessing the value of US volatility information

We begin our assessment of the importance of US equity market volatility data and its usefulness for improving the modelling and forecasting of the realized volatility in other international equity markets by looking at the in-sample contribution of US-based volatility information to the model. We then extend the analysis by using standard forecast evaluation techniques to determine whether these in-sample gains carry over into the out-of-sample forecast environment.

Before evaluating the in-sample fit of the augmented HAR model in Eq. (5), it will be convenient to condense the representation of the model somewhat. For this purpose,

[15] The official trading hours of the New York Stock Exchange (NYSE) are from 9:30 to 16:00 Eastern Standard Time (EST), which is 14:30–21:00 Coordinated Universal Time (UTC) in (northern hemisphere) winter. Of the foreign equity markets that we include, the first one to open the next day is the Australian Securities Exchange (ASX) in Sydney at 10:00 Australian Eastern Standard Time (AEST), which is 00:00 UTC. During (northern hemisphere) summer, the UTC closing time for the US market is 20:00 UTC, while the ASX in Sydney opens at 23:00 UTC. Hence, there is a three-hour gap between New York closing and Sydney opening. Also, the switches to and from Daylight Saving Time (DST) do not occur on the same days. For the US, DST is '*on*' from March to November, while for Australia, DST is '*off*' from April to October. However, this is immaterial for our discussion, as it does not cause any overlap in trading hours.

Fig. 2. Autocorrelation function (ACF) and partial ACF (PACF) plots of all (log) RV series.

let us define $\boldsymbol{x}_t = \left[1 \;\; \log \mathrm{RV}_t^{(d)} \;\; \log \mathrm{RV}_t^{(w)} \; \log \mathrm{RV}_t^{(m)}\right]$ as the (1×4) vector of HAR components (including an intercept term) of the foreign equity market of interest, and let the two (1×3) vectors containing US equity volatility information be denoted by $\boldsymbol{x}_t^{\mathrm{VIX}} = \left[\log \mathrm{VIX}_t^{(d)} \;\; \log \mathrm{VIX}_t^{(w)} \;\; \log \mathrm{VIX}_t^{(m)}\right]$ and $\boldsymbol{x}_t^{\mathrm{US}} = \left[\log \mathrm{RV}_{t,\mathrm{US}}^{(d)} \;\; \log \mathrm{RV}_{t,\mathrm{US}}^{(w)} \;\; \log \mathrm{RV}_{t,\mathrm{US}}^{(m)}\right]$. We further define $y_{t+1} = \log \mathrm{RV}_{t+1}$. Then, we can express the augmented HAR model in Eq. (5) in the following compact form:

$$y_{t+1} = \overbrace{\boldsymbol{x}_t \boldsymbol{\beta}}^{\text{local volatility info}} + \underbrace{\boldsymbol{x}_t^{\mathrm{VIX}} \boldsymbol{\beta}_{\mathrm{VIX}} + \boldsymbol{x}_t^{\mathrm{US}} \boldsymbol{\beta}_{\mathrm{US}}}_{\text{US volatility info}} + \epsilon_{t+1}^{\mathrm{US}}, \tag{6}$$

where $\boldsymbol{\beta} = \left[\beta_0 \;\; \beta^{(d)} \;\; \beta^{(w)} \;\; \beta^{(m)}\right]'$, and $\boldsymbol{\beta}_{\mathrm{VIX}} = \left[\beta_{\mathrm{VIX}}^{(d)} \;\; \beta_{\mathrm{VIX}}^{(w)} \;\; \beta_{\mathrm{VIX}}^{(m)}\right]'$ and $\boldsymbol{\beta}_{\mathrm{US}} = \left[\beta_{\mathrm{US}}^{(d)} \;\; \beta_{\mathrm{US}}^{(w)} \;\; \beta_{\mathrm{US}}^{(m)}\right]'$ are the corresponding (4×1), (3×1) and (3×1) dimensional foreign and US parameter vectors, respectively. Similarly, the local equity market's

HAR model in Eq. (4) can be written compactly as:

$$y_{t+1} = \boldsymbol{x}_t \boldsymbol{b} + \epsilon_{t+1}, \tag{7}$$

where $\boldsymbol{x}_t$ is as defined above, $\boldsymbol{b} = \left[b_0 \ b^{(d)} \ b^{(w)} \ b^{(m)}\right]'$, and ϵ_{t+1} is an error term.

4.1. In-sample evaluation

We fit the HAR model in Eq. (6) to three sample periods, in order to gauge the magnitude and significance of the estimated parameters in Eq. (6). We first estimate the model over the full data set available, then also consider the two sub-periods leading up to and following the Lehman Brothers collapse on September 15, 2008. Estimation results for the full period are shown in Table 2, while estimation results for the two sub-periods are provided in Table A.1 and Table A.2 in the Appendix. In each table, the first column shows the foreign equity index of interest and the second the time period over which the model in Eq. (6) was fitted, while the remaining columns show the set of 10 point estimates of the augmented HAR model parameters, and two χ^2 test statistics of a joint test of significance of all US parameters being different from zero (null hypothesis is $\mathcal{H}_0 : [\boldsymbol{\beta}_{\text{VIX}}; \boldsymbol{\beta}_{\text{US}}] = \mathbf{0}_{6\times 1}$) and only those of the US log RV series being different from zero (null hypothesis is $\mathcal{H}_0 : \boldsymbol{\beta}_{\text{US}} = \mathbf{0}_{3\times 1}$). In square brackets below the parameter estimates (χ^2-test statistics), we show two-sided (one-sided) p-values computed using a heteroskedasticity and autocorrelation consistent (HAC) variance/covariance matrix estimator.[16]

In addition to the tabulated in-sample estimation results, we also provide graphical representations of the $\boldsymbol{\beta}$ parameter estimates (excluding the intercept) over the three sub-periods in Fig. 3. Each plot in Fig. 3 shows point estimates (very thin blue line) and the corresponding 95% confidence intervals (light blue shading) for the full sample period. We then superimpose the point estimates obtained from the pre and post Lehman Brothers collapse periods (thick red and thin black lines, respectively) on these plots.

The most notable in-sample fitting results can be summarised as follows.[17] First, US equity market volatility data from the previous trading day are highly informative. A formal test of the null hypothesis $\mathcal{H}_0 : [\boldsymbol{\beta}_{\text{VIX}}; \boldsymbol{\beta}_{\text{US}}] = \mathbf{0}_{6\times 1}$ is rejected strongly by the data for all equity markets of interest. The values of the χ^2_{US}- test statistic are between 95.09 (lowest) for the Hang Seng and 511.43 (highest) for the AEX over the full sample period. As the 1% upper tail critical value of a χ^2 random variable with six degrees of freedom is 16.81, we can see that these are fairly strong rejections. When assessing the significance of the log RV US predictors separately from the log VIX, as is shown in the last column of Table 2, we can see that these remain highly significant, with p-values of less than 1% in general, with the only exceptions being the Bovespa and KOSPI series, which are not affected significantly by lagged US RV information.

Second, it is evident from the plots in Fig. 3 that the estimates are quite stable over the three sample periods, generally remaining inside (or at least close to) the 95% confidence intervals (CI) of the full sample period estimates.[18] Looking at the magnitudes of the parameter estimates, we can see that the daily and weekly $\log \text{VIX}_t$ components are highly significant. Moreover, the daily $\log \text{VIX}_t$ component is positive, while the weekly component is negative. The negative sign on the $\hat{\beta}^{(w)}_{\text{VIX}}$ coefficient is somewhat surprising, as it suggests that the weekly VIX component has a negative effect on the high frequency daily volatility component of the foreign equity market of interest.[19] Furthermore, we find a mixed picture in terms of significance for the US HAR components. That is, we find the daily US HAR component to be highly significant for all of the foreign equity indices except for the three North and South American indices and the KOSPI. These results are consistent with the χ^2_{US}- and χ^2_{RV}-test statistic results, which show that the Bovespa and KOSPI in particular are not affected significantly by lagged US RV information. Moreover, due to the general trading hour overlap between the three North and South American equity markets and the NYSE, most of the US-based equity market volatility information is probably transferred to the three North and South American equity indices on the same trading day, potentially being responsible for the insignificant daily US HAR component. In addition to the daily component, we also find the monthly US HAR component to be significantly different from zero at the 1% level for all European indices and the All Ordinaries.

4.2. Out-of-sample forecast evaluation

Given the strong in-sample evidence of the importance of lagged US-based equity market volatility information for the determination of the international equity market volatility, we now assess the value of this information within an out-of-sample forecast environment. Below, we begin by outlining the general prediction setting and evaluation criteria that we use, then proceed to present the out-of-sample forecast evaluation results.

4.2.1. Prediction setting

We follow the standard literature on realized volatility forecasting (see Andersen et al., 2007; Corsi & Renó,

16 We use a standard Bartlett kernel and a Newey and West (1994) rule of thumb bandwidth set equal to $4(T/100)^{2/9}$.

17 We would like to emphasize here that we offer only a descriptive assessment of the in-sample results, and are not interested in a structural interpretation of these estimates *per se*. As was pointed out by a referee, the parameter estimates that we report in the tables are reduced form estimates, and care must be taken to not interpret them as structural ones.

18 Note here that we have plotted the confidence interval for the full sample period, which will contain much tighter intervals than the smaller pre and post Lehman Brothers collapse periods, due to the larger number of observations in the absence of any severe structural breaks. Thus, if these intervals include the point estimates of the two subperiods most of the time, we can take this as indicating that no substantial structural breaks have influenced the parameter estimates.

19 It should be clear here that the two weekly components are correlated, due to the cumulative construction of these series. Although it may seem that the negative sign could be attributed to this correlation, one would also expect to see highly inflated standard errors with multicollinearity issues, resulting in largely insignificant point estimates. However, this is not the case here. Thus, we do not believe that the opposite sign structure is driven purely by the correlatedness between these two components.

Table 2
Augmented HAR model parameter estimates over the full sample period.

Equity index	Sample period	$\hat{\boldsymbol{\beta}}$				$\hat{\boldsymbol{\beta}}_{\mathrm{VIX}}$			$\hat{\boldsymbol{\beta}}_{\mathrm{US}}$			χ^2_{US}-stat	χ^2_{RV}-stat
FTSE 100	04.02.2000–13.11.2015	−0.1103	0.1319	0.4250	0.3176	1.1338	−0.7812	−0.1645	0.0796	−0.0071	−0.1289	468.78	29.49
United Kingdom		[0.0165]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0248]	[0.0000]	[0.8676]	[0.0027]	[0.0000]	[0.0000]
Nikkei 225	07.02.2000–13.11.2015	0.1301	0.2971	0.3302	0.2779	0.8267	−0.6297	−0.1994	0.1023	−0.0566	0.0033	252.75	30.85
Japan		[0.0078]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0085]	[0.0000]	[0.1349]	[0.9364]	[0.0000]	[0.0000]
DAX	03.02.2000–13.11.2015	−0.0252	0.1723	0.4360	0.3063	1.1279	−0.8449	−0.1554	0.0915	−0.0364	−0.1002	393.11	23.93
Germany		[0.5620]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0387]	[0.0000]	[0.4017]	[0.0339]	[0.0000]	[0.0000]
All Ordinaries	07.02.2000–13.11.2015	0.0838	0.0368	0.3720	0.5229	0.6772	−0.3721	−0.2950	0.2708	−0.0646	−0.1933	452.67	180.45
Australia		[0.0766]	[0.0603]	[0.0000]	[0.0000]	[0.0000]	[0.0028]	[0.0002]	[0.0000]	[0.1530]	[0.0001]	[0.0000]	[0.0000]
CAC 40	03.02.2000–13.11.2015	−0.0391	0.1431	0.4785	0.2525	1.2060	−0.9286	−0.1060	0.0866	−0.0203	−0.1160	484.65	30.08
France		[0.3208]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.1089]	[0.0000]	[0.6045]	[0.0033]	[0.0000]	[0.0000]
Hang Seng	03.02.2000–13.11.2015	0.0970	0.1322	0.4103	0.3765	0.6160	−0.5222	−0.0708	0.0470	0.0429	−0.0737	95.09	13.77
Hong Kong		[0.0349]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.3784]	[0.0120]	[0.2621]	[0.0726]	[0.0000]	[0.0032]
KOSPI	07.02.2000–13.11.2015	0.0734	0.2893	0.4128	0.2499	0.8755	−0.8524	−0.0339	0.0102	0.0333	−0.0102	207.64	3.50
South Korea		[0.0944]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.6525]	[0.5439]	[0.3432]	[0.8033]	[0.0000]	[0.3210]
AEX	03.02.2000–13.11.2015	−0.0576	0.1460	0.4822	0.2636	1.2354	−0.9707	−0.1128	0.1020	−0.0124	−0.1327	511.43	38.96
The Netherlands		[0.1557]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0884]	[0.0000]	[0.7501]	[0.0011]	[0.0000]	[0.0000]
Swiss Market Index	04.02.2000–13.11.2015	−0.0089	0.1783	0.4877	0.2555	1.0473	−0.8159	−0.1286	0.0463	0.0194	−0.1058	422.33	16.04
Switzerland		[0.7973]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0422]	[0.0039]	[0.5450]	[0.0038]	[0.0000]	[0.0011]
IBEX 35	04.02.2000–13.11.2015	−0.0290	0.1889	0.4884	0.2546	1.0647	−0.8797	−0.0357	0.0634	−0.0185	−0.1336	382.94	25.34
Spain		[0.4776]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.5867]	[0.0015]	[0.6204]	[0.0004]	[0.0000]	[0.0000]
S&P CNX Nifty	07.08.2002–13.11.2015	0.1624	0.2663	0.3800	0.2817	0.5777	−0.5863	−0.0159	0.1513	−0.0210	−0.0873	200.38	58.48
India		[0.0065]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.8650]	[0.0000]	[0.6721]	[0.1279]	[0.0000]	[0.0000]
IPC Mexico	03.02.2000–13.11.2015	0.0470	0.1420	0.2148	0.5839	1.1118	−0.6908	−0.3059	−0.0024	0.1191	−0.2130	269.58	17.41
Mexico		[0.4040]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0006]	[0.9273]	[0.0124]	[0.0000]	[0.0000]	[0.0006]
Bovespa	04.02.2000–12.11.2015	0.3182	0.2504	0.3621	0.2467	0.7810	−0.4710	−0.2896	−0.0054	−0.0134	0.0367	165.31	0.73
Brazil		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0003]	[0.7893]	[0.7403]	[0.4167]	[0.0000]	[0.8664]
S&P TSX	05.06.2002–13.11.2015	−0.0835	0.1531	0.3783	0.4155	1.1951	−0.8073	−0.1860	−0.0080	0.0150	−0.1636	273.36	20.91
Canada		[0.0741]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0310]	[0.7308]	[0.7640]	[0.0021]	[0.0000]	[0.0001]
Euro STOXX 50	03.02.2000–13.11.2015	−0.0223	0.0790	0.4335	0.3447	1.2180	−0.8929	−0.1431	0.1798	−0.0364	−0.1910	393.92	60.33
Euro Area		[0.6539]	[0.0054]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0885]	[0.0000]	[0.4811]	[0.0007]	[0.0000]	[0.0000]
FT Straits Times	03.02.2000–18.09.2015	0.1254	0.2262	0.3737	0.3219	0.5266	−0.3673	−0.1998	0.0849	−0.0390	0.0236	163.59	40.46
Singapore		[0.0035]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0016]	[0.0000]	[0.2057]	[0.4809]	[0.0000]	[0.0000]
FTSE MIB	03.02.2000–12.11.2015	−0.0271	0.1790	0.4731	0.2643	1.1828	−1.0343	−0.0089	0.0635	0.0012	−0.1292	437.33	22.45
Italy		[0.5304]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9004]	[0.0006]	[0.9750]	[0.0014]	[0.0000]	[0.0001]

Notes: The table reports OLS regression estimates of the augmented HAR model parameters in Eq. (6) for each foreign equity index. Columns one and two show the equity indices and the corresponding full sample fitting periods. Columns three to 12 show the OLS parameter estimates, together with (two-sided) p-values, computed using heteroskedasticity and autocorrelation (HAC) robust standard errors, in square brackets below the estimates. The last two columns show the χ^2-test statistics (χ^2_{US}-stat and χ^2_{RV}-stat) of a joint significance test with null hypotheses of $\mathcal{H}_0 : [\boldsymbol{\beta}_{\mathrm{VIX}};\ \boldsymbol{\beta}_{\mathrm{US}}] = \mathbf{0}_{6\times 1}$ and $\mathcal{H}_0 : \boldsymbol{\beta}_{\mathrm{US}} = \mathbf{0}_{3\times 1}$, respectively, with corresponding (HAC-based) p-values in brackets below.

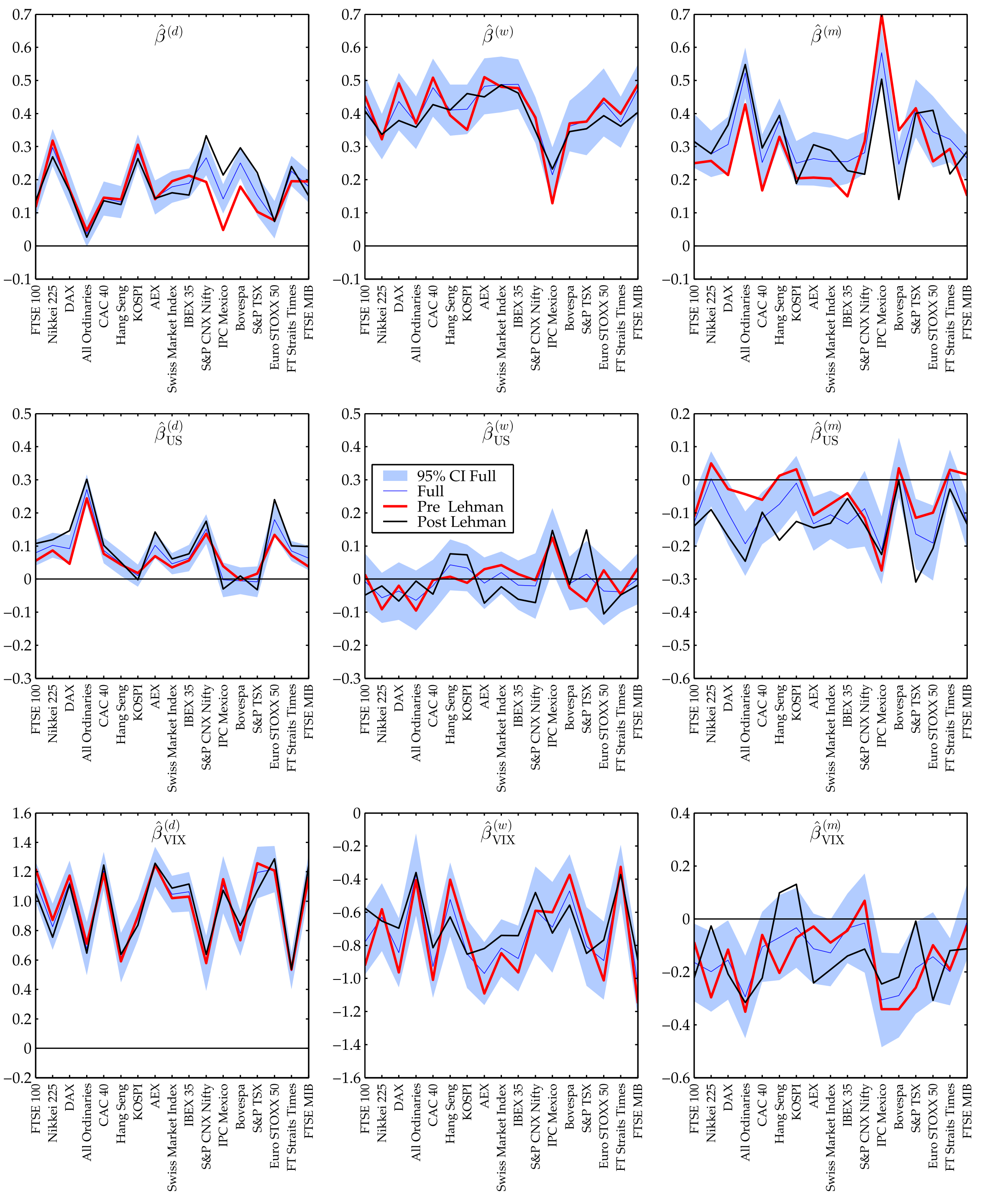

Fig. 3. Plots of all parameter estimates from the augmented HAR model over the full period and the pre and post Lehman Brothers collapse periods. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2012, and others), and implement a '*direct*' forecasting approach.[20] That is, we define the (normalised) h-period log RV series as:

$$y_t^{(h)} = \frac{1}{h}\sum_{j=1}^{h} y_{t-j+1} = \frac{1}{h}\sum_{j=1}^{h} \log \mathrm{RV}_{t-j+1}, \tag{8}$$

and re-formulate the predictive relations in Eqs. (6) and (7) for the general h-step-ahead long-horizon regression

[20] See Chevillon (2007), Chevillon and Hendry (2005), Clements and Hendry (1996), Marcellino, Stock, and Watson (2006), and Pesaran, Pick, and Timmermann (2011), among others, for a motivation, evaluation and comparison of the direct forecasting approach to iterated forecasts.

setting as:

$$y_t^{(h)} = \boldsymbol{x}_{t-h}\boldsymbol{\beta}^{(h)} + \boldsymbol{x}_{t-h}^{\text{VIX}}\boldsymbol{\beta}_{\text{VIX}}^{(h)} + \boldsymbol{x}_{t-h}^{\text{US}}\boldsymbol{\beta}_{\text{US}}^{(h)} + \epsilon_t^{\text{US}} \tag{9}$$

$$y_t^{(h)} = \boldsymbol{x}_{t-h}\boldsymbol{b}^{(h)} + \epsilon_t, \tag{10}$$

then compute h-step-ahead forecasts as

$$\hat{y}_{t+h|t}^{\text{US}} = \boldsymbol{x}_t\hat{\boldsymbol{\beta}}^{(h)} + \boldsymbol{x}_t^{\text{VIX}}\hat{\boldsymbol{\beta}}_{\text{VIX}}^{(h)} + \boldsymbol{x}_t^{\text{US}}\hat{\boldsymbol{\beta}}_{\text{US}}^{(h)} \tag{11}$$

$$\hat{y}_{t+h|t} = \boldsymbol{x}_t\hat{\boldsymbol{b}}^{(h)}. \tag{12}$$

The h superscripts on the $\boldsymbol{\beta}_{\bullet}^{(h)}$ and $\boldsymbol{b}^{(h)}$ terms (and their estimates) indicate that these are from the h-period offset (or long-horizon predictive) regressions in Eqs. (9) and (10).[21] The forecast errors that correspond to the predictions in Eqs. (11) and (12) are defined as:

$$\hat{e}_{t+h|t}^{\text{US}} = y_{t+h}^{(h)} - \hat{y}_{t+h|t}^{\text{US}} \tag{13}$$

$$\hat{e}_{t+h|t} = y_{t+h}^{(h)} - \hat{y}_{t+h|t}. \tag{14}$$

Mean squared forecast errors (MSFEs) are computed as:

$$\text{MSFE} = \frac{1}{T_{os}}\sum_{t=T_{is}}^{T}(\hat{e}_{t+h|t})^2 \tag{15}$$

$$\text{MSFE}_{(\text{US})} = \frac{1}{T_{os}}\sum_{t=T_{is}}^{T}(\hat{e}_{t+h|t}^{\text{US}})^2, \tag{16}$$

respectively, for the two models. The terms T_{os} and T_{is} denote the numbers of out-of-sample and in-sample observations, where $T_{os} = T - T_{is} - h + 1$, and T is the full sample size.

We use the first 500 observations, corresponding to approximately two years of data, as the in-sample fitting period. We consider 500 observations to be large enough to give reasonably precise estimates of all of the parameters required to initialise the out-of-sample forecasts. Following Corsi and Renó (2012), Neely, Rapach, Tu, and Zhou (2014), Rapach et al. (2013) and others, we then use an expanding window (or recursive) forecasting scheme, where we add an extra observation to the 500 in-sample data points and then re-estimate the models to produce recursively updated parameter estimates and forecasts. Overall, this gives us a minimum of around 2600 data points that can be used to conduct a statistically meaningful out-of-sample forecast evaluation. We should stress again here that we use rather large in-sample fitting and out-of-sample evaluation periods, in order to ensure that our general conclusions regarding the improvements in forecast performances are not sensitive to the choices of these two windows.

4.2.2. *Evaluation criteria*

We assess the out-of-sample forecast performance of the augmented HAR model in Eq. (6) by following the approaches of Corsi and Renó (2012) and the recent literature on forecasting the equity premium (see Campbell & Thompson, 2008; Neely et al., 2014; Rapach et al., 2013, and many others), and evaluate the forecasts in terms of the Clark and West (2007) mean squared forecast error (MSFE) adjusted t-statistic (denoted CW-statistic) and the Campbell and Thompson (2008) out-of-sample R^2 (denoted R_{os}^2 henceforth).[22] Since the augmented HAR model in Eq. (6) nests the standard HAR model in Eq. (7), we utilize the Clark and West (2007) MSFE-adjusted t-statistic, which corrects for the bias that arises when the DM test is used to compare nested models.

Following the suggestion by Clark and West (2007, p. 294), the simplest way to compute the MSFE-adjusted t-statistic is to form the sequence:

$$\text{CW}_{t+h} = \underbrace{(\hat{e}_{t+h|t})^2 - (\hat{e}_{t+h|t}^{\text{US}})^2}_{\text{DM}_{t+h}} + \underbrace{\left(\hat{y}_{t+h|t} - \hat{y}_{t+h|t}^{\text{US}}\right)^2}_{\text{adj}_{t+h}}. \tag{17}$$

The DM_{t+h} term in the first part of Eq. (17) is the standard Diebold and Mariano (1995) sequence that is computed to test for (unconditional) superior predictive ability. The second term, adj_{t+h}, is an adjustment term that arises due to the nested nature of the models being compared, and performs a bias correction (see Clark & West, 2007, for more details). The CW-statistic (for horizon h) is then computed as:

$$\text{CW-statistic} = \frac{\overline{\text{CW}}}{\sqrt{\mathbb{V}\text{ar}(\overline{\text{CW}})}}, \tag{18}$$

where $\overline{\text{CW}} = T_{os}^{-1}\sum_{t=T_{is}}^{T}\text{CW}_{t+h}$ and $\mathbb{V}\text{ar}(\overline{\text{CW}})$ is the variance of the sample mean, which can be obtained simply as the HAC-robust t-statistic on the intercept term from a regression of CW_{t+h} on a constant.[23]

The CW-statistic implements a test of the null hypothesis that the MSFE of the benchmark HAR model, which does not include US equity market volatility information, is equal to that of the augmented HAR model's forecast in Eq. (6), against the one-sided alternative hypothesis that the benchmark's MSFE is greater than that of the augmented HAR model. Hence, a rejection of the null hypothesis suggests that the forecasts from the augmented HAR model are *significantly* smaller than those from the benchmark HAR model on average. It should be highlighted again here that the CW-statistic is particularly suitable in the given context, as it is designed for the comparison of *nested* (forecasting) models. Our benchmark model yields the standard HAR model, which can be obtained from the augmented HAR model by restricting $[\boldsymbol{\beta}_{\text{VIX}}; \boldsymbol{\beta}_{\text{US}}]$ in Eq. (6) to $\mathbf{0}_{6\times1}$.

The R_{os}^2 of Campbell and Thompson (2008) is computed as follows. Let $\text{MSFE}_{(\text{US})}$ be the MSFE from the augmented HAR model including US volatility information, and let

21 We report in-sample estimation results from the long-horizon regressions on the full sample in Table A.3, Table A.4, and Table A.5 in the Appendix.

22 Note here that we are performing simple pairwise forecast comparisons between the augmented and benchmark HAR models for each foreign equity market's log RV series, rather than comparing forecasts from many models. Thus, a Diebold and Mariano (1995) (DM) type test of unconditional predictive ability is sufficient for our purpose of assessing the contribution of US-based volatility information to each foreign equity market's volatility forecasts.

23 See also the discussion in Section 2.1 of Diebold (2015) for more background on this in the context of the traditional Diebold–Mariano (DM) statistic.

Table 3
One-step-ahead out-of-sample forecast evaluation results (expanding window).

Equity index	Country	Out-of-sample period	T_{os}	MSFE	Rel-MSFE	R^2_{os}	CW-stat	p-value
FTSE 100	United Kingdom	14.03.2002–13.11.2015	3356	0.0582	0.8772	0.1228	14.7187	0.0000
Nikkei 225	Japan	22.04.2002–13.11.2015	3171	0.0656	0.9071	0.0929	11.3231	0.0000
DAX	Germany	12.03.2002–13.11.2015	3374	0.0612	0.8905	0.1095	15.3556	0.0000
All Ordinaries	Australia	21.03.2002–13.11.2015	3315	0.0899	0.8552	0.1448	15.4533	0.0000
CAC 40	France	15.03.2002–13.11.2015	3389	0.0554	0.8598	0.1402	15.5369	0.0000
Hang Seng	Hong Kong	19.04.2002–13.11.2015	3005	0.0621	0.9544	0.0456	8.4199	0.0000
KOSPI	South Korea	25.04.2002–13.11.2015	3239	0.0539	0.9277	0.0723	11.9394	0.0000
AEX	The Netherlands	18.03.2002–13.11.2015	3389	0.0564	0.8585	0.1415	15.5860	0.0000
Swiss Market Index	Switzerland	22.03.2002–13.11.2015	3333	0.0440	0.8763	0.1237	14.5667	0.0000
IBEX 35	Spain	27.03.2002–13.11.2015	3357	0.0550	0.8935	0.1065	14.6317	0.0000
S&P CNX Nifty	India	15.09.2004–13.11.2015	2659	0.0810	0.9336	0.0664	10.0383	0.0000
IPC Mexico	Mexico	19.03.2002–13.11.2015	3336	0.0928	0.9210	0.0790	11.4184	0.0000
Bovespa	Brazil	17.04.2002–12.11.2015	3250	0.0617	0.9521	0.0479	11.1674	0.0000
S&P TSX	Canada	24.06.2004–13.11.2015	2790	0.0800	0.9153	0.0847	10.0294	0.0000
Euro STOXX 50	Euro Area	11.03.2002–13.11.2015	3373	0.0822	0.8645	0.1355	13.0201	0.0000
FT Straits Times	Singapore	01.04.2002–18.09.2015	3237	0.0377	0.9317	0.0683	10.1945	0.0000
FTSE MIB	Italy	20.03.2002–12.11.2015	3356	0.0599	0.8894	0.1106	15.7027	0.0000

Notes: The table reports the one-step-ahead out-of-sample forecast evaluation results using an expanding estimation window for the 17 foreign equity markets that we consider. We produce the first out-of-sample forecast using an initial 500 (in-sample) data points, then expand this window. Columns one to four show the equity markets of interest, the corresponding country, the out-of-sample evaluation period and the number of out-of-sample observations T_{os}. Columns five to seven then show the mean squared forecast errors (MSFEs) of the benchmark HAR model (without US volatility information), the relative MSFE (Rel-MSFE), computed as MSFE(US)/MSFE, where MSFE(US) and MSFE are from the augmented and benchmark HAR models respectively, and the Campbell and Thompson (2008) out-of-sample R^2 (R^2_{os}), computed as $R^2_{os} = 1 - \text{MSFE(US)}/\text{MSFE}$. The last two columns report the Clark–West (CW) test statistics and the corresponding one-sided asymptotic p-values.

MSFE denote the mean squared forecast error from the benchmark HAR model. Then, the R^2_{os} comparing the performances of the two forecasts is defined as:

$$R^2_{os} = 1 - \frac{\text{MSFE}_{(\text{US})}}{\text{MSFE}}. \tag{19}$$

Intuitively, the R^2_{os} statistic in Eq. (19) measures the proposed model's MSFE reduction relative to the benchmark model. If $R^2_{os} > 0$, the proposed model performs better than the benchmark model, while $R^2_{os} < 0$ suggests that the benchmark model performs better.

In addition to the CW-statistic of Clark and West (2007) and the out-of-sample R^2 of Campbell and Thompson (2008), we also compute the cumulative difference between the squared forecast errors of the two HAR models over the out-of-sample period. This cumulative difference (denoted cumSFE) is used commonly in the forecasting literature as a tool for highlighting the predictive performance over time of the proposed model relative to the benchmark model (see Goyal & Welch, 2008; Rapach et al., 2013, among many others). In our setting, this difference is defined as

$$\text{cumSFE}_{t+h} = \sum_{\tau=T_{is}}^{t} \left((\hat{e}_{\tau+h|\tau})^2 - (\hat{e}^{\text{US}}_{\tau+h|\tau})^2 \right),$$
$$\forall t = T_{is}, \ldots, T - G. \tag{20}$$

The cumSFE sequence allows us to analyse the changes over time in the forecast performances of the two models. A value of the cumSFE series that is above zero indicates that the cumulative sum of the squared forecast errors of the benchmark model is larger than that of the proposed augmented HAR forecasts, indicating that the benchmark's forecasts are less accurate. Moreover, an upward-sloping cumSFE sequence means that the proposed augmented HAR model produces *consistently* better predictions than the benchmark HAR model (i.e., without US volatility information).

4.2.3. Forecast evaluation results

One-step-ahead results. Table 3 presents the one-step-ahead out-of-sample forecast evaluation results for all 17 international equity markets that we consider, using an expanding (recursive) estimation window, with the initial in-sample period consisting of $T_{is} = 500$ observations. The first four columns in Table 3 show the foreign equity index of interest, the corresponding country, the actual out-of-sample evaluation period, and the effective number of out-of-sample observations T_{os} that are used. Columns five to seven show the MSFE of the benchmark HAR model, the relative MSFE (denoted Rel-MSFE and computed as $\text{MSFE}_{(\text{US})}/\text{MSFE}$), and the R^2_{os} of Campbell and Thompson (2008). The last two columns then show the Clark and West (2007) MSFE-adjusted t-statistic (CW-statistic) and the corresponding one-sided p-values.

The evaluation results in Table 3 show the strong positive effect of information about US equity market volatility on the out-of-sample forecasts of log RV in global equity markets. The CW-statistic is in excess of 8.4 for all 17 international equity markets that we consider, resulting in p-values that are effectively zero. The out-of-sample R^2 values of Campbell and Thompson (2008) are as high as 14.48%, 14.15%, 14.02% and 13.55% for the All Ordinaries, AEX, CAC 40 and Euro STOXX 50, respectively, with the two lowest values, 4.79% and 4.56%, being recorded for the Bovespa and Hang Seng. Note here that these R^2_{os} magnitudes are considerable. To put them in perspective, compare them to those reported by Patton and Sheppard (2015), which allow the volatility to be split into bad and good volatility components (in addition to various other considerations related to leverage and signed jumps) and which yield R^2_{os} improvements of (only) about 2.5%–3%

points at best, at the one-step-ahead horizon (see Table 6 of Patton & Sheppard, 2015). Although it is difficult to compare our findings to theirs directly, since we consider different information sets, it should still be clear that the forecast improvements from augmenting the benchmark local HAR model with US-based volatility information are substantial. Note here also that we are using sample sizes of at least 2600 observations for the out-of-sample evaluation periods, and up to 3300. Thus, our test results are not sensitive to, or driven by, '*small sample issues*'.

We provide additional evidence of the strength of our out-of-sample forecast results by examining the evolution over time of the cumulative difference between the squared forecast errors from the augmented HAR model and those of the benchmark HAR model. This cumSFE series (at the one-step-ahead horizon, $h = 1$), as defined in Eq. (20), is plotted as the thin blue line in Fig. 4. Recall that the cumSFE series is defined such that an increasing value indicates an improvement in the augmented HAR model's predictive performance relative to the benchmark HAR model (i.e., the benchmark HAR model produces larger one-step-ahead out-of-sample forecast errors). In addition to the expanding (recursive) window based cumSFE series shown in Fig. 4, we also compute the cumSFE series based on forecasts from a rolling window scheme, i.e., one that constructs the forecasts using a fixed-length estimation window of 500 observations when rolling through the out-of-sample period. This series is plotted as the thick orange line in Fig. 4. Our intention here is to provide a visual indication that our expanding (recursive) window based out-of-sample forecast evaluation results are broadly similar to those obtained from a rolling window based set-up, and therefore are not sensitive to this choice.

Examining the cumSFE series shown in Fig. 4, we can summarise the most interesting results from these plots as follows. First, the cumSFE is (nearly) uniformly above zero for the entire out-of-sample evaluation period and for all 17 foreign equity markets that we consider. The main exceptions are the Bovespa index for Brazil and the Hang Seng index for Hong Kong, which do not appear to be above zero consistently until about October 2007, but which increase steadily thereafter. Second, the cumSFE series increases (nearly) monotonically for all series over the full out-of-sample period. There are occasional instances of '*flattening off*' for some of the 17 equity markets, occurring largely around the time period between September 2008 and June 2010. Nonetheless, if one was to draw a hypothetical straight line from the beginning of the out-of-sample period until its end in November 13, 2015, one would find the cumSFE series to line up to such a straight line fairly closely. This highlights the consistent and steady improvement over time that is provided by the inclusion of US volatility information when forecasting the volatility in other international equity markets.

Third, it is interesting to observe that the cumulative improvement of the augmented HAR model over the benchmark HAR is strongest for the All Ordinaries, the Euro STOXX 50, the CAC 40, the DAX and the AEX, and weakest for the Hang Seng, the FT Straits Times and the Bovespa equity indices. Overall, it is clear that, apart from the All Ordinaries, the European equity indices benefit the most from the inclusion of US-based equity market volatility information. The strong improvement in the log RV forecasts of the All Ordinaries makes sense because of the narrow time gap between NYSE closing in the US and ASX opening in Australia. Nonetheless, it is somewhat surprising to see here that the predictive improvement is much weaker for the other four Asian equity indices, namely the Nikkei 225, the Hang Seng, the FT Straits Times, and the KOSPI, where the trading gap is similarly short as for the All Ordinaries.[24] Of these four equity indices, the Nikkei 225 shows the largest forecast improvements when US volatility information is included, though the improvements are considerably smaller than for the All Ordinaries index.

Looking at the one-step-ahead out-of-sample forecast evaluation results presented in Table 3, we can see that, in general, the predictability pattern in the European equity markets is fairly homogenous across the eight indices that we include. The improvement in the out-of-sample R^2 of Campbell and Thompson (2008) is between 10.65% (IBEX 35) and 14.15% (AEX). The improvements for the three North and South American equity indices are smaller than for the European equity markets overall, with the Brazilian Bovespa showing the smallest gain (4.79%). In regard to this result, we conjecture that the general trading hour overlap between these markets and the NYSE means that most of the US-based equity market volatility information is transferred on the same trading day. The NYSE is open from 14:30 to 21:00 UTC (during winter). The IPC Mexico and S&P TSX trade over the same hours as the NYSE, while the Bovespa is open from 13:00 to 20:00 UTC. The HAR components of the respective foreign equity markets seem to absorb and carry most of the relevant volatility information in real time, thereby reducing the importance of lagged US volatility information.[25] Overall, our results highlight the strong out-of-sample predictive content of US volatility information for volatility forecasts in a broad range of international equity markets.

Multi-step-ahead results. Our multi-step-ahead out-of-sample forecast evaluation results are presented in Table 4. We follow Corsi and Renó (2012) and construct (normalised) multi-period log RV forecasts for horizons of $h = 5$, 10 and 22 steps ahead, as defined in Eq. (8). Table 4 is split into three parts, with each part corresponding to one of the three forecast horizons that we consider. The column entries in Table 4 contain the same information as the one-step-ahead evaluation results reported in Table 3.

Before discussing the multi-step-ahead forecast evaluation results, we would like to stress that we take particular care when computing the HAC standard errors that

24 Both the Nikkei 225 and the KOSPI open at 00:00 UTC during summer, the same as the All Ordinaries, while the FT Straits Times and Hang Seng open at 01:00 and 01:20, respectively.

25 In a somewhat different context, Nikkinen, Mohammed, Petri, and Äjiö (2006) found that Latin American countries are not affected by US news announcements, which highlights the fact that they are less integrated with the US. Also, in the news effect and announcement literature, Brand, Buncic, and Turunen (2010) showed that European equity and bond markets react less to news from the US, such as initial unemployment claims, after conditioning on ECB announcements.

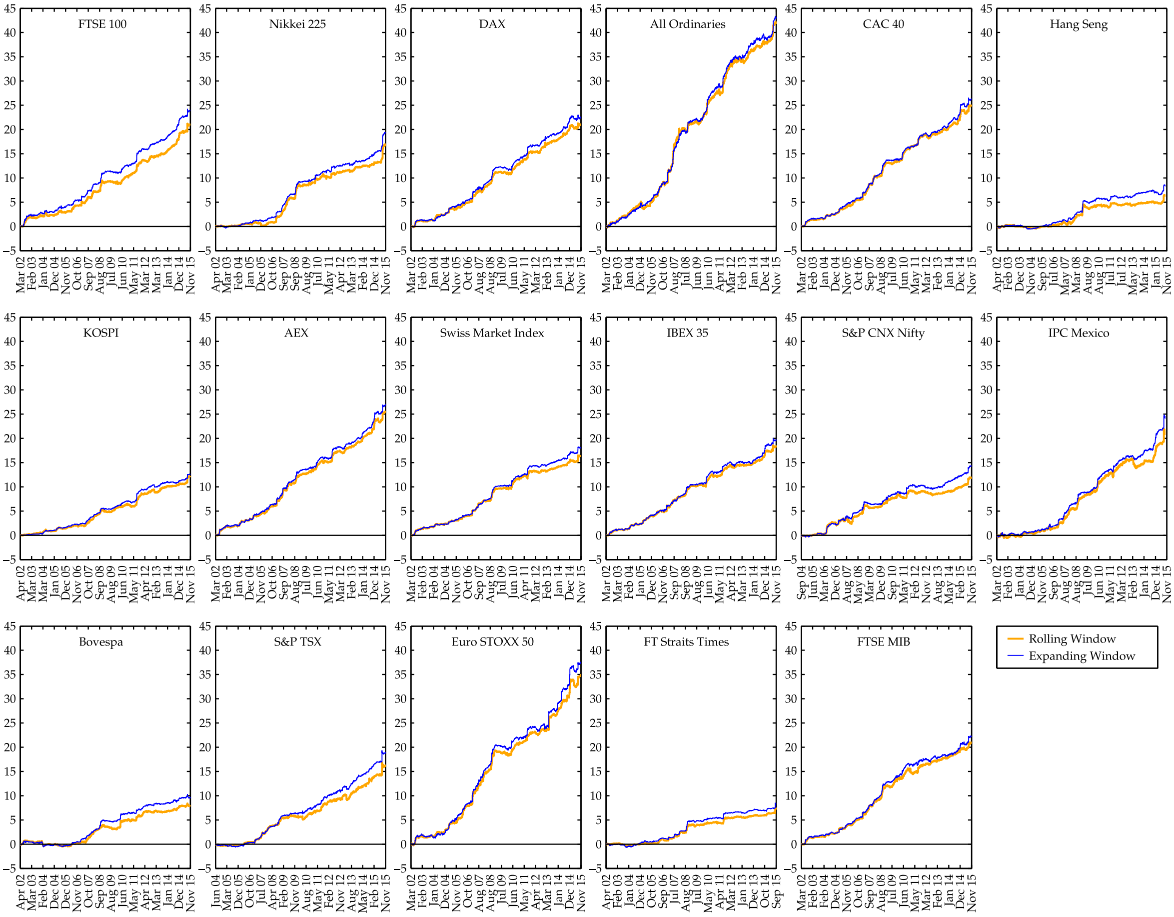

Fig. 4. Time series evolution of the cumulative difference between the squared one-step-ahead forecast errors from the benchmark HAR model and those from the augmented HAR model (cumSFE). The thin (blue) lines show the results computed on an expanding estimation window, using an initial in-sample fitting period of 500 observations. The thick (orange) lines show the corresponding rolling window (fixed $T_{is} = 500$) results. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

are needed to construct the p-values of the CW-statistic. It is well known that h-step-ahead forecast errors follow at least an MA($h-1$) process. When computing the differences of the squared forecast errors from the two competing models in order to construct the CW-statistic, the CW_{t+h} sequence itself will be autocorrelated for $h > 1$. This autocorrelation can be sizable for large values of h. We employ a pre-whitening step, using an ARMA (1, 1) as the approximating model for the CW_{t+h} sequence so as to reduce the initial autocorrelation in the series, then apply a quadratic spectral (QS) kernel-based non-parametric HAC estimator to the residuals from the ARMA (1, 1) model. Following Andrews and Monahan (1992), we choose the bandwidth optimally, with an AR(1) as the approximating model for the ARMA (1, 1) (pre-whitened) residuals, then re-colour to obtain the required HAC standard errors.[26]

We can see from the multi-step-ahead forecast evaluation results in Table 4 that the forecast improvements relative to the benchmark HAR model remain highly significant for all 17 international equity markets at the 5-day-ahead (one week), 10-day-ahead (two week), and 22-day-ahead (one month) horizons. At the 22-day horizon, the forecast improvements are only insignificant for the KOSPI and the S&P CNX Nifty.[27]

To summarise the out-of-sample forecast evaluating results that we have presented in this section, it is clear that including lagged US equity market volatility information leads to substantial improvements in the out-of-sample predictions of volatility in all 17 of the international equity markets that we analyze. Moreover, this improvement has

[26] That is, using the notation of Andrews and Monahan (1992), the bandwidth parameter is set to $1.3221\left[\hat{\alpha}(2)\,T_{os}\right]^{1/5}$, where the constant $\hat{\alpha}(2) = 4\hat{\rho}^2/(1-\hat{\rho})^4$, and $\hat{\rho}$ is the AR(1) parameter estimate obtained from an AR(1) regression of the (pre-whitened) residual series obtained from the ARMA(1, 1) model fitted to the CW_{t+h} sequence. We then '*re-colour*' again to obtain the HAC variance, using the ratio of the square of the ARMA lag polynomials (see Andrews & Monahan, 1992 for more details of the exact computations).

[27] For more information about the influences of the different predictor variables, consult the long-horizon predictive regression results reported in Table A.3, Table A.4, and Table A.5 in the Appendix.

Table 4
Multiple-step-ahead out-of-sample forecast evaluation results (expanding window).

Equity index	Country	Out-of-sample period	T_{os}	MSFE	Rel-MSFE	R^2_{os}	CW-stat	p-value
Forecast horizon $h = 5$								
FTSE 100	United Kingdom	26.03.2002–13.11.2015	3348	0.0377	0.8826	0.1174	10.2683	0.0000
Nikkei 225	Japan	07.05.2002–13.11.2015	3163	0.0438	0.9123	0.0877	6.9091	0.0000
DAX	Germany	22.03.2002–13.11.2015	3366	0.0412	0.9105	0.0895	9.7591	0.0000
All Ordinaries	Australia	04.04.2002–13.11.2015	3307	0.0397	0.8515	0.1485	9.6919	0.0000
CAC 40	France	27.03.2002–13.11.2015	3381	0.0382	0.8768	0.1232	10.3148	0.0000
Hang Seng	Hong Kong	02.05.2002–13.11.2015	2997	0.0311	0.9440	0.0560	4.8934	0.0000
KOSPI	South Korea	08.05.2002–13.11.2015	3231	0.0350	0.9618	0.0382	5.5161	0.0000
AEX	The Netherlands	28.03.2002–13.11.2015	3381	0.0403	0.8853	0.1147	10.7585	0.0000
Swiss Market Index	Switzerland	05.04.2002–13.11.2015	3325	0.0316	0.9031	0.0969	9.5770	0.0000
IBEX 35	Spain	10.04.2002–13.11.2015	3349	0.0377	0.9084	0.0916	9.3822	0.0000
S&P CNX Nifty	India	27.09.2004–13.11.2015	2651	0.0472	0.9512	0.0488	7.2642	0.0000
IPC Mexico	Mexico	03.04.2002–13.11.2015	3328	0.0459	0.8873	0.1127	9.1160	0.0000
Bovespa	Brazil	29.04.2002–12.11.2015	3242	0.0371	0.9539	0.0461	5.7047	0.0000
S&P TSX	Canada	08.07.2004–13.11.2015	2782	0.0465	0.9191	0.0809	7.7913	0.0000
Euro STOXX 50	Euro Area	21.03.2002–13.11.2015	3365	0.0494	0.8696	0.1304	9.6366	0.0000
FT Straits Times	Singapore	11.04.2002–18.09.2015	3229	0.0211	0.9166	0.0834	6.4696	0.0000
FTSE MIB	Italy	03.04.2002–12.11.2015	3348	0.0394	0.9247	0.0753	9.5552	0.0000
Forecast horizon $h = 10$								
FTSE 100	United Kingdom	11.04.2002–13.11.2015	3338	0.0390	0.9311	0.0689	8.0319	0.0000
Nikkei 225	Japan	21.05.2002–13.11.2015	3153	0.0429	0.9433	0.0567	5.4364	0.0000
DAX	Germany	09.04.2002–13.11.2015	3356	0.0427	0.9455	0.0545	7.2399	0.0000
All Ordinaries	Australia	18.04.2002–13.11.2015	3297	0.0382	0.8972	0.1028	7.8199	0.0000
CAC 40	France	12.04.2002–13.11.2015	3371	0.0407	0.9205	0.0795	8.0689	0.0000
Hang Seng	Hong Kong	16.05.2002–13.11.2015	2987	0.0287	0.9559	0.0441	4.5394	0.0000
KOSPI	South Korea	22.05.2002–13.11.2015	3221	0.0349	0.9879	0.0121	3.4735	0.0003
AEX	The Netherlands	15.04.2002–13.11.2015	3371	0.0436	0.9236	0.0764	8.4435	0.0000
Swiss Market Index	Switzerland	19.04.2002–13.11.2015	3315	0.0351	0.9463	0.0537	7.7335	0.0000
IBEX 35	Spain	24.04.2002–13.11.2015	3339	0.0391	0.9491	0.0509	7.1849	0.0000
S&P CNX Nifty	India	11.10.2004–13.11.2015	2641	0.0454	1.0046	−0.0046	4.2106	0.0000
IPC Mexico	Mexico	17.04.2002–13.11.2015	3318	0.0418	0.9262	0.0738	7.6535	0.0000
Bovespa	Brazil	14.05.2002–12.11.2015	3232	0.0362	0.9812	0.0188	3.9384	0.0000
S&P TSX	Canada	22.07.2004–13.11.2015	2772	0.0456	0.9407	0.0593	6.6146	0.0000
Euro STOXX 50	Euro Area	08.04.2002–13.11.2015	3355	0.0498	0.9221	0.0779	7.7728	0.0000
FT Straits Times	Singapore	25.04.2002–18.09.2015	3219	0.0204	0.9540	0.0460	5.3990	0.0000
FTSE MIB	Italy	17.04.2002–12.11.2015	3338	0.0412	0.9637	0.0363	6.8724	0.0000
Forecast horizon $h = 22$								
FTSE 100	United Kingdom	16.05.2002–13.11.2015	3314	0.0461	0.9628	0.0372	5.9062	0.0000
Nikkei 225	Japan	25.06.2002–13.11.2015	3129	0.0486	0.9782	0.0218	4.3789	0.0000
DAX	Germany	14.05.2002–13.11.2015	3332	0.0500	0.9783	0.0217	5.5171	0.0000
All Ordinaries	Australia	23.05.2002–13.11.2015	3273	0.0410	0.9381	0.0619	6.1348	0.0000
CAC 40	France	17.05.2002–13.11.2015	3347	0.0478	0.9485	0.0515	6.3290	0.0000
Hang Seng	Hong Kong	21.06.2002–13.11.2015	2963	0.0281	0.9978	0.0022	3.4927	0.0002
KOSPI	South Korea	28.06.2002–13.11.2015	3197	0.0390	1.0362	−0.0362	0.8022	0.2112
AEX	The Netherlands	20.05.2002–13.11.2015	3347	0.0524	0.9518	0.0482	6.3770	0.0000
Swiss Market Index	Switzerland	24.05.2002–13.11.2015	3291	0.0437	1.0065	−0.0065	4.4579	0.0000
IBEX 35	Spain	30.05.2002–13.11.2015	3315	0.0437	0.9686	0.0314	5.9966	0.0000
S&P CNX Nifty	India	22.11.2004–13.11.2015	2617	0.0494	1.0602	−0.0602	−0.2516	0.5993
IPC Mexico	Mexico	22.05.2002–13.11.2015	3294	0.0424	0.9858	0.0142	5.4811	0.0000
Bovespa	Brazil	19.06.2002–12.11.2015	3208	0.0399	1.0095	−0.0095	2.9363	0.0017
S&P TSX	Canada	26.08.2004–13.11.2015	2748	0.0490	0.9675	0.0325	5.1390	0.0000
Euro STOXX 50	Euro Area	13.05.2002–13.11.2015	3331	0.0553	0.9515	0.0485	6.5706	0.0000
FT Straits Times	Singapore	31.05.2002–18.09.2015	3195	0.0242	1.0026	−0.0026	4.4795	0.0000
FTSE MIB	Italy	22.05.2002–12.11.2015	3314	0.0461	0.9785	0.0215	4.8580	0.0000

Notes: The table reports the multi-step-ahead out-of-sample forecast evaluation results for the 17 international equity markets that we consider. Forecasts for horizons $h = 5$, 10 and 22 are shown in the top, middle and bottom panels, respectively. The target variable is the (normalised) multi-period log RV, as defined in Eq. (8). The columns are the same as those described in Table 3. The p-values corresponding to the CW-statistic are computed from HAC robust standard errors, where we conduct a *pre-whitening* step using an ARMA (1, 1) model for the CW_{t+h} sequence in order to reduce the initial autocorrelation in the series, then apply a quadratic spectral (QS) kernel based non-parametric HAC estimator to the ARMA (1, 1) residuals. We follow Andrews and Monahan (1992) and choose the bandwidth optimally with an AR(1) as the approximating model, then *re-colour* to obtain the HAC standard errors of the CW_{t+h} sequence.

a lasting impact, affecting forecasts as far as one month ahead. The equity markets that are impacted most by the US volatility information are the Australian All Ordinaries index and all of the European equity indices in our sample. The weakest results are obtained for the South American equity markets, and some of the Asian markets.

5. Robustness checks

In this section, we address some pertinent concerns in relation to the robustness of our out-of-sample forecast evaluation results.[28] In particular, we address questions related to:

(i) most of the out-of-sample forecasting power coming from the log VIX,
(ii) the role of each foreign equity market's own forward-looking volatility information, and
(iii) the importance of other European and/or Asian equity markets' realized volatilities.

All of the tables and figures required to support our discussion below are provided in the Appendix. Here, we simply summarize the main findings of the robustness checks. In all of the evaluations that we present, our reference model is the augmented HAR model, which uses only US volatility information. To conserve space and to improve the readability of the supporting figures and tables that are provided, we only report out-of-sample evaluation results based on an expanding (recursive) estimation window, using the first 500 data points for the initial in-sample fitting. In all figures, we draw the reference results from the augmented HAR model in Eq. (6) with a blue line, to facilitate the comparison to previously plotted results.

5.1. Does the VIX drive all of the forecast improvement results?

It is evident from the results reported in Table 2 that the log VIX HAR components capture a substantial part of the overall in-sample improvement when both forward-looking and backward-looking US volatility information are included in the prediction model. This can be seen from the relative magnitude of the $\hat{\boldsymbol{\beta}}_{\mathrm{VIX}}$ and $\hat{\boldsymbol{\beta}}_{\mathrm{US}}$ coefficients, as well as the χ^2_{US} and χ^2_{RV}-statistics. We determine how much of the out-of-sample forecast improvement is driven by the VIX predictor alone by removing $\boldsymbol{x}_t^{\mathrm{VIX}}$ from the augmented HAR in Eq. (6) and repeating the out-of-sample forecast evaluations, again against the benchmark HAR model in Eq. (7) as before. These evaluation results are reported in Table A.6, Figure A.1 and Table A.7.

Overall, we can see that the VIX plays an important role in predicting the volatility in all 17 of the international equity markets that we consider. Nevertheless, the predictive performance is heterogeneous, and depends on both the forecast horizon and the foreign equity market being analysed. For instance, at the one-step-ahead horizon, we can see from Table A.6 that the forecast improvements remain highly significant for all 17 international equity markets. The lowest CW-statistic recorded now drops to around four (S&P TSX), while the largest one is still over 16 (All Ordinaries). However, the out-of-sample R^2 values are uniformly lower, with some of them being as low as 0.69% and 0.84% for the Bovespa and S&P TSX one-step-ahead forecasts, though that for the All Ordinaries is still rather high, at 12.59%. Comparing the cumSFE series of the full augmented HAR model (blue line) to that of the one that only includes US RV HAR components as regressors (brown line), plotted in Figure A.1, we can see that, apart from the All Ordinaries, and also the FT Straits Times, the S&P CNX Nifty and the Hang Seng to a lesser extent, the slopes of the cumSFE series are subdued considerably, with those of the Bovespa and S&P TSX in particular remaining rather flat over the entire out-of-sample period. For most of the other international equity market indices, the VIX HAR components account for approximately half of the cumulative predictive gains.

One can see from the longer forecast horizon evaluation results reported in Table A.7 that the performance of the augmented HAR model without the VIX HAR components diminishes quickly. Although the CW-statistic remains significant at the 1% level for all 17 equity markets at the five-day-ahead horizon, the overall improvement in the forecasts is noticeably weaker, resulting in much smaller R^2_{os} values. Again, the only exception here is the All Ordinaries series, which yields an R^2_{os} of 9.53%. The improvements deteriorate further for the 10- and 22-day-ahead prediction horizons. Nevertheless, 14 of the 17 forecast improvements remain significant at the 1% level for the 10-day-ahead horizon, though some of the R^2_{os} values are rather small and/or negative. The R^2_{os} for the All Ordinaries stays sizeable, at 7.00%, followed by the Nikkei 225 and the IPC Mexico, with R^2_{os} values of around 3.3%. At the 22-day-ahead horizon, only the All Ordinaries and the Nikkei 225 retain significant and sizable predictive improvements in terms of out-of-sample R^2 values.

In summary, we can conclude that the improvements in forecasts up to one week ahead are significant and sizeable, and, with the exception of the Bovespa and S&P TSX equity indices, are *not* driven solely by the VIX HAR components. Nevertheless, it is clear that the amount of predictive information contained in the VIX when forecasting volatility in international equity markets is large, and becomes increasingly important when constructing longer horizon predictions.

5.2. Controlling for other forward-looking volatility

We have seen that a substantial part of the out-of-sample predictive gains for some of the 17 foreign equity markets is due to forward-looking volatility information, which we capture by including the (US) VIX in the augmented HAR model in Eq. (6). Two questions that arise are whether the S&P 500 option implied volatility index (VIX) captures *all* of the relevant forward-looking volatility information for all markets, and how informative a foreign equity market's own option implied forward-looking volatility information is.[29] To assess the importance of forward-looking volatility information, as contained in the option implied volatility indices of each foreign equity

[28] An earlier version of this paper also assessed the impact of increasing the size of the in-sample fitting period to 1000 observations and using the Dow Jones Industrial Average as the headline US equity index on the out-of-sample results. Overall, our findings are not affected by these choices. These additional results are available upon request.

[29] We thank an anonymous referee for pointing this out to us.

market's own VIX series, we obtain VIX data for 13 equity indices from Bloomberg and add local VIX HAR components to Eq. (6) as additional predictors.[30] The 13 equity markets for which VIX data are available are listed below.

Entry	Region	Equity market's volatility index	Country	Data begins
1	Oceania	ASX200 VOL INDEX	Australia	03.01.2008
2		HSI VOL INDEX	Hong Kong	03.01.2001
3	Asia	NIKKEI VOL INDEX	Japan	05.01.2001
4		KOSPI 200 VOL INDEX	South Korea	03.01.2003
5		INDIA NSE VOL INDEX	India	02.11.2007
6		VDAX NEW	Germany	03.01.1992
7		VAEX AEX VOL	The Netherlands	04.01.2000
8	Europe	CAC40 VOL INDEX	France	04.01.2000
9		FTSE100 VOL INDEX	United Kingdom	05.01.2000
10		EURO50 VIX	Euro Area	04.01.1999
11		SP TSX60 VOL INDEX	Canada	02.10.2009
12	Americas	MEXICO VOL INDEX	Mexico	29.03.2004
13		CBOE BRAZIL ETF VOL INDEX	Brazil	17.03.2011

To clarify what we do, let $\boldsymbol{x}^{\mathrm{VIX}}_{t,\mathrm{FC}} = \left[\log \mathrm{VIX}^{(d)}_{t,\mathrm{FC}} \ \log \mathrm{VIX}^{(w)}_{t,\mathrm{FC}} \ \log \mathrm{VIX}^{(m)}_{t,\mathrm{FC}}\right]$ be a (1×3) vector of local VIX HAR components, where the standard daily, weekly and monthly components are computed as before. We assess the value added by including local forward-looking volatility information in addition to the US predictors by modifying Eq. (6) to:

$$y_{t+1} = \overbrace{\boldsymbol{x}_t\boldsymbol{\beta}}^{\text{local volatility info}} + \underbrace{\boldsymbol{x}^{\mathrm{VIX}}_t\boldsymbol{\beta}_{\mathrm{VIX}} + \boldsymbol{x}^{\mathrm{US}}_t\boldsymbol{\beta}_{\mathrm{US}}}_{\text{US volatility info}} + \overbrace{\boldsymbol{x}^{\mathrm{VIX}}_{t,\mathrm{FC}}\boldsymbol{\beta}^{\mathrm{VIX}}_{\mathrm{FC}}}^{\substack{\text{forward-looking}\\ \text{local volatility info}}} + \epsilon^{\mathrm{US}}_{t+1}, \tag{21}$$

where $\boldsymbol{\beta}^{\mathrm{VIX}}_{\mathrm{FC}} = \left[\beta^{\mathrm{VIX}(d)}_{\mathrm{FC}} \ \beta^{\mathrm{VIX}(w)}_{\mathrm{FC}} \ \beta^{\mathrm{VIX}(m)}_{\mathrm{FC}}\right]'$ is a (3×1) vector of parameters that captures the impact of the foreign country's local VIX information. All of the other terms in Eq. (21) are as defined previously.

As is evident from the list of VIX indices above, we do not have any option implied volatility data available for the Swiss Market Index, the IBEX 35, the FT Straits Times and the FTSE MIB. Also, the available (local) VIX data for some of the equity markets that we include do not go as far back as our RV data (i.e., to the beginning of 2000). Rather than shortening the out-of-sample evaluation period or excluding these equity markets from the robustness analysis, we decided to replace the local market's VIX HAR predictor vector $\boldsymbol{x}^{\mathrm{VIX}}_{t,\mathrm{FC}}$ in Eq. (21) with a European (or Asian) VIX HAR '*factor*' predictor vector, which we denote by $\boldsymbol{f}^{\mathrm{VIX}}_{t,\mathrm{EU}}$ (or $\boldsymbol{f}^{\mathrm{VIX}}_{t,\mathrm{ASIA}}$ for Asia). That is, let $\mathcal{X}(\mathrm{EU}) = \log\{[(\mathrm{VDAX\ NEW})\ (\mathrm{VAEX\ AEX\ VOL})\ (\mathrm{CAC40\ VOL\ INDEX})\ (\mathrm{FTSE100\ VOL\ INDEX})\ (\mathrm{EURO50\ VIX})]\}$ be the $(T \times 5)$ log-transformed data matrix consisting of all of the European VIX indices listed under entries 6–10 above. Then, the European VIX HAR factor is defined as the (1×3) vector $\boldsymbol{f}^{\mathrm{VIX}}_{t,\mathrm{EU}} = [f^{\mathrm{VIX}\,(d)}_{t,\mathrm{EU}} \ f^{\mathrm{VIX}\,(w)}_{t,\mathrm{EU}} \ f^{\mathrm{VIX}\,(m)}_{t,\mathrm{EU}}]$, where $f^{\mathrm{VIX}}_{t,\mathrm{EU}}$ is the first principal component of $\mathcal{X}(\mathrm{EU})$, with the daily, weekly and monthly HAR components (i.e., $f^{\mathrm{VIX}\,(d)}_{t,\mathrm{EU}}$, $f^{\mathrm{VIX}\,(w)}_{t,\mathrm{EU}}$, and $f^{\mathrm{VIX}\,(m)}_{t,\mathrm{EU}}$) computed as before. Similarly, for $\boldsymbol{f}^{\mathrm{VIX}}_{t,\mathrm{ASIA}}$, the first principal component is extracted from $\mathcal{X}(\mathrm{ASIA}) = \log\{[(\mathrm{HSI\ VOL\ INDEX})\ (\mathrm{NIKKEI\ VOL\ INDEX})\ (\mathrm{KOSPI\ 200\ VOL\ INDEX})]\}$. We then construct forecasts from Eq. (21) for all 17 international equity markets, using $\boldsymbol{f}^{\mathrm{VIX}}_{t,\mathrm{EU}}$ in place of $\boldsymbol{x}^{\mathrm{VIX}}_{t,\mathrm{FC}}$ for the Swiss Market Index and the IBEX 35, FT Straits Times, FTSE MIB, All Ordinaries, S&P CNX Nifty, Bovespa and S&P TSX indices.[31] These are then compared to the forecasts constructed from the augmented HAR model in Eq. (6), which only includes US volatility information in addition to the local HAR RV components.

Before presenting and discussing these results, we would like to emphasise here that, since we are interested chiefly in the out-of-sample predictive performance of US volatility information for each of the 17 international equity markets that we consider, we only report the out-of-sample evaluation results. Also, when constructing forecasts from factor-based regression models, it is common to extract the factors recursively when rolling through the out-of-sample period so as to avoid concerns related to look-ahead biases; that is, using future data when constructing the factors at time t. In order to tilt the out-of-sample prediction results using the European (or Asian) VIX HAR factor in favour of the local VIX model in Eq. (21), we use the full sample data to compute $\boldsymbol{f}^{\mathrm{VIX}}_{t,\mathrm{EU}}$ (or $\boldsymbol{f}^{\mathrm{VIX}}_{t,\mathrm{ASIA}}$) once and then roll through the out-of-sample data, instead of extracting the factor recursively. This should work in favour of the eight equity markets listed above for which no VIX data are available and the factor-based approach is used.

Initially, we again present a visual assessment of the out-of-sample forecast gains by plotting the cumSFE sequences of our augmented HAR model of Eq. (6) and the model that adds local VIX information (or a European VIX factor) to the predictor set, as defined in Eq. (21) in Figure A.2.[32] As before, both sequences are again computed relative to the local HAR model given in Eq. (7), with the forecast horizon being one step ahead. That is, the blue lines in Figure A.2 are the same as the blue lines plotted in Fig. 4.

[30] Bloomberg also has VIX indices for Russia and South Africa, but these are not listed here because they are not used in our analysis. Also, there are two VDAX indices: an old version, with the mnemonic `VDAX VSMI`, and a new version. We use the new version, with mnemonic `VDAX NEW`.

[31] Since the beginning date of the KOSPI 200 VOL INDEX is in 2003, the sample and forecasting periods for the Asian countries are shortened correspondingly.

[32] Using $\boldsymbol{f}^{\mathrm{VIX}}_{t,\mathrm{ASIA}}$ in place of $\boldsymbol{f}^{\mathrm{VIX}}_{t,\mathrm{EU}}$ produces consistently worse forecasts; to conserve space, the results are not reported here, but they are available upon request.

The green lines in Figure A.2 are the cumSFE sequences of our augmented HAR model that adds local forward-looking volatility information to the augmented HAR model as defined in Eq. (21) (the legend entry is + FC VIX HAR).[33] Recall that the model in Eq. (21), which adds local forward-looking volatility information to the predictor set, produces consistently better out-of-sample forecasts if the green line in Figure A.2 is consistently above the blue one. As we can see from Figure A.2, this is only the case for the Nikkei 225, Hang Seng, KOSPI and Euro STOXX 50, and very slightly for the DAX. Visually, the improvement seems to be strongest for the Hang Seng series, which is driven largely by a single episode that occurred at around the time of the Lehman Brothers' collapse in September/October 2008. For the DAX, KOSPI and Euro STOXX 50, the improvement appears to be rather marginal, while it is noticeable from about the end of 2011 onwards for the Nikkei 225.

To formally gauge the magnitude of any potential out-of-sample forecast improvements, we compute the gain in out-of-sample R^2 from adding local VIX information to the augmented HAR model. That is, we define $\Delta R^2_{os}(h) =$ [R^2_{os} computed from Eq. (21)–R^2_{os} computed from Eq. (6)], where h denotes the forecast horizon that is being evaluated, i.e., $h = 1, 5, 10, 22$. When $\Delta R^2_{os}(h) > 0$, there is an increase in R^2_{os} from adding local VIX information to the predictor set in the augmented HAR model. The statistical significance is examined again within a Clark and West (2007) MSFE-adjusted t-test environment, since we are examining the predictive gain from adding local VIX information to the augmented HAR model in Eq. (6); that is, the augmented HAR model of Eq. (6) is nested in the model with local VIX information in Eq. (21). Table A.8 reports the predictive gains in terms of $\Delta R^2_{os}(h)$ for $h = 1, 5, 10, 22$ in the last four columns. To avoid cluttering the table with extra columns showing the magnitudes of the CW-statistics, we have merely added asterisks next to the $\Delta R^2_{os}(h)$ entries that yield significant CW-statistics. We use standard asterisk notation to denote significance at the 1%, 5%, and 10% levels, respectively.[34]

We can see from the evaluation results that are reported in Table A.8 that the change in the out-of-sample R^2 values as a result of including local VIX HAR components in the augmented HAR model of (6) is negative for six of the 17 equity markets at the one-step-ahead horizon that we consider. The importance of this predictor variable deteriorates further with an increasing h, producing only three positive ΔR^2_{os} values out of 17 at the 22-day-ahead horizon. Most of the non-negative increases in ΔR^2_{os} are rather small in magnitude, with notable exceptions being the improvements recorded for the Hang Seng (3.13%), the Euro STOXX 50 (1.43%), the Nikkei 225 and KOSPI (each around 1.4%) and the DAX (0.9%), at the one-step-ahead horizon. Moreover, these improvements are statistically significant. From the long-horizon evaluations, it is evident that the improvements remain consistently significant, though small at times, up to 22 days ahead for the Euro STOXX 50, and up to 10 steps ahead for the KOSPI index, the DAX, Hang Seng and the IBEX 35, with the later two being only weakly significant at the 10-day-ahead horizon.

To summarise our results as to the robustness to local volatility information, we conclude that for most of the equity markets there is only a very slight improvement in out-of-sample performances, with six (for $h = 1$) or more (for $h > 1$) markets in fact producing negative ΔR^2_{os} values. At the one-step-ahead horizon, only around three to four equity markets improve significantly and achieve sizeable gains, with the improvements in R^2_{os} being 1%–3%. However, these gains deteriorate with the forecast horizon, and are unimportant at $h = 22$. Overall, we conclude that adding local VIX data to the augmented HAR model in Eq. (6) yields small or no forecast gains, with the most notable exception of the Euro STOXX 50, and, at shorter horizons, the Nikkei 225, the DAX and the Hang Seng VIX information.[35]

5.3. *Controlling for RV information in other European and/or Asian equity markets*

As a last robustness check, we analyze whether the realized volatility in other European and/or Asian equity markets includes relevant information that could be utilised to improve out-of-sample forecast performance. Rather than selecting a few dominant European or Asian equity markets and then adding their HAR component vectors into Eq. (21) one at a time as extra control variables for each of the international equity markets that we consider, we again prefer to extract a common RV factor from the European and Asian realized volatility information using principal components.[36] To formalise this, let $\boldsymbol{\mathcal{Y}}(\mathrm{EU}) = \log\{[\mathrm{RV(DAX)}\ \mathrm{RV(CAC\ 40)}\ \mathrm{RV(AEX)}\ \mathrm{RV(Swiss\ Market\ Index)}\ \mathrm{RV(IBEX\ 35)}\ \mathrm{RV(Euro\ STOXX\ 50)}\ \mathrm{RV(FTSE\ MIB)}]\}$ denote

[33] Note that everything in these plots is kept as in previous figures in order to facilitate comparisons. Some of the countries have different beginning dates for the out-of-sample evaluation, due to the lack of available VIX data, so the plots for the Nikkei 225, the Hang Seng, the KOSPI and the IPC Mexico are shifted somewhat, due to the later out-of-sample starting periods.

[34] That is, *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

[35] The Euro STOXX 50 and the DAX seem to have the most liquid and mature VIX indices. At this point, it is not clear why the other equity markets' VIX indices are not informative for long horizon forecasts at least, even if short horizons are affected the most by spillover effects.

[36] Specifying, say, 11 European and Asian markets to be used one at a time as controls for the potentially relevant RV information contained in these other equity markets would seem feasible here. However, this raises the possibility of too many statistical tests being carried out, an issue which is known as the '*multiple comparisons*' problem in the statistics literature. As a solution, one could use a Bonferroni type of correction when evaluating the out-of-sample performance; that is, adjust the significance level of the test based on the number of additional tests that are constructed. However, it is not clear to us whether this is justified when implementing the MSFE-adjusted t-test on the nested model comparisons of Clark and West (2007). Moreover, it would be cumbersome to report the evaluation results in an informative way, as one would have 11 prediction evaluations for each international equity market and forecast horizon. In order to stay within the same testing environment and simplify the presentation of the results, we extract a European and an Asian RV factor, rather than including additional RV predictors one at a time as extra controls. As was done with the VIX series in Section 5.2, we again extract the factors from the full sample period only once, rather than recursively as new information becomes available.

the $(T \times 8)$ vector of log-transformed RV data for all European equity indices that are available to us. The European RV HAR factor is then defined as the (1×3) vector $\boldsymbol{f}^{RV}_{t,\text{EU}} = [f^{RV\,(d)}_{t,\text{EU}}\ f^{RV\,(w)}_{t,\text{EU}}\ f^{RV\,(m)}_{t,\text{EU}}]$, where $f^{RV}_{t,\text{EU}}$ is the first principal component of $\mathcal{Y}(\text{EU})$, with the daily, weekly and monthly HAR components computed as before. The Asian RV factor (denoted by $\boldsymbol{f}^{RV}_{t,\text{ASIA}}$ henceforth) is computed as the first principal component from $\mathcal{Y}(\text{ASIA}) = \log\{[\text{RV(Nikkei 225) RV(Hang Seng) RV(KOSPI) RV(FT Straits Times)}]\}$.[37]

We assess the importance of RV information in other European and/or Asian equity markets by taking the augmented HAR model that adds local VIX data as predictors, defined in Eq. (21), and further adding $\boldsymbol{f}^{RV}_{t,\text{EU}}$ and $\boldsymbol{f}^{RV}_{t,\text{ASIA}}$ to it as regressors. That is, we form the predictive regression model:

$$y_{t+1} = \underbrace{\overbrace{\boldsymbol{x}_t\boldsymbol{\beta}}^{\text{local volatility info}} + \underbrace{\boldsymbol{x}^{\text{VIX}}_t\boldsymbol{\beta}_{\text{VIX}} + \boldsymbol{x}^{\text{US}}_t\boldsymbol{\beta}_{\text{US}}}_{\text{US volatility info}}}_{\text{augmented HAR as inEq. (6)}} + \overbrace{\boldsymbol{x}^{\text{VIX}}_{t,\text{FC}}\boldsymbol{\beta}^{\text{VIX}}_{\text{FC}}}^{\substack{\text{forward-looking}\\ \text{local volatility info}}}$$
$$+ \underbrace{\boldsymbol{f}^{RV}_{t,\text{EU}}\boldsymbol{\beta}^{\boldsymbol{f}}_{\text{EU}} + \boldsymbol{f}^{RV}_{t,\text{ASIA}}\boldsymbol{\beta}^{\boldsymbol{f}}_{\text{ASIA}}}_{\text{other RV info}} + \epsilon^{\text{US}}_{t+1}, \qquad (22)$$

where $\boldsymbol{f}^{RV}_{t,\text{EU}}$ and $\boldsymbol{f}^{RV}_{t,\text{EU}}$ are the (1×3)-dimensional European and Asian RV HAR factor vectors defined above, and $\boldsymbol{\beta}^{\boldsymbol{f}}_{\text{EU}}$ and $\boldsymbol{\beta}^{\boldsymbol{f}}_{\text{ASIA}}$ are corresponding (3×1) parameter vectors that capture their influence on the international RV. Improvements in out-of-sample forecasts relative to our augmented HAR model are examined in the same setting as in Section 5.2; that is, informally by the magnitude of the $\Delta R^2_{os}(h)$, statistically using the Clark and West (2007) MSFE-adjusted t-test, and visually from plots of the cumSFE sequence. These evaluation results are reported in Figure A.3 and Table A.9. Figure A.3 shows the incremental improvement in the cumSFE from including other RV information, in the form of a European RV factor HAR and an Asian RV factor HAR, in addition to the predictor set of the augmented HAR with local VIX information defined in Eq. (21). The blue line in Figure A.3 again shows the cumSFE of the augmented HAR as a reference point, as was done before. The red line shows the cumSFE when only the European RV factor HAR vector $\boldsymbol{f}^{RV}_{t,\text{EU}}$ is included in Eq. (21) in addition to local VIX information (legend entry + FC VIX HAR + f(EU) HAR). The light green line in Figure A.3 shows the improvement when both the European RV factor HAR vector $\boldsymbol{f}^{RV}_{t,\text{EU}}$ and the Asian RV factor HAR vector $\boldsymbol{f}^{RV}_{t,\text{ASIA}}$ are added to Eq. (21) as predictors (legend entry + f(ASIA) HAR).

From the reported results, we can summarise the effect of adding other RV information into the predictor set in the form of factors as follows. First, examining the time series evolution of the cumSFE sequence visually, one can see that there is no improvement, or at the very best only a very mild improvement, in the out-of-sample forecasts as a result of adding other RV information that is not already realised from the addition of the local VIX series assessed earlier. In fact, the results for some equity markets worsen (see for instance the cumSFE series for the Bovespa, the IPC Mexico, the S&P CNX Nifty, and the All Ordinaries index). Second, conditioning on the Asian RV factor HAR generally produces marginally *worse* out-of-sample forecasts.[38] This can be seen most clearly from the FT Straits Times and the IPC Mexico, and also somewhat more mildly from the DAX, the Euro STOXX 50, the Swiss Market Index and the KOSPI series. For these equity markets, the loss in precision from adding irrelevant predictors worsens the out-of-sample forecast performance. Third, it is evident from the multiple-horizon statistical comparison in Table A.9 that any gains in R^2_{os} over the benchmark augmented HAR model and their significance levels are very similar to those obtained by only incorporating local VIX information, as was done in Eq. (21), see Table A.8. Moreover, again in line with the results in Section 5.2, any forecast gains that are statistically significant at the one-step-ahead horizon disappear fairly quickly as h increases, with the 22-day-ahead forecast even for the Euro STOXX 50 resulting in a rather small and statistically insignificant improvement.

Overall, we conclude this last robustness check with the finding that, once we condition on local VIX information, as described in Section 5.2, including additional RV data in the predictor set does not add any further information to improve the out-of-sample forecasts of RV in international equity markets.

6. Conclusion

This study extends the work of Rapach et al. (2013) and investigates whether US-based equity market volatility information has predictive value for volatility forecasts in a large cross-section of international equity markets. We assess the role of the US by augmenting the benchmark HAR model of Corsi (2009) with daily, weekly and monthly US RV and log VIX HAR components, and evaluating the in-sample and out-of-sample contributions of this information to realized volatility in international equity markets. We find the US to play a strong role as a

37 For the European RV data, the first three principal components explain 89.1745%, 4.6748%, and 1.8267%, respectively, of the variation in $\mathcal{Y}(\text{EU})$. Thus, using only the first principal component seems to be justified, as it explains nearly 90% of the variation in the data. For the Asian RV data, these values are 68.9685%, 15.4803%, and 11.2654%, respectively. These results are less clear as to whether one factor is enough to capture all of the important movements in $\mathcal{Y}(\text{ASIA})$. We address the issue that more than one factor may be driving $\mathcal{Y}(\text{ASIA})$ by also performing forecast evaluations using a HAR structure on the first two factors, together with equally weighted and R^2 weighted linear combinations. The latter was performed in order to keep the number of additional regressors added small, so as to minimise overfitting and the ensuing poor out-of-sample performance. However, the forecasts in all of these assessments were always worse than those based on the first PC only.

38 We have also include current time, i.e., $t + 1$, factors for Asia when forming forecasts for the European and North and South American indices, but the difference between using lagged or current time information is immaterial, producing the same statistical conclusions in terms of significance levels.

source of relevant volatility information, being particularly important for the Australian and all of the European equity markets that we consider, with a sizeable part of this relevant volatility information coming from forward-looking (or implied) volatility.

Using a large out-of-sample forecast evaluation period, we find that the volatility forecasts for all 17 equity markets improve substantially and are highly statistically significant when US volatility information is included in the predictor set. The daily out-of-sample R^2 values range between 4.56% (Hang Seng) and 14.48% (All Ordinaries), and are above 10% for nine of the 17 equity markets that we analyse. Moreover, our results show that the Australian and all of the European equity markets benefit the most from the inclusion of US-based volatility information, while the South and North American equity markets and some of the Asian markets benefit the least. An assessment of the forecast performance over time shows that this improvement in predictive performance is consistent over the entire out-of-sample period, and is not driven solely by a few individual events. Moreover, we show that the improvements remain significant for forecast horizons of up to 22 days ahead for 15 of the 17 equity markets, still yielding sizable out-of-sample R^2 values of around 5%–6% for four of the 17 equity markets that we include.

One interesting finding from our in-sample analysis is that the low frequency US volatility component has a negative effect. That is, the parameter estimates on the weekly log VIX HAR component are negative and highly significant for all 17 equity markets. The values that we obtain range from -1.03 to -0.37, with the majority being in the range -0.9 to -0.8. The monthly US RV HAR component is significantly negative for 12 of the 17 equity markets, with values largely ranging from -0.20 to -0.10. So far, there does not seem to have been any discussion in the literature as to why this negative effect occurs, and what economic forces lie behind it, particularly with regard to the weekly log VIX HAR component.

In summary, our analysis confirms that the US plays a leading role as a source of equity market information. This role is important not only for international equity *return* forecasts, as documented by Rapach et al. (2013), but also for forecasts of the *volatility* in international equity markets.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.ijforecast.2016.05.001.

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