The role of risk-neutral moments in forecasting future realised volatility: An international perspective

Junyu Zhang
Department of Accountancy and Finance
Otago Business School, University of Otago
Dunedin 9054, New Zealand
junyu.zhang@postgrad.otago.ac.nz

Xinfeng Ruan
Department of Accountancy and Finance
Otago Business School, University of Otago
Dunedin 9054, New Zealand
xinfeng.ruan@otago.ac.nz

Jin E. Zhang
Department of Accountancy and Finance
Otago Business School, University of Otago
Dunedin 9054, New Zealand
jin.zhang@otago.ac.nz

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Abstract

This paper estimates the predictability of future volatility on eleven stock markets by using the risk-neutral moments of corresponding international proxy ETFs. Our evidence shows that the risk-neutral standard deviation and excess kurtosis can positively and negatively predict the future volatility, respectively, while the predictive significance of risk-neutral skewness is relatively weaker but can negatively predict the future volatility in some locations. Results from model confidence set analysis show that incorporating location-based risk-neutral moments into the HAR-RV model can improve the predictability of future volatility in some markets, while volatilities in all markets are sensitive to international-combined risk-neutral moments, where these aggregated factors can significantly enhance the predictive power.

1 Introduction

Since market volatility is a crucial parameter in many types of financial models, an increasing number of studies have been investigating the predictability of future volatility of the market recently. This paper, to the best of our knowledge, is the first paper to investigate the predictive power of the both second and higher-order risk-neutral moments of international indices proxies ETFs towards future volatility of local markets, by conducting both the in-sample and out-of-sample analyses. Further, we also compare the models that we develop to each other, and identify the optimal models for each location via model confidence set (MCS) analysis. The majority of previous papers that investigates volatility forecasting apply ex-post factors as explanatory variables, while researchers have begun to look into the predictive ability of ex-ante predictors (such as implied volatility) recently. Drawing upon the use of 11 iShare country-/region-specific ETFs, our paper expands the previous studies and uses risk-neutral standard deviation (VOL), skewness ($SKEW$), and excess kurtosis ($KURT$), which are second, third, and fourth risk-neutral moments of our proxy ETFs computed from the formulae from Bakshi, Kapadia, and Madan (2003), respectively, as predictors to provide new evidence of the international predictability of future volatility.

Studying the international predictability of future volatility can mainly: 1) improve the accuracy of pricing models for some financial products, such as options pricing models that include Vega or the models for pricing the variance swaps; 2) reduce errors in measuring expected loss in financial risk management (e.g. the more accurate value at risk (VaR) of the international investment). 3) provide indicators to develop hedging strategies. On the other hand, most of the literature related to the volatility prediction uses ex-post predictors (see Balaban, Bayar, and Faff, 2006; Diebold and Yilmaz, 2012; Li and Giles, 2015; Mittnik, Robinzonov, and Spindler, 2015; Wang et al., 2016; Zhang et al., 2019a, among others). Only a few papers try to investigate the predictability of future market volatility via option-implied measures, and most of the international studies focus on the implied volatility only (see Yang and Zhou, 2017; Liang, Wei, and Zhang, 2020, among others). However, fewer articles estimate the predictive power of higher-order risk-neutral moments toward global future volatility other than studying a single market (Byun and Kim, 2013). Additionally, Canina and Figlewski (1993) and Christensen and Prabhala (1998) draw different conclusions about the information content extracted by implied volatility, the latter shred lights on that information from options can provide more useful implicit information than latent variables. Therefore, our study aims to bridge the gap between literature by providing new international evidence of the predictive ability of second to fourth risk-neutral moments towards future volatility. To the best of our effort, we cover eight developed markets and three emerging markets that have all available data set in our research window and some of the markets have never been studied related this topic, that is, international predictability of volatility via risk-neutral moments.

Since the concept of realised volatility has been given by Andersen and Bollerslev (1998), it has been widely studied in the academy. In previous literature, such as in Andersen et al. (2001), Andersen et al. (2003), Andersen, Bollerslev, and Meddahi (2005), and Andersen, Bollerslev, and Diebold (2007), researchers find models based on the past realised market volatility can provide useful information for predicting the future return volatility because the auto-correlation widely exists in the market. However, after Corsi (2009) proposed a relatively simple model, the heterogeneous autoregressive realised volatility (HAR-RV), which includes the long-memory return volatility in the model, many researchers began to adopt this model as a benchmark to develop more specific models. For instance, Bandi, Russell, and Yang (2013) use HAR models to study the time-varying noise in the market; Corsi, Pirino, and Reno (2010), and Patton and Sheppard (2015) incorporate signed jumps as new factors into the model; and Wang et al. (2016), and Zhang et al. (2019a) develop new methods to improve the performance of HAR-RV or to choose the optimal model. However, models above all estimate the historical and ex-post factors in a single market. For papers that are close to our study, Balaban, Bayar, and Faff (2006) apply several models to forecast the future stock market volatility in fifteen countries within a ten-year window but only compare the absolute errors. Wen et al. (2019) apply the models based on HAR-RV to forecast realised volatility of crude oil futures, which conduct in- and out-of-sample tests and use model confidence set analysis to identify the optimal models among a pool of models. Moreover, for studies related to ex-ante predictors, Canina and Figlewski (1993) discover the relationship between the Black and Scholes (1973) implied volatility and the realised volatility, while Christensen and Prabhala (1998) find that the implied volatility of S&P 100 can significantly predict the future realised volatility. Yang and Zhou (2017) provide evidence of the spillover of implied volatility between eleven countries. Nevertheless, Zhang, Ma, and Liao (2020) is the first study that incorporates implied volatility into HAR-RV models to forecast future global volatility, and it finds that the implied volatility can predict future volatility in eight developed markets.

To provide evidence for new predictors and expand previous studies to more markets, in this paper, we use the second to fourth risk-neutral moments of 11 international proxy ETFs to predict the future volatility of the local markets. First, we compute the risk-neutral moments following Bakshi, Kapadia, and Madan (2003) estimator. Compared with the lag realised volatility, risk-neutral standard deviation, skewness, and excess kurtosis may reflect the market expectation of future returns and potentially provide more information to future volatility. Thus, we firstly conduct the in- and out-of-sample tests on the HAR-RV model as the benchmark estimation. Then, we include risk-neutral models to the fundamental HAR-RV model and construct a set of HAR-RV-moments class models and run the same tests as the benchmark model. Since many studies, such as Yang and Zhou (2017), and Zhang, Wang, and Ma (2021), prove that volatility spillover widely exists among cross-nation markets, and thus, the risk-neutral moments may also include information flows for other markets. Therefore, we developed combined factors using GDP-weighted, equally-weighted, and first-principal-component combinations. Lastly, we conduct the model confidence set analysis to identify the optimal model among our pool of models. However, our main purpose is not to find the best-existed model for predicting future volatility but to provide new evidence to show the worthiness of including higher-order risk-neutral moments in predictive models. Our results show that the risk-neutral standard deviation and excess kurtosis can generally significantly positively and negatively predict future volatility, while a few significant results for risk-neutral skewness in some specific locations reveals that they can positively predict future volatility. Results from MCS analysis show that the combination of risk-neutral moments can generally improve the predictability in most locations.

The remainder of this paper is organised as follows: Section 2 explains our models and methodology. Section 3 describes the data collection and summary statistics. Section 4 presents our empirical results that include the in- and out-of-sample tests as well as the model comparison. Lastly, section 5 provides the conclusion of our study.

2 Methodology

2.1 Risk-neutral moments

To produce risk indicators for the local market, we compute the risk-neutral standard deviation (VOL), skewness($SKEW$), and excess kurtosis($KURT$) for each proxy, by using the formulae derived by Bakshi, Kapadia, and Madan (2003): [1]

$$VOL_{t,\tau} = \sqrt{\frac{e^{r\tau}V_{t,\tau} - \mu_{t,\tau}^2}{\tau}} \tag{1}$$

$$SKEW_{t,\tau} = \frac{e^{r\tau}W_{t,\tau} - 3\mu_{t,\tau}e^{r\tau}V_{t,\tau} + 2\mu_{t,\tau}^3}{[e^{r\tau}V_{t,\tau} - \mu_{t,\tau}^2]^{3/2}} \tag{2}$$

$$KURT_{t,\tau} = \frac{e^{r\tau}X_{t,\tau} - 4\mu_{t,\tau}e^{r\tau}W_{t,\tau} + 6e^{r\tau}\mu_{t,\tau}^2 V_{t,\tau} - 3\mu_{t,\tau}^4}{[e^{r\tau}V_{t,\tau} - \mu_{t,\tau}^2]^2} - 3 \tag{3}$$

$$V_{t,\tau} = \int_{S_t}^{\infty} \frac{2(1 - \ln[\frac{K}{S_t}])}{K^2} C_{t,\tau;K}\, dK + \int_0^{S_t} \frac{2(1 + \ln[\frac{S_t}{K}])}{K^2} P_{t,\tau;K}\, dK \tag{4}$$

$$W_{t,\tau} = \int_{S_t}^{\infty} \frac{6\ln[\frac{K}{S_t}] - 3(\ln[\frac{K}{S_t}])^2}{K^2} C_{t,\tau;K}\, dK - \int_0^{S_t} \frac{6\ln[\frac{S_t}{K}] + 3(\ln[\frac{S_t}{K}])^2}{K^2} P_{t,\tau;K}\, dK \tag{5}$$

[1]Although formulae from Bakshi, Kapadia, and Madan (2003) are for European options, the difference is minor when they are applied on American options (Gkionis et al., 2021). Additionally, we retrieve implied volatilities from OptionMetrics, which are converted from option prices by binomial models, and thus the moments we computed are reconstructed mimic European style options.

$$X_{t,\tau} = \int_{S_t}^{\infty} \frac{12(\ln[\frac{K}{S_t}])^2 - 4(\ln[\frac{K}{S_t}])^3}{K^2} C_{t,\tau;K}\, dK + \int_{0}^{S_t} \frac{12(\ln[\frac{S_t}{K}])^2 + 4(\ln[\frac{S_t}{K}])^3}{K^2} P_{t,\tau;K}\, dK \quad (6)$$

$$\mu_{t,\tau} = e^{r\tau} - 1 - \frac{e^{r\tau}}{2} V_{t,\tau} - \frac{e^{r\tau}}{6} W_{t,\tau} - \frac{e^{r\tau}}{24} X_{t,\tau}, \quad (7)$$

where C and P are prices of a call and a put option; K, S, and r are the strike price of options, the price of underlying assets, and the risk-free rate with the same term as the maturity of options, respectively.

To enhance the precision of model-free option measures, we interpolate and extrapolate the moneyness following the method adopted by Chang, Christoffersen, and Jacobs (2013) and Ruan and Zhang (2019). [2] First, we filter the standardised options with a maturity of 30 days. For each day, we construct a fine grid containing 1000 moneyness levels (K/S) evenly between 0.01% and 300%. We use cubic splines to interpolate the implied volatility within the range of obtained moneyness. For the moneyness levels locate out of the existing options, we use the constant implied volatility as the same value as options with the lowest or highest collectable moneyness. Then, by the use of Black and Scholes (1973) model, we convert implied volatilities to options prices,[3] where for options with moneyness larger than 1, their implied volatilities are converted to call prices, and options with moneyness lower than 1, the function for puts will be applied. Additionally, prices of options with negative or zero interpolated implied volatilities are set to zero. Dividends are assumed to be paid continuously, and yields are calculated as annual dividends within the past year divided by the current price. Further, we use cubic splines to interpolate interest rates for specific maturities. From equation (4) to equation (6), trapezoidal approach is applied for integration.

2.2 Global risk-neutral moments

In our analysis, we firstly conduct the in-sample and out-of-sample tests for each country/region separately. However, to incorporate the diffusion effect around the uncertainty

[2] Compared to the calculation using the retrievable data only, interpolation and extrapolation techniques can improve the accuracy (see Aschakulporn and Zhang, 2021).

[3] We applied Black and Scholes (1973) to compute the prices as the mimic European-style options.

between markets, we create global risk-neutral moments. As methodology in most of the research about the general effects among assets, we compute the weighted global risk-neutral moments across all regions in observation as the common method of combination (see Baker and Wurgler, 2006, Jiang et al., 2019, among others), which can simply combine the potential cross-market effects into the factor. In addition, to consider the size of the economy of these countries/regions, we apply the equally-weighted and GDP-weighted strategies separately in weighted aggregation.

Further, since the most recent papers, such as Stock and Watson (2002), Ludvigson and Ng (2009), Degiannakis and Filis (2017), Liang, Wei, and Zhang (2020), and Zhang, Ma, and Liao (2020), reveal that drawing on dimension reduction techniques, the information flows from first-principal-components-aggregated indices can provide extra latent information in time-series analysis, especially in market uncertainty related studies. Therefore, we adopt loading scores from the first principal component of each moment to construct three global risk-neutral moments separately.

2.3 Prediction models

Taking advantage of high-frequency data and the formula of daily realised variance proposed by Andersen and Bollerslev (1998), we define our daily realised volatility as the square root of the sum of the intra-daily squared returns and the daily realised volatility are annualised:

$$RV_t = \sum_{n=1}^{N} r_{t,n}^2, \tag{8}$$

$$Rvol_t = \sqrt{\frac{252}{N} RV_t}, \tag{9}$$

where $Rvol_t$ represents the realised volatility on the trading day t; $r_{t,n}$ is the n-th intraday return on the day t; and N is the total number of the sample returns, where we use data with five-minutes sampling intervals in this paper.

Similarly, our longer horizon realised volatility is defined as:

$$Rvol_{t-h+1:t} = \sqrt{\frac{252}{h}\sum_{d=1}^{h} RV_d}, \tag{10}$$

where $Rvol_{t-h+1:t}$ represents the realised volatility from trading day $t-h+1$ to t, where h is the days within the horizon of the lag realised volatility; RV_d is the daily realised variance from day $t-h+1$ to t.

Our benchmark model is the HAR-RV, as firstly proposed by Corsi (2009), which includes long-memory and multi-scaling features where it incorporates daily, weekly, and monthly realised volatility. Similar to models adopted by Corsi (2009), Byun and Kim (2013), Wen et al. (2019), Zhang, Ma, and Liao (2020), and Liang, Wei, and Zhang (2020), our model are expressed as:

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i} Rvol_{i,t} + \beta_{2,i} Rvol_{i,t-4:t} + \beta_{3,i} Rvol_{i,t-21:t} + \epsilon_{t+1}, \tag{11}$$

where $Rvol_{i,t+1}$ is the future one-day realised volatility for each location; $Rvol_{i,t}$, $Rvol_{i,t-21:t}$, and $Rvol_{i,t-21:t}$ are lag daily, weekly, and monthly annualised realised volatility for each location, respectively; and ϵ_{t+1} is the error term of the model.

Then, we incorporate the risk-neutral moments into the original HAR-RV model to investigate whether these moments can provide further dynamics for the volatility of specific indices proxies, and we denote these model as HAR-RV-IV, HAR-RV-IS, and HAR-RV-IK, since VOL, $SKEW$, and $KURT$ imply risk-neutral volatility, skewness, and kurtosis, respectively:

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i} Rvol_{i,t} + \beta_{2,i} Rvol_{i,t-4:t} + \beta_{3,i} Rvol_{i,t-21:t} + \beta_{4,i} MOM_{i,t} + \epsilon_{t+1}, \tag{12}$$

where $MOM_{i,t}$ is one of the risk-neutral moments we computed for a specific indices proxy.

Next, we include all the moments into the model for each specific index proxy and they are denoted as HAR-RV-MOM:

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i} Rvol_{i,t} + \beta_{2,i} Rvol_{i,t-4:t} + \beta_{3,i} Rvol_{i,t-21:t} + \sum_{k=1}^{3} \beta_{i,k} MOM_{i,k,t} + \epsilon_{t+1}, \quad (13)$$

where $MOM_{i,k,t}$ is one of the risk-neutral moments we computed, and the model includes the three moments for the measurement of each index proxy.

Further, to investigate the predictive powers of international-combined risk-neutral moments and the performance of models, we compute the international factors for risk-neutral moments across all country-/region-proxies via equally- and GDP-weighted strategy and the combination of the first principal component. Moreover, to measure the overall effects of these combined moments, we also estimate models that pool all three moments that are combined by a certain method. Models can be expressed as:

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i} Rvol_{i,t} + \beta_{2,i} Rvol_{i,t-4:t} + \beta_{3,i} Rvol_{i,t-21:t} + \beta_{4,i} MOM_{GDP,t} + \epsilon_{t+1}, \quad (14)$$

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i} Rvol_{i,t} + \beta_{2,i} Rvol_{i,t-4:t} + \beta_{3,i} Rvol_{i,t-21:t} + \beta_{4,i} MOM_{EW,t} + \epsilon_{t+1}, \quad (15)$$

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i} Rvol_{i,t} + \beta_{2,i} Rvol_{i,t-4:t} + \beta_{3,i} Rvol_{i,t-21:t} + \beta_{4,i} MOM_{PCA,t} + \epsilon_{t+1}, \quad (16)$$

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i} Rvol_{i,t} + \beta_{2,i} Rvol_{i,t-4:t} + \beta_{3,i} Rvol_{i,t-21:t} + \sum_{k=1}^{3} \beta_{i,k} MOM_{comb,k,t} + \epsilon_{t+1}, \quad (17)$$

where $MOM_{GDP,t}$, $MOM_{EW,t}$, and $MOM_{PCA,t}$ represent the combined specific moments across all indices proxies by using the GDP-weighted, equally-weighted, and first-principal-component combination method.[4] Equation (17) is the combination model that includes the three combined risk-neutral moments, where $MOM_{comb,k,t}$ represents one of the three combined risk-neutral moments via the same combination method. Since our local samples are from different markets, each exchange has different market close dates during a year (e.g. public holidays), but our proxies for risk-neutral moments cal-

[4] Table A.1 and Table A.2 show the eigenvalues and loading scores for each principal component, respectively. The evidence shows that the first principal component explains the most of variance, and thus we only include the first principal component in our combined factors.

culation are all listed in the US market. Because our purpose is to use these proxies to provide information flows for local markets, we first match each daily risk-neutral moment of our proxies to local market open days and discard unmatched data on both sides to symmetrise the information flows. Then, for GDP- or equal-weighted combination, we aggregate risk-neutral moments for all available markets on the same day to keep as much information as possible. However, we drop dates that include any missing data to construct the first-principal-component indices, for which technique strictly required balance datasets.

3 Data

In this paper, we use options of the iShare country- and region-specific ETFs as well as SPDR S&P 500 ETF to compute the risk-neutral moments. Since the construction of some combined factors requires balance data, and also to make sure all available data can be matched, as well as to avoid data during extreme market turmoil, to the best of our effort, we select the ETFs available between 1 January 2000 and 31 December 2019. Location include Australia (EWA), Brazil (EWZ), Canada (EWC), Germany (EWG), Hong Kong(EWH), Japan (EWJ), Mexico(EWW), South Korea (EWY), Spain (EWP), the United Kingdom (EWU), and the United States(SPY). We adopt these US-listed ETFs as international proxies because: First, the United States owns the most liquid market with the largest capitalisation in the world; Second, international investors can easily participate and market data can be easily accessed; Third, these ETFs have similar attributes, and behaviours of these ETFs are not significantly different from their underlying indices (Phengpis and Swanson, 2009). The reason to choose the SPY as our US proxy is because its features are more similar to the selected ETFs than other available vehicles.

Our options data are retrieved from OptionMetrics, and in order to maximise the use of these proxies, the implied volatilities and strike prices are collected from volatility surface files.[5] Prices of ETFs are collected from CRSP, and risk-free rates are interpolated from the zero-curve provided by OptionMetrics.

Since this paper aims to measure the predictability of local realised volatility by using our international proxies, we collate the daily realised volatility computed from 5-minute high-frequency data from the Oxford-Man Institute of Quantitative Finance Realized Library.[6] The corresponding local realised volatility are from Australia (.AORD), Brazil (.BVSP), Canada (.GSPTSE), Germany (.GDAXI), Hong Kong(.HSI), Japan (.N225), Mexico(.MXX), South Korea (.KS11), Spain (.SMSI), the United Kingdom (.FTSE), and the United States(.SPX). To simplify and clearly denote the measures, the rest of the paper will use location to indicate the realised volatility of local indices ($Rvol$) and risk-neutral moments of country-/region-specific ETFs (VOL, $SKEW$, and $KURT$).

(Insert Table 1 here)

Table 1 presents the summary statistics of the variables. The highest $Rvol$ is from Spain at about 16.11%, while the lowest is from Australia at about 9.04%. The distribution of $Rvol$ for all the locations is positively skewed and leptokurtic. The p-values for $Rvol$ from Jarque–Bera test (Jarque and Bera, 1987) are all lower than 0.01, which also rejects the null hypothesis that states $Rvol$ is normally distributed. For risk-neutral moments from the indices proxies, means of VOl are larger than $Rvol$, which reveals that risk-neutral standard deviation, an ex-ante indicator, generally includes a premium for the expectation of future volatility. Means of $SKEW$ are negative in all locations, which indicates that most of the time, market risk-neutral returns are negatively skewed, while means of $KURT$ are positive, which indicates tail-risks generally exist in the market. $Rvol$, VOL, $SKEW$ and $KURT$ are generally not normally distributed except the Jarque–Bera test fails to reject the $KURT$ of the United Kingdom. P-values for all variables from Augmented Dickey Fuller test (Fuller, 2009) are all lower than the 0.05 level, and that from

[5] Volatility surface files provide the standardised implied volatilities for deltas from -0.90 to +0.90 with the increment of 0.05, and maturities of 10, 30, 60, 91, 122, 152, 182, 273, 365, 547, and 730, based on kernel smoothing algorithm.

[6] https://realized.oxford-man.ox.ac.uk/

Ljung–Box test (Ljung and Box, 1978) (with lags of 5 and 10, respectively) are all smaller than 0.01, which prove that the four variables of interest are all stationary.

4 Empirical results

4.1 Predictive power of risk-neutral moments

In this section, we first estimate the predictive ability of each risk-neutral moment and the combined moments through in-sample and out-of-sample tests. For the in-sample test, we use all the data during the periods and report the slope coefficients on columns 2, 5, and 8, and the adjusted coefficients of determination on columns 4, 7, and 10 in Table 3, Table 4, Table 5, and Table 6. For the out-of-sample test, we applied the methodology similar to Welch and Goyal (2008), Rapach, Strauss, and Zhou (2010), Neumann and Skiadopoulos (2013), and Huang and Kilic (2019), and report out-of-sample adjusted coefficients of determination (R^2_{os}) on columns 4, 7, and 10 in the tables above. Also, to estimate the significance level of R^2_{os}s, we follow Clark and West (2007) to calculate the t-statistics and p-value of the adjusted mean squared prediction error (MSPE). Formulae for R^2_{os} and statistics are expressed as:

$$R^2_{os,Rvol} = 1 - \frac{\sum_{t=n}^{N-1}(Rvol_{t+1} - \widehat{Rvol}_{t+1|t})^2}{\sum_{t=n}^{N-1}(Rvol_{t+1} - \overline{Rvol}_{t+1|t})^2}, \tag{18}$$

where $Rvol$ represents the daily realised volatility; n and N are the counts of the last observation in the initial estimation and numbers of overall observations, respectively. $\widehat{Rvol}_{t+1|t}$ is the forecasted realised volatility, which estimates by data from time 1 to time t, and $\overline{Rvol}_{t+1|t}$ refers to mean realised volatility from time 1 to time t.

$$f_{t+1,Rvol} = (Rvol_{t+1} - \overline{Rvol}_{t+1|t})^2 - [(Rvol_{t+1} - \widehat{Rvol}_{t+1|t})^2 - (\overline{Rvol}_{t+1|t} - \widehat{Rvol}_{t+1|t})^2], \tag{19}$$

The series of f_{t+1} are regressed on a constant to retrieve the zero coefficient, where t-statistics are estimated from Newey and West (1986) standard errors with the comparison to critical values of the one-tail t-test. Only significantly positive R^2_{os} indicates the superior performance of models.

In Table 2, evidence shows that the slope coefficients between future realised volatility and daily, weekly, and monthly lag *Rvol*, respectively, are all positive and statistically significant among these international indices. These results are generally consistent with Corsi (2009), but our international evidence shows that the coefficients of daily *Rvol* are much larger than the weekly and monthly ones within our estimation window. The results from the out-of-sample test also support the predictive ability of models internationally. Next, we incorporate the risk-neutral moments of our indices proxies into the model, where results are shown in Table 3. For the in-sample test, all the slope coefficients of VOL are statistically significant and adjusted coefficients of determination are all larger than that in Table 2, which reveals that VOL can provide extra explanatory information and predictive ability to the fundamental models and these are consistent with the findings from Byun and Kim (2013), and Liang, Wei, and Zhang (2020). For most locations, $KURT$ also helps improve the predictability of future realised volatility in terms of the significant slope coefficients and larger *Adj.*R^2s, but slope coefficients are negative, except for the insignificant coefficient for Brazil. By definition, $KURT$ is the adjusted forth cumulant scaled by the variance of the risk-neutral returns. When the risk-neutral standard deviation is high, the risk-neutral kurtosis may decrease with a more positive expectation of market stability. This may cause the $KURT$ negatively predict the future fluctuation of the market. On the other hand, the predictive ability of $SKEW$ is relatively weaker in some locations, where there are only results with statistically significant coefficients with levels of 0.01 in the United States and South Korea, 0.05 in Mexico, and 0.10 in Canada. Similar to Byun and Kim (2013), our results show $SKEW$ has positive predictive power and larger *Adj.*R^2 among these locations. This result implies that the increase of speculation in the market can cause future instability in the market.

(Insert Table 4, Table 5, Table 6 here)

Next, we estimate the predictability of future realised volatility by using the global combined risk-neutral measures. Table 4 reports results from the estimation of the predictive power of GDP-combined risk-neutral moments towards future volatility. Results show that the slope coefficients of GDP-combined VOL and $Adj.R^2$ of models from Australia, Canada, Germany, Hong Kong, Japan, Spain, United Kingdom become more significant and higher, respectively, than those models with risk-neutral moments from individual location. Similarly, the significance of coefficients of GDP-combined $SKEW$ and $KURT$ are generally strengthened for these countries or regions. Nonetheless, compared with the GDP-weighted-combined risk-neutral moments, equally-weighted-combined risk-neutral moments reached a similar result but less significance level (which are shown in Table 5). These bits of evidence reveal that the market dynamics and stability of a market can be affected by the other markets around the world, and thus indirectly affect the volatility predictability, in which related evidence given by Rapach, Strauss, and Zhou (2013), Gagnon, Power, and Toupin (2016), and Chen et al. (2019). However, the dynamics of proxies represented by the uncertainty of high-GDP location may provide better forecasting performance. Drawing upon dimension deduction techniques, we combine the risk-neutral moments and separate the first principal components from the overall dataset with the PCA estimation. PCA approach can help us to identify the principal component with the largest contribution to the dependent variable, which is independent to other components, from the information flow of data. Predictive powers of risk-neutral first principal component indices toward future volatility are presented in Table 6. Results are generally consistent with the previous tables, but some statistics are different in levels, which confirm the results that we estimated above but provide other potential models by an alternative information extraction process.

(Insert Table 7 here)

Moreover, we also incorporate three risk-neutral moments in single models and report in Table 7. In this part, we can intuitively compare the advantage of these factor combination methods to our samples. Among these models, HAR-RV-MOM-EW and HAR-RV-

MOM-PCA generally show three significant slope coefficients for the three risk-neutral moments at the same time. However, they do not necessarily indicate the highest $Adj.R^2$ and R^2_{os}. Considering the evidence provided by Neumann and Skiadopoulos (2013), which proves the inter predictability between risk-neutral moments, our results imply that the combined indices by using equally weighted and PCA techniques can effectively avoid the collinearity between risk-neutral moments, while this will not promise to provide better prediction of future volatility in our samples.

4.2 Model confidence set (MCS) analysis

To further intuitively compare the models we constructed, we borrow the model confidence set developed by Hansen, Lunde, and Nason (2011), which can directly compare and indicate the best models in a pool of models. In order to compare these models, loss functions have to be defined at the beginning of the measurement. Therefore, following Kristjanpoller and Minutolo (2016), Ma et al. (2017), and Liang, Wei, and Zhang (2020), we define heteroscedasticity-adjusted mean squared error (HMSE) and heteroscedasticity-adjusted mean absolute error (HMAE) as our loss functions, which can be presented as:

$$HMSE = \frac{1}{m-n}\sum_{t=n}^{m-1}(1-\frac{\widehat{Rvol_{i,t+1}}}{Rvol_{i,t+1}})^2 \tag{20}$$

and

$$HMAE = \frac{1}{m-n}\sum_{t=n}^{m-1}|1-\frac{\widehat{Rvol_{i,t+1}}}{Rvol_{i,t+1}}|, \tag{21}$$

where $Rvol_{i,t+1}$ represents the realised volatility for index i on day $t+1$, and $\widehat{Rvol_{i,t+1}}$ denotes the predicted volatility computed from one of our predicting model. n and m are the number of observations of the initial training set and the number of overall observations, respectively.

In regard to the statistics of the MCS, following Kristjanpoller and Minutolo (2016), Ma et al. (2017), Wen et al. (2019), Zhang et al. (2019b), and Liang, Wei, and Zhang (2020), we adopt the range-based statistic (t_{Range}) and semi-quadratic statistic (t_{SQ}), which can be expressed as:

$$t_{Range} = \frac{|\bar{d}_{i,uv}|}{\sqrt{\widehat{var}(\bar{d}_{i,uv})}} \qquad for\ u, v \in \mathcal{M}, \tag{22}$$

and

$$t_{SQ} = \frac{(\bar{d}_{i,uv})^2}{\widehat{var}(\bar{d}_{i,uv})} \qquad for\ u, v \in \mathcal{M}, \tag{23}$$

where $d_{i,uv} \equiv L_{i,u} - L_{i,v}$, L_i denotes the value calculated from the loss function, while $\widehat{var}(\bar{d}_{i,uv})$ is the estimates of variance of $\bar{d}_i$. In MCS analysis, the higher p-value reveals the more significant result of forecasting, and thus we highlight all results above the 0.25 significance level in the following analysis.

4.2.1 Comparison of models with individual risk-neutral moments

(Insert Table 8)

First, we compare the models that incorporate specific risk-neutral moments of returns on each location ETFs and p-values are reported in Table 8. Results show that models that include all three orders of location-specific risk-neutral moments are optimal for Germany, Japan, South Korea, and the United States, in terms of the significance of the loss function measure of HMAE by using Range and semi-quadratic t-statistics. The superior model for Hong Kong and Spain is HAR-RV-IK, but HAR-RV-IV for the United Kingdom. However, the location-specific moment-embedded models for Australia, Brazil, Canada, and Mexico cannot outperform the benchmark model (HAR-RV). These reveal that even the risk-neutral moments of these location-specific ETFs are significantly related to the future volatility of the local indices and models have higher adjusted coefficients of determination, but the information caught by these ETFs is not stationary enough to reduce the predictive errors in out-of-sample analysis, compared with the benchmark models. Regarding measurements by the other loss function measure HMSE, the results are generally consistent except that the both highest p-values for Australia and the United States belong to HAR-RV-IK, but the p-values for which superior models indicated by using HMAE are also significant with the use of HMSE.

4.2.2 Comparison of models with weighted risk-neutral moments

(Insert Table 9 here)

Table 9 present the result of the comparison of models incorporating GDP-weighted risk-neutral moments. One can easily find that the models that include one of or all the three GDP-weighted risk-neutral moments perform significantly better than the benchmark model. With the measurement by HMAE, the ideal model is HAR-RV-IK-GDP in Australia, Brazil, Canada, Germany, Japan, Mexico, South Korea, Spain, and the United States, while the HAR-RV-MOM-GDP model is only superior in Hong Kong and the United Kingdom. This result is not such a surprise because the United States is currently the dominant market globally, in terms of its largest capitalisation in the world. The KURT of SPY, which proxy to the implied excess kurtosis of the US market, can provide significantly valuable information in most local volatility predictions. Also, based on the GDP-weighted excess kurtosis, other GDP-weighted moments can enhance the predictive power of models in Hong Kong and the United Kingdom. These results are also confirmed by the semi-quadratic t-statistics of HMAE in the table. For the measurement of Range and semi-quadratic t-statistics of HMSE, results are generally the same in most of the locations, even though the optimal models for Brazil and Mexico become HAR-RV-MOM-GDP, but HAR-RV-IK-GDP is also significant with the analysis of HMSE.

(Insert Table 10 here)

Alternatively, we also compared the models that incorporated global-equally-weighted risk-neutral moments, where results are shown in Table 10. The significance of models incorporating specific moments are consistent between the two tables, except for the models measured by Range and semi-quadratic of HAME for Mexico, which indicate that the ideal model becomes HAR-RV-MOM-EW. This evidence implies that, for average aggregation approaches of international risk-neutral measures, the different weights in our study are not the critical factor affecting the model accuracy among the three aggregated risk-neutral moments, if we aim to compare the three moments. The reason is the existence of financial integration and the common trend between these moments globally (Gagnon, Power, and Toupin, 2016). The co-movement will significantly reduce the effect of different weights allocation. Compared with location-based implied risk-neutral moments, these results prove that the weighted aggregation of movement can enhance the predictability of future volatility in many location and are robust in our results using different statistics.

4.2.3 Comparison of models with PC-aggregated risk-neutral moments

(Insert Table 11 here)

We also measure and compare the diffusion model that includes the factors of risk-neutral moments constructed by the first principal component. Table 11 provides the evidence that the HAR-RV-IK-PCA is the ideal model for all locations. The principal component extracted from information flow of the dataset can theoretically reflect different dimensions of information from the data, and is not affected by the other components where the covariance between these components are minimised. The trend of international market movement represented by principal component combination can be statistically explained by the dynamics of the markets. Therefore, these consistent results confirm that in the global scenario, the international risk-neutral excess kurtosis, as a combined index, can contribute forecasting power to volatility prediction by concentrating on the most important principal component (i.e the first principal component), which is also generally consistent with findings from previous sections.

4.2.4 Comparison of the pool of models

(Insert Table 12 here)

Further, we also pool all of our estimating models together and compare them by using Range and semi-quadratic t-statistics, where p-values of the model confidence set analysis are shown in Table 12 and Table 13. The comparison allows us to identify the ideal model in our pool for specific locations and also helps analyse the preferred combination method in general. In Table 12, the results by measuring HMAE show that the most suitable models are different from location to location. HAR-RV-IK-PCA model is most appropriate for measuring the future volatility of Australia, Canada, Mexico, and Spain, while HAR-RV-MOM-GDP is most accurate for Brazil, Hong Kong and the United Kingdom. For Germany, the HAR-RV-IK-GDP is superior, and HAR-RV-MOM is most suitable for predicting the volatility of Japan, South Korea, and the United States. Additionally, the results by measuring HMSE are also generally consistent with that by HMAE except for the results for Japan and the United States. Whereas, the optimal model for Japan and the United States are HAR-RV-IK-GDP and HAR-RV-IK-PCA, respectively, by measuring HMSE, but the p-values of MCS measured by HMAE of HAR-RV-MOM for both Japan and the United States are also statistically significant. Our results are also robust by using the semi-quadratic t-statistics reported in Table 13, where the best models are also the same as those in Table 12 in terms of different locations and both loss functions. Generally, for all the locations, the models embedded with higher-order risk-neutral moments, especially the risk-neutral excess kurtosis, have better performance in forecasting future volatility than models that include lag short-term and longer-term realised volatility or risk-neutral standard deviation only. Except for Japan and the United States, most locations have consistent results among all of the sub-tests of MCS analysis. International-combined risk-neutral moments for Australia, Brazil, Canada, Germany, Hong Kong, Mexico, Spain, and the United Kingdom significantly contribute to the predictability of future volatility, and results are robust among all analyses. With regard to the combination strategy, GDP-weighted and PCA combinations are superior, compared with the equally-weighted combination. Local risk-neutral moments of South Korea can more accurately predict future realised volatility, compared with globally combined indicators. The best prediction model for future volatility of Japan and the United States appears to be models that include all local risk-neutral moments or include international-combined risk-neutral excess kurtosis by using different estimation methods, while all results point to these models, and they are generally significant in most measurements.

4.3 The role of the United States in international volatility prediction

4.3.1 Predictive power of risk-neutral moments of SPY

(Insert Table 14 here)

Previous sections indicate that international-combined risk-neutral moments have better predictability of future volatility, compared to location-based individual moments of a few ETFs. On the other hand, as the evidence from Rapach, Strauss, and Zhou (2013), Gagnon, Power, and Toupin (2016), and Chen et al. (2019), some parameters in international markets are related to and probably can be forecasted by the indicators from the US market. Therefore, we tried to use risk-neutral moments of SPY to represent the uncertainty indicators of the US market and estimated the predictability of local future volatilities for all locations excluding the US market. Results of the predictive power of moments of SPY are reported in Table 14. Compared to Table 3, the predictive power of moments of SPY is stronger than moments of some country-/region-specific ETFs in volatility prediction of individual location, in terms of slope coefficients and out-of-sample coefficients of determination. However, the results of some locations are weaker, but others are stronger than those in Table 4 and Table 5. Generally, these bits of evidence are inconsistent among different markets, and thus we conduct MCS analysis to show the role of SPY in the international prediction intuitively.

4.3.2 Comparison of models incorporating risk-neutral moments of SPY

(Insert Table 15, Table 16, Table 17, and Table 18 here)

Table 15 compares models incorporating risk-neutral moments of SPY and the benchmark models. One can easily find that models incorporating moments of SPY can significantly improve the prediction, especially models with the inclusion of risk-neutral excess kurtosis, which is the ideal model among SPY moment embedded models for Australia, Brazil, Canada, Germany, Japan, and Spain. In contrast, the models incorporating the risk-neutral standard deviation of SPY are ideal for Hong Kong, Mexico, and the United Kingdom. However, the volatility of the South Korean market can be better forecasted by including all moments of SPY. These results reveal that the US market uncertainty indicators significantly contribute to the international volatility prediction. Then, we decompose the comparison by categorising models with one of the three risk-neutral moments. For models incorporating VOL, evidence shows that the risk-neutral standard deviation of SPY plays a dominated role in volatility prediction for Canada, Germany, Hong Kong, Mexico, South Korea and the United Kingdom, while GDP-weighted-aggregated VOL is the ideal external factor for the rest of markets, which indicates the information from other location also helps improve the predictability in these markets (Table 16). Regarding models embedding the risk-neutral skewness, the predictive powers in most of the locations are dominated by the risk-neutral skewness of SPY, except for Germany, where the international information flow can significantly provide information for the forecasting (Table 17). Interestingly, for the risk-neutral excess kurtosis, HAR-RV-IK-GDP is the optimal model for Canada, Germany, Hong Kong, Japan, Mexico, South Korea, Spain, and the United Kingdom in terms of p-values of both MCS t-statistics and measures given by both loss functions (Table 18). Nonetheless, the ideal model for Australia is HAR-RV-IK-EW, while that for Brazil are HAR-RV-GDP and HAR-RV-SPY measured by HMAE and HMSE, respectively.

Next, we also estimate p-values from the MCS test for the pool of models together with the models with SPY moments in the locations excluding the United States market and findings are reported in Table 19 and Table 20. The results show that the HAR-RV-MOM-SPY is the ideal model for South Korea with the p-value of the HMAE measure, but the optimal model becomes HAR-RV-IV-SPY if HMSE is the loss measure instead. Aside from these South Korea, the results in this part are consistent with our previous ones. To sum up, the risk-neutral moments of SPY significantly contribute to the predictive power in weighted measures, but it is not dominated level in some locations. That is, the global combination can still provide valuable information to predict the future volatility of many local markets.

5 Conclusion

This paper provided evidence of whether risk-neutral moments of 11 iShare country-/region-specific ETFs can predict the future volatility of international capital markets. To achieve this, we conducted both in-sample and out-of-sample tests for several models, including testing the predictive power of individual and international-combined risk-neutral moments towards one-day-ahead realised volatility. Results show that both the short-term and long-term lag realised volatility can significantly predict the future volatility from the fundamental models (HAR-RV) in terms of the significance of slope coefficients and out-of-sample coefficients of determination. Next, we incorporate risk-neutral moments into the fundamental models. The results show that even if we retain the lag realised volatility factors, risk-neutral moments generally have significant relationships with the future volatility in terms of slope coefficients, which implies the risk-neutral moments can provide idiosyncratic information for future market volatility. However, with regard to the adjusted and out-of-sample coefficients of determination, the prediction accuracy varies among these models.

Further, we conduct the model confidence set analysis in the second part. First, we conduct MCS tests for comparing the predictive accuracy of models that include risk-neutral moments of each ETF of each location. Results show that at least one individual risk-neutral moment or all three moments of ETFs of Germany, Hong Kong, Japan, South Korea, Spain, the United Kingdom, and the United States can significantly improve the accuracy of the HAR-RV model. Then, we also compare the significance between models embedded with one of and all three international risk-neutral moments and present according to categories of factors aggregated by GDP-weighted, equally weighted, and PCA combination separately. Evidence shows that the combination of risk-neutral moments can significantly improve the prediction of future volatility as the ideal models for all locations are models that incorporates international-combined factors. Next, we try to find out the optimal models in the pool of all models constructed in our study and these bits of results show that, generally, models that include international-aggregated risk-neutral moments perform better than the fundamental models in all of our sample markets. Nonetheless, the optimal models for specific locations are different. Regarding the minimum errors in our results, the most appropriate models for different locations are HAR-RV-IK-PCA for Australia, Canada, Mexico, and Spain; HAR-RV-MOM-GDP for Brazil, Hong Kong, and the United Kingdom; HAR-RV-IK-GDP for Germany; HAR-RV-MOM for South Korea; but HAR-RV-MOM or HAR-RV-IK-GDP for Japan, and HAR-RV-MOM or HAR-RV-IK-PCA the United States, by using the different loss functions. These results are robust by using the alternative t-statistics in the MCS test. Overall, our results indicates that the risk-neutral moments, which can represent the sentiment and expectation of future market, are valuable to consider and incorporate into the international market volatility prediction.

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Table 1: Summary statistics

Location	Variable	Mean	Std	Skew	Exc. kurt	Min	Max	ADF	JB	Q5	Q10
Australia	*Rvol*	0.090375	0.042645	2.594474	12.99468	0.028662	0.534539	<0.01	<0.01	<0.01	<0.01
	VOL	0.308306	0.100613	1.705207	6.801053	0.132158	1.221913	<0.01	<0.01	<0.01	<0.01
	SKEW	-0.62066	0.942825	1.641339	5.90038	-4.41403	6.192901	<0.01	<0.01	<0.01	<0.01
	KURT	5.911309	3.160092	0.847889	4.194148	-1.94213	33.04477	<0.01	<0.01	<0.01	<0.01
Brazil	*Rvol*	0.148233	0.057473	2.431866	14.93938	0.03613	0.79831	<0.01	<0.01	<0.01	<0.01
	VOL	0.327097	0.08519	1.177574	1.7556	0.160526	0.738407	<0.01	<0.01	<0.01	<0.01
	SKEW	-0.80502	0.281897	0.260398	0.955089	-1.76515	0.662705	<0.01	<0.01	<0.01	<0.01
	KURT	1.080704	0.496086	0.464126	0.720317	-0.56083	3.231825	<0.01	<0.01	<0.01	<0.01
Canada	*Rvol*	0.091625	0.052961	3.715143	31.87094	0.02112	0.903691	<0.01	<0.01	<0.01	<0.01
	VOL	0.270694	0.075487	1.410792	6.681122	0.117917	0.919516	<0.01	<0.01	<0.01	<0.01
	SKEW	-0.94621	0.719441	1.253539	4.911316	-3.03244	3.608743	<0.01	<0.01	<0.01	<0.01
	KURT	6.590018	3.081058	0.106942	-0.42322	0.164409	20.5305	0.013	<0.01	<0.01	<0.01
Germany	*Rvol*	0.139898	0.071082	2.443612	10.95479	0.0323	0.778497	<0.01	<0.01	<0.01	<0.01
	VOL	0.241545	0.090932	1.715604	3.717652	0.110074	0.699042	<0.01	<0.01	<0.01	<0.01
	SKEW	-1.00261	0.436082	2.041665	8.544107	-2.64511	2.467737	<0.01	<0.01	<0.01	<0.01
	KURT	2.70084	1.370327	1.595157	3.75088	-0.85793	10.18833	<0.01	<0.01	<0.01	<0.01
Hong Kong	*Rvol*	0.112332	0.044387	3.04449	19.07664	0.033223	0.555432	<0.01	<0.01	<0.01	<0.01
	VOL	0.221876	0.085142	2.150213	5.644329	0.123256	0.773132	<0.01	<0.01	<0.01	<0.01
	SKEW	-0.93112	0.492273	0.453483	5.318069	-3.59271	3.417263	<0.01	<0.01	<0.01	<0.01
	KURT	3.016822	1.905335	2.007448	4.4135	-0.11996	14.809	0.044	<0.01	<0.01	<0.01
Japan	*Rvol*	0.116329	0.065878	3.733828	24.31431	0.03155	0.87106	<0.01	<0.01	<0.01	<0.01
	VOL	0.191297	0.078307	3.129426	15.62675	0.085559	0.729055	<0.01	<0.01	<0.01	<0.01
	SKEW	-0.81963	0.52042	2.597626	20.6323	-2.67972	5.033833	<0.01	<0.01	<0.01	<0.01
	KURT	1.989241	1.886325	4.430617	36.37532	-2.33789	28.90059	<0.01	<0.01	<0.01	<0.01
Mexico	*Rvol*	0.112598	0.056853	4.756454	55.0839	0.038066	1.147453	<0.01	<0.01	<0.01	<0.01
	VOL	0.239973	0.062971	1.518025	3.491499	0.122932	0.558896	<0.01	<0.01	<0.01	<0.01
	SKEW	-1.04896	0.25625	0.537981	2.682976	-2.04887	0.719889	<0.01	<0.01	<0.01	<0.01
	KURT	1.78396	0.654871	0.735369	0.50056	0.406337	5.252617	<0.01	<0.01	<0.01	<0.01
South Korea	*Rvol*	0.096494	0.044783	4.371435	37.27676	0.0378	0.756875	<0.01	<0.01	<0.01	<0.01
	VOL	0.244116	0.074531	1.959727	5.779402	0.135899	0.681937	<0.01	<0.01	<0.01	<0.01
	SKEW	-0.96344	0.37573	0.780311	4.433725	-2.17046	1.620131	<0.01	<0.01	<0.01	<0.01
	KURT	2.098354	0.93789	1.742558	7.441876	0.13253	9.239648	<0.01	<0.01	<0.01	<0.01
Spain	*Rvol*	0.161123	0.085336	3.614514	29.1841	0.038657	1.240358	<0.01	<0.01	<0.01	<0.01
	VOL	0.358816	0.118177	0.861872	1.310978	0.147286	1.018401	<0.01	<0.01	<0.01	<0.01
	SKEW	-1.02868	0.72859	1.21787	4.745333	-4.15427	2.978685	<0.01	<0.01	<0.01	<0.01
	KURT	4.648838	3.175864	0.397251	-0.85861	-0.43233	16.28506	0.01	<0.01	<0.01	<0.01
United Kingdom	*Rvol*	0.124871	0.067362	3.764158	34.66649	0.018307	1.202591	<0.01	<0.01	<0.01	<0.01
	VOL	0.384368	0.206681	3.09107	14.34524	0.116143	2.01985	<0.01	<0.01	<0.01	<0.01
	SKEW	-0.78676	0.903255	0.623916	1.336994	-4.25634	2.814924	<0.01	<0.01	<0.01	<0.01
	KURT	5.982887	2.695697	-0.03521	0.134595	-2.7667	21.46698	<0.01	0.317	<0.01	<0.01
United States	*Rvol*	0.107935	0.070668	2.928775	16.87749	0.017534	0.969471	<0.01	<0.01	<0.01	<0.01
	VOL	0.159719	0.05677	1.720936	3.799838	0.081058	0.445374	<0.01	<0.01	<0.01	<0.01
	SKEW	-1.61163	0.273488	-0.85627	0.900351	-2.70134	-0.95634	<0.01	<0.01	<0.01	<0.01
	KURT	3.271895	1.143037	1.197083	1.522735	1.26773	8.447102	<0.01	<0.01	<0.01	<0.01

This table reports the summary statistics for daily realised volatility (*Rvol*), risk-neutral standard deviation (*VOL*), skewness (*SKEW*), and excess kurtosis (*KURT*). Columns ADF, JB, and Q5(10) report p-values of Augmented Dickey Fuller test (Fuller, 2009), Jarque–Bera test (Jarque and Bera, 1987), and Ljung–Box test (Ljung and Box, 1978) with 5 (and 10) lags, respectively.

Table 2: Predictive power of fundamental models

Location [1]	Model [2]	Intercept [3]	$Rvol_{i,t}$ [4]	$Rvol_{i,t-4:t}$ [5]	$Rvol_{i,t-21:t}$ [6]	$Adj.R^2$ [7]	R^2_{os} [8]	Nobs. [9]
Australia	HAR-RV	0.0163***	0.2229***	0.0226***	0.0135***	0.3700	0.2819***	2464.0
		(6.63)	(4.78)	(7.26)	(4.82)		(8.69)	
Brazil	HAR-RV	0.0255***	0.3848***	0.0145***	0.0126***	0.4188	0.4424***	2404.0
		(6.59)	(7.65)	(4.09)	(4.14)		(8.81)	
Canada	HAR-RV	0.0133***	0.2886***	0.0173***	0.0167***	0.4644	0.6859***	2462.0
		(4.99)	(4.42)	(4.55)	(4.71)		(10.58)	
Germany	HAR-RV	0.0109***	0.3485***	0.0226***	0.0124***	0.6225	0.6071***	2469.0
		(4.25)	(5.37)	(5.95)	(3.68)		(9.48)	
Hong Kong	HAR-RV	0.0203***	0.2469***	0.0206***	0.0144***	0.3753	0.3198***	2396.0
		(5.25)	(5.23)	(6.66)	(5.61)		(8.00)	
Japan	HAR-RV	0.0214***	0.4108***	0.0124***	0.0119***	0.4355	0.3959***	2364.0
		(6.44)	(6.17)	(3.65)	(4.39)		(7.59)	
Mexico	HAR-RV	0.0318***	0.2078***	0.0163***	0.0142***	0.2563	0.2504***	2443.0
		(6.16)	(5.79)	(3.46)	(3.99)		(4.94)	
South Korea	HAR-RV	0.0130***	0.4719***	0.0097**	0.0143***	0.5301	0.3815***	2387.0
		(5.00)	(4.79)	(2.50)	(4.24)		(7.33)	
Spain	HAR-RV	0.0222***	0.4092***	0.0161***	0.0115***	0.5290	0.5467***	2486.0
		(4.67)	(9.09)	(3.99)	(3.65)		(9.65)	
United Kingdom	HAR-RV	0.0198***	0.2322***	0.0227***	0.0141***	0.4370	0.2439***	2470.0
		(4.26)	(4.53)	(5.34)	(3.61)		(5.20)	
United States	HAR-RV	0.0121***	0.4138***	0.0170***	0.0114***	0.5621	0.6735***	2512.0
		(5.34)	(7.27)	(4.68)	(4.30)		(7.77)	

The third to seventh columns present coefficients of the Intercept, *Rvol* on daily, weekly and monthly horizons, and the adjusted coefficient of determination from the in-sample test, respectively. The eighth column presents the coefficient of determination from the out-of-sample test. Newey and West (1986) t-statistics are reported in the parentheses. *, ** and *** indicate the significance level at 0.10, 0.05 and 0.01, respectively.

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i}Rvol_{i,t} + \beta_{2,i}Rvol_{i,t-4:t} + \beta_{3,i}Rvol_{i,t-21:t} + \epsilon_{t+1},$$

Table 3: Predictive power of each moment for each location

Location	VOL			$SKEW$			$KURT$		
	β	$Adj.R^2$	R^2_{OS}	β	$Adj.R^2$	R^2_{OS}	β	$Adj.R^2$	R^2_{OS}
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Australia	0.0459***	0.3784	0.2467***	-0.0006	0.3700	0.2812***	-0.0007***	0.3726	0.2815***
	(3.68)		(8.58)	(-0.98)		(8.64)	(-3.17)		(8.71)
Brazil	0.0920***	0.4306	0.4448***	0.0048	0.4191	0.4436***	-0.0032	0.4193	0.4418***
	(4.53)		(8.77)	(0.99)		(8.75)	(-1.42)		(8.63)
Canada	0.0342***	0.4659	0.6559***	0.0013*	0.4645	0.6788***	-0.0014***	0.4688	0.6623***
	(2.58)		(9.37)	(1.91)		(10.34)	(-4.17)		(10.42)
Germany	0.1148***	0.6300	0.6035***	0.0030	0.6227	0.6031***	-0.0029***	0.6249	0.6053***
	(5.32)		(9.67)	(1.51)		(9.41)	(-4.50)		(9.66)
Hong Kong	0.0441***	0.3808	0.2859***	-0.0003	0.3750	0.3177***	-0.0007*	0.3758	0.3099***
	(3.18)		(7.75)	(-0.17)		(7.98)	(-1.83)		(8.22)
Japan	0.0665**	0.4401	0.3899***	0.0028	0.4357	0.3939***	-0.0018***	0.4377	0.3978***
	(2.18)		(7.50)	(1.61)		(7.61)	(-3.81)		(7.80)
Mexico	0.2922***	0.2981	0.2830***	0.0116**	0.2587	0.2287***	-0.0072***	0.2625	0.2334***
	(6.99)		(4.42)	(2.57)		(4.78)	(-4.15)		(4.64)
South Korea	0.1395***	0.5476	0.4071***	0.0043***	0.5312	0.3806***	-0.0022***	0.5319	0.3726***
	(6.73)		(7.26)	(2.68)		(7.55)	(-3.37)		(7.49)
Spain	0.0503***	0.5320	0.5388***	0.0015	0.5290	0.5416***	-0.0024***	0.5351	0.5568***
	(3.11)		(8.90)	(1.42)		(9.51)	(-4.93)		(10.29)
United Kingdom	0.0152***	0.4394	0.2480***	0.0008	0.4377	0.2471***	-0.0013***	0.4402	0.2463***
	(2.89)		(5.26)	(0.84)		(5.24)	(-3.09)		(5.09)
United States	0.6589***	0.6096	0.7044***	0.0095***	0.5630	0.6768***	-0.0033***	0.5640	0.6774***
	(9.92)		(7.37)	(3.12)		(7.94)	(-4.82)		(8.15)

The second, fifth and eighth columns present coefficients of the VOL, $SKEW$ and $KURT$ of specific ETFs embedded within the local HAR-RV model from the in-sample test, where we named these models as HAR-RV-IV, HAR-RV-IS, HAR-RV-IK in this paper. The third, sixth and ninth columns present the adjusted R squared of the regression from the in-sample test. The fourth, seventh and tenth columns are the R^2_{OS} from the out-of-sample test. Newey and West (1986) t-statistics are reported in the parentheses. *, ** and *** indicate the significance level at 0.10, 0.05 and 0.01, respectively.

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i} Rvol_{i,t} + \beta_{2,i} Rvol_{i,t-4:t} + \beta_{3,i} Rvol_{i,t-21:t} + \beta_{4,i} MOM_{i,t} + \epsilon_{t+1},$$

Table 4: Predictive power of each international GDP-weighted combined moment for each location

Location	*VOL*			*SKEW*			*KURT*		
	β	$Adj.R^2$	R^2_{OS}	β	$Adj.R^2$	R^2_{OS}	β	$Adj.R^2$	R^2_{OS}
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Australia	0.1608***	0.3979	0.3157***	0.0075**	0.3712	0.2820***	-0.0047***	0.3778	0.2945***
	(5.67)		(9.52)	(2.45)		(8.70)	(-4.40)		(9.35)
Brazil	0.0884***	0.4250	0.4511***	0.0102**	0.4199	0.4421***	-0.0036***	0.4213	0.4464***
	(4.07)		(9.00)	(2.37)		(8.83)	(-3.03)		(8.96)
Canada	0.2207***	0.4849	0.6451***	0.0111***	0.4661	0.6881***	-0.0062***	0.4713	0.6895***
	(4.62)		(11.01)	(3.56)		(10.49)	(-5.26)		(11.09)
Germany	0.2146***	0.6341	0.6111***	0.0092***	0.6231	0.6081***	-0.0047***	0.6249	0.6097***
	(6.40)		(9.63)	(2.68)		(9.43)	(-4.49)		(9.57)
Hong Kong	0.1298***	0.3948	0.3413***	0.0050	0.3756	0.3174***	-0.0036***	0.3796	0.3187***
	(4.87)		(8.03)	(1.50)		(7.96)	(-3.55)		(8.33)
Japan	0.1071***	0.4439	0.4131***	0.0152***	0.4376	0.3937***	-0.0065***	0.4424	0.4026***
	(4.29)		(7.76)	(3.07)		(7.48)	(-6.42)		(8.00)
Mexico	0.1591***	0.2734	0.2621***	0.0090**	0.2571	0.2499***	-0.0048***	0.2609	0.2502***
	(4.31)		(5.73)	(2.04)		(5.06)	(-3.70)		(5.59)
South Korea	0.1282***	0.5446	0.3762***	0.0044*	0.5303	0.3826***	-0.0034***	0.5335	0.3763***
	(4.53)		(7.29)	(1.75)		(7.38)	(-4.24)		(7.66)
Spain	0.2319***	0.5429	0.5487***	0.0086*	0.5293	0.5457***	-0.0095***	0.5358	0.5524***
	(4.56)		(9.50)	(1.85)		(9.71)	(-5.44)		(10.32)
United Kingdom	0.4682***	0.4911	0.3082***	0.0133***	0.4386	0.2473***	-0.0086***	0.4462	0.2581***
	(8.23)		(7.02)	(3.24)		(5.44)	(-5.57)		(5.99)
United States	0.2779***	0.5783	0.6629***	0.0150***	0.5639	0.6762***	-0.0080***	0.5684	0.6752***
	(5.73)		(7.63)	(3.56)		(7.81)	(-6.36)		(8.38)

The second, fifth and eighth columns present coefficients of the GDP-weighted VOL, $SKEW$ and $KURT$ of all locations embedded within the local HAR-RV model from the in-sample test, where we named these models as HAR-RV-IV-GDP, HAR-RV-IS-GDP, HAR-RV-IK-GDP in this paper. The third, sixth and ninth columns present the adjusted R squared of the regression from the in-sample test. The fourth, seventh and tenth columns are the R^2_{OS} from the out-of-sample test. Newey and West (1986) t-statistics are reported in the parentheses. *, ** and *** indicate the significance level at 0.10, 0.05 and 0.01, respectively.

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i}Rvol_{i,t} + \beta_{2,i}Rvol_{i,t-4:t} + \beta_{3,i}Rvol_{i,t-21:t} + \beta_{4,i}MOM_{GDP,t} + \epsilon_{t+1},$$

Table 5: Predictive power of each international equally weighted combined moment for each location

Location	VOL			$SKEW$			$KURT$		
	β	$Adj.R^2$	R^2_{OS}	β	$Adj.R^2$	R^2_{OS}	β	$Adj.R^2$	R^2_{OS}
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Australia	0.1343***	0.3929	0.2981***	0.0047**	0.3707	0.2776***	-0.0036***	0.3772	0.2927***
	(5.32)		(9.06)	(1.98)		(8.54)	(-4.06)		(9.36)
Brazil	0.0741***	0.4238	0.4474***	0.0071*	0.4196	0.4389***	-0.0033***	0.4217	0.4443***
	(3.93)		(8.83)	(1.92)		(8.79)	(-3.05)		(9.13)
Canada	0.1304***	0.4753	0.6252***	0.0085***	0.4659	0.6797***	-0.0055***	0.4723	0.6796***
	(3.93)		(10.37)	(3.01)		(10.27)	(-4.59)		(11.41)
Germany	0.1383***	0.6290	0.5980***	0.0096***	0.6236	0.6055***	-0.0042***	0.6254	0.6085***
	(5.42)		(9.41)	(3.23)		(9.34)	(-4.50)		(9.66)
Hong Kong	0.1134***	0.3922	0.3280***	0.0024	0.3752	0.3164***	-0.0031***	0.3799	0.3168***
	(4.90)		(7.86)	(0.90)		(7.87)	(-3.77)		(8.34)
Japan	0.0827***	0.4414	0.4051***	0.0041	0.4356	0.3926***	-0.0042***	0.4397	0.3988***
	(3.83)		(7.54)	(0.96)		(7.42)	(-5.24)		(8.03)
Mexico	0.1378***	0.2709	0.2604***	0.0073*	0.2572	0.2453***	-0.0037***	0.2604	0.2321***
	(4.17)		(5.40)	(1.94)		(4.95)	(-3.03)		(5.28)
South Korea	0.0910***	0.5396	0.3675***	0.0033	0.5303	0.3833***	-0.0034***	0.5351	0.3732***
	(4.18)		(7.10)	(1.58)		(7.35)	(-4.45)		(7.52)
Spain	0.1507***	0.5367	0.5391***	0.0036	0.5289	0.5449***	-0.0088***	0.5373	0.5470***
	(3.86)		(9.04)	(0.91)		(9.63)	(-5.29)		(10.45)
United Kingdom	0.3364***	0.4735	0.2792***	0.0093***	0.4382	0.2412***	-0.0068***	0.4456	0.2498***
	(6.60)		(6.07)	(2.64)		(5.29)	(-5.27)		(5.69)
United States	0.1486***	0.5693	0.6597***	0.0115***	0.5637	0.6720***	-0.0058***	0.5675	0.6650***
	(4.63)		(7.49)	(3.26)		(7.64)	(-4.62)		(8.11)

The second, fifth and eighth columns present coefficients of the equally weighted VOL, $SKEW$ and $KURT$ of all the location embedded within the local HAR-RV model from the in-sample test, where we named them as HAR-RV-IV-EW, HAR-RV-IS-EW, HAR-RV-IK-EW in this paper. The third, sixth and ninth columns present the adjusted R squared of the regression from the in-sample test. The fourth, seventh and tenth columns are the R^2_{OS} from the out-of-sample test. Newey and West (1986) t-statistics are reported in the parentheses. *, ** and *** indicate the significance level at 0.10, 0.05 and 0.01, respectively.

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i} Rvol_{i,t} + \beta_{2,i} Rvol_{i,t-4:t} + \beta_{3,i} Rvol_{i,t-21:t} + \beta_{4,i} MOM_{EW,t} + \epsilon_{t+1},$$

Table 6: Predictive power of each international first-principal-component-combined moment for each location

Location	*VOL*			*SKEW*			*KURT*		
	β	$Adj.R^2$	R^2_{OS}	β	$Adj.R^2$	R^2_{OS}	β	$Adj.R^2$	R^2_{OS}
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Australia	0.0046***	0.4060	0.3132***	0.0006	0.3741	0.2932***	-0.0018***	0.3788	0.3112***
	(5.83)		(8.80)	(1.24)		(8.07)	(-3.71)		(8.99)
Brazil	0.0024***	0.4312	0.4504***	0.0012*	0.4256	0.4366***	-0.0012**	0.4259	0.4449***
	(3.78)		(7.96)	(1.70)		(7.83)	(-2.02)		(8.11)
Canada	0.0051***	0.4605	0.5698***	0.0014**	0.4435	0.6516***	-0.0029***	0.4487	0.6725***
	(3.94)		(9.34)	(2.12)		(9.35)	(-4.03)		(10.97)
Germany	0.0044***	0.6138	0.5731***	0.0016***	0.6068	0.5804***	-0.0019***	0.6075	0.5848***
	(5.53)		(8.78)	(2.66)		(8.63)	(-3.70)		(8.94)
Hong Kong	0.0034***	0.3863	0.3159***	0.0002	0.3670	0.2974***	-0.0012***	0.3695	0.3047***
	(4.21)		(7.09)	(0.36)		(7.01)	(-2.90)		(7.59)
Japan	0.0027***	0.4308	0.3867***	-0.0005	0.4223	0.3760***	-0.0022***	0.4258	0.3824***
	(4.05)		(7.63)	(-0.57)		(7.62)	(-4.59)		(8.24)
Mexico	0.0057***	0.2777	0.2604***	0.0012	0.2516	0.2427***	-0.0015**	0.2528	0.2384***
	(4.49)		(4.88)	(1.56)		(4.28)	(-2.14)		(4.73)
South Korea	0.0030***	0.5351	0.3341***	0.0000	0.5230	0.3491***	-0.0016***	0.5264	0.3376***
	(4.29)		(6.35)	(0.06)		(6.58)	(-3.77)		(7.00)
Spain	0.0046***	0.5195	0.4989***	0.0001	0.5106	0.5029***	-0.0056***	0.5196	0.5154***
	(3.48)		(8.21)	(0.09)		(8.68)	(-5.32)		(10.01)
United Kingdom	0.0120***	0.4844	0.2575***	0.0012	0.4355	0.2063***	-0.0031***	0.4404	0.2234***
	(7.28)		(5.59)	(1.45)		(4.34)	(-4.11)		(4.70)
United States	0.0067***	0.5778	0.6281***	0.0018**	0.5646	0.6576***	-0.0027***	0.5669	0.6570***
	(4.80)		(6.93)	(2.40)		(7.19)	(-3.47)		(8.15)

The second, fifth and eighth columns present coefficients of the PCA-aggregated VOL, $SKEW$ and $KURT$ of all the location embedded within the local HAR-RV model from the in-sample test, where we named them as HAR-RV-IV-PCA, HAR-RV-IS-PCA, HAR-RV-IK-PCA in this paper. The third, sixth and ninth columns present the adjusted R squared of the regression from the in-sample test. The fourth, seventh and tenth columns are the R^2_{OS} from the out-of-sample test. Newey and West (1986) t-statistics are reported in the parentheses. *, ** and *** indicate the significance level at 0.10, 0.05 and 0.01, respectively.

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i}Rvol_{i,t} + \beta_{2,i}Rvol_{i,t-4:t} + \beta_{3,i}Rvol_{i,t-21:t} + \beta_{4,i}MOM_{PCA,t} + \epsilon_{t+1},$$

Table 7: Predictive power of three moments for individual location

Location [1]	Model [2]	β_{VOL} [3]	β_{SKEW} [4]	β_{KURT} [5]	$Adj.R^2$ [6]	R^2_{OS} [7]	Location [8]	Model [9]	β_{VOL} [10]	β_{SKEW} [11]	β_{KURT} [12]	$Adj.R^2$ [13]	R^2_{OS} [14]
Australia	HAR-RV-MOM	0.0539***	0.0008	-0.0011***	0.3834	0.2532***	Mexico	HAR-RV-MOM	0.2914***	0.0084	-0.0033**	0.3023	0.2546***
		(3.94)	(1.08)	(-3.72)		(8.44)			(7.07)	(1.56)	(-1.99)		(4.25)
	HAR-RV-MOM-GDP	0.1541***	0.0034	-0.0006	0.3980	0.3091***		HAR-RV-MOM-GDP	0.1576***	0.0065	0.0001	0.2733	0.2507***
		(5.13)	(1.01)	(-0.57)		(9.48)			(3.96)	(1.30)	(0.05)		(5.93)
	HAR-RV-MOM-EW	0.1239***	0.0090***	-0.0030***	0.3984	0.3106***		HAR-RV-MOM-EW	0.1294***	0.0132***	-0.0031***	0.2751	0.2411***
		(5.24)	(3.24)	(-3.44)		(9.48)			(4.16)	(2.98)	(-2.67)		(5.76)
	HAR-RV-MOM-PCA	0.0045***	0.0024***	-0.0018***	0.4124	0.3152***		HAR-RV-MOM-PCA	0.0061***	0.0035***	-0.0012	0.2839	0.2373***
		(5.86)	(3.51)	(-3.18)		(9.19)			(4.63)	(3.04)	(-1.48)		(5.26)
Brazil	HAR-RV-MOM	0.1003***	0.0063	0.0049	0.4308	0.4400***	South Korea	HAR-RV-MOM	0.1513***	0.0066***	-0.0012*	0.5517	0.4096***
		(4.31)	(0.82)	(1.21)		(8.82)			(7.24)	(3.76)	(-1.66)		(7.72)
	HAR-RV-MOM-GDP	0.0838***	0.0082*	-0.0002	0.4255	0.4457***		HAR-RV-MOM-GDP	0.1223***	-0.0025	-0.0012	0.5445	0.3747***
		(3.79)	(1.72)	(-0.19)		(9.02)			(4.16)	(-0.78)	(-1.41)		(7.57)
	HAR-RV-MOM-EW	0.0660***	0.0124***	-0.0032***	0.4278	0.4476***		HAR-RV-MOM-EW	0.0845***	0.0050**	-0.0034***	0.5442	0.3767***
		(3.71)	(2.96)	(-2.89)		(9.17)			(4.15)	(2.20)	(-4.74)		(7.45)
	HAR-RV-MOM-PCA	0.0025***	0.0030***	-0.0018***	0.4359	0.4520***		HAR-RV-MOM-PCA	0.0029***	0.0008	-0.0017***	0.5376	0.3290***
		(4.23)	(3.22)	(-2.60)		(8.32)			(4.31)	(1.50)	(-3.73)		(7.10)
Canada	HAR-RV-MOM	0.0629***	0.0014**	-0.0019***	0.4738	0.6152***	Spain	HAR-RV-MOM	0.0948***	0.0011	-0.0037***	0.5442	0.5446***
		(3.34)	(1.99)	(-4.48)		(8.87)			(4.27)	(0.94)	(-5.39)		(9.54)
	HAR-RV-MOM-GDP	0.2026***	0.0001	-0.0042***	0.4877	0.6417***		HAR-RV-MOM-GDP	0.1997***	-0.0059	-0.0062***	0.5449	0.5475***
		(4.37)	(0.02)	(-3.69)		(11.01)			(4.03)	(-1.11)	(-4.46)		(9.88)
	HAR-RV-MOM-EW	0.1441***	0.0111***	-0.0071***	0.4890	0.6395***		HAR-RV-MOM-EW	0.1429***	0.0082*	-0.0090***	0.5449	0.5468***
		(4.37)	(3.77)	(-5.58)		(10.83)			(3.84)	(1.94)	(-5.49)		(9.78)
	HAR-RV-MOM-PCA	0.0059***	0.0029***	-0.0052***	0.4780	0.5946***		HAR-RV-MOM-PCA	0.0048***	0.0026**	-0.0070***	0.5307	0.5127***
		(4.69)	(3.52)	(-5.93)		(10.06)			(3.77)	(2.45)	(-5.61)		(9.84)
Germany	HAR-RV-MOM	0.1342***	0.0074***	-0.0039***	0.6352	0.6049***	United Kingdom	HAR-RV-MOM	0.0137***	0.0005	-0.0012***	0.4413	0.2489***
		(6.35)	(3.23)	(-5.21)		(9.80)			(2.58)	(0.45)	(-2.67)		(5.17)
	HAR-RV-MOM-GDP	0.2033***	0.0039	-0.0014	0.6342	0.6078***		HAR-RV-MOM-GDP	0.4500***	-0.0004	-0.0028*	0.4915	0.3025***
		(5.91)	(0.97)	(-1.16)		(9.59)			(7.58)	(-0.07)	(-1.78)		(7.41)
	HAR-RV-MOM-EW	0.1327***	0.0136***	-0.0049***	0.6338	0.6056***		HAR-RV-MOM-EW	0.3387***	0.0131***	-0.0081***	0.4857	0.2949***
		(5.53)	(4.30)	(-4.98)		(9.47)			(7.46)	(3.43)	(-6.79)		(6.76)
	HAR-RV-MOM-PCA	0.0045***	0.0034***	-0.0033***	0.6195	0.5843***		HAR-RV-MOM-PCA	0.0118***	0.0032***	-0.0043***	0.4933	0.2686***
		(5.95)	(4.44)	(-5.12)		(8.86)			(8.23)	(3.27)	(-4.55)		(6.29)
Hong Kong	HAR-RV-MOM	0.0950***	0.0008	-0.0031***	0.3906	0.2677***	United States	HAR-RV-MOM	0.6498***	-0.0071	-0.0028	0.6096	0.7031***
		(4.11)	(0.47)	(-4.23)		(8.30)			(9.71)	(-0.70)	(-1.21)		(7.45)
	HAR-RV-MOM-GDP	0.1298***	0.0006	0.0000	0.3943	0.3383***		HAR-RV-MOM-GDP	0.2569***	0.0042	-0.0058***	0.5820	0.6659***
		(4.39)	(0.17)	(0.04)		(8.11)			(5.71)	(0.81)	(-4.15)		(8.21)
	HAR-RV-MOM-EW	0.1046***	0.0052*	-0.0023***	0.3945	0.3317***		HAR-RV-MOM-EW	0.1514***	0.0153***	-0.0071***	0.5784	0.6627***
		(4.75)	(1.75)	(-2.93)		(8.07)			(5.00)	(4.26)	(-5.64)		(7.83)
	HAR-RV-MOM-PCA	0.0033***	0.0012*	-0.0008	0.3872	0.3061***		HAR-RV-MOM-PCA	0.0069***	0.0034***	-0.0045***	0.5868	0.6394***
		(4.04)	(1.73)	(-1.55)		(7.05)			(5.53)	(3.92)	(-5.29)		(7.78)
Japan	HAR-RV-MOM	0.0999***	0.0012	-0.0033***	0.4468	0.3970***							
		(3.09)	(0.53)	(-5.92)		(8.16)							
	HAR-RV-MOM-GDP	0.0794***	0.0083	-0.0030**	0.4458	0.4068***							
		(2.76)	(1.58)	(-2.25)		(7.84)							
	HAR-RV-MOM-EW	0.0654***	0.0082*	-0.0035***	0.4438	0.4047***							
		(2.83)	(1.88)	(-3.61)		(7.80)							
	HAR-RV-MOM-PCA	0.0024***	0.0009	-0.0016**	0.4316	0.3908***							
		(3.27)	(0.92)	(-2.41)		(8.17)							

The third, fourth, fifth, tenth, eleventh and twelfth columns present coefficients of the VOL, $SKEW$ and $KURT$ of each model from the in-sample test, where we named them as HAR-RV-IV-PCA, HAR-RV-IS-PCA, HAR-RV-IK-PCA in this paper. The third, sixth and ninth columns present the adjusted R squared of the regression from the in-sample test. The fourth, seventh and tenth columns are the R^2_{OS} from the out-of-sample test. Newey and West (1986) t-statistics are reported in the parentheses. *, ** and *** indicate the significance level at 0.10, 0.05 and 0.01, respectively.

$$Rvol_{i,t+1} = \beta_0 + \beta_{1,i} Rvol_{i,t} + \beta_{2,i} Rvol_{i,t-4:t} + \beta_{3,i} Rvol_{i,t-21:t} + \sum_{k=1}^{3} \beta_{i,k} MOM_{i,k,t} + \epsilon_{t+1},$$

Table 8: Model confidence set p-values of models that include individual moments

	HMAE-Range(max)										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	**1.0000**	**1.0000**	**1.0000**	0.0150	0.0040	0.0000	**1.0000**	0.0110	0.0000	0.0550	0.0000
HAR-RV-IV	0.0040	0.0000	0.0000	0.0150	0.0040	0.0000	**0.5530**	0.0110	0.0000	**1.0000**	0.0250
HAR-RV-IS	**0.5230**	**0.3020**	0.0000	0.0150	0.0040	0.0000	0.0000	**0.3440**	0.0000	0.0130	0.0000
HAR-RV-IK	**0.5230**	0.0000	0.0000	**0.7220**	**1.0000**	0.0660	0.0000	0.1210	**1.0000**	0.0000	**0.5950**
HAR-RV-MOM	0.0010	0.0000	0.0000	**1.0000**	0.0040	**1.0000**	0.0000	**1.0000**	0.0000	0.0000	**1.0000**
	HMSE-Range(max)										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	**0.8470**	**1.0000**	**1.0000**	0.0090	0.0010	0.0000	**1.0000**	0.0000	0.0000	0.1220	0.0000
HAR-RV-IV	0.0030	0.0000	0.0000	0.0090	0.0010	0.0000	**0.3930**	0.0000	0.0000	**1.0000**	0.0020
HAR-RV-IS	**0.8470**	**0.3460**	0.0000	0.0040	0.0010	0.0000	0.0000	0.0050	0.0000	0.1130	0.0020
HAR-RV-IK	**1.0000**	0.0000	0.0000	**0.9780**	**1.0000**	**0.9400**	0.0000	0.0040	**1.0000**	0.0010	**1.0000**
HAR-RV-MOM	0.0020	0.0000	0.0000	**1.0000**	0.0010	**1.0000**	0.0000	**1.0000**	0.0000	0.0040	**0.7580**
	HMAE-SQ										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	**1.0000**	**1.0000**	**1.0000**	0.0080	0.0060	0.0000	**1.0000**	0.0220	0.0000	0.0460	0.0000
HAR-RV-IV	0.0140	0.0000	0.0000	0.0180	0.0060	0.0000	**0.5440**	0.0170	0.0000	**1.0000**	0.0520
HAR-RV-IS	**0.5150**	**0.2670**	0.0000	0.0040	0.0060	0.0000	0.0000	**0.3380**	0.0000	0.0040	0.0070
HAR-RV-IK	**0.5150**	0.0000	0.0000	**0.7070**	**1.0000**	0.0640	0.0000	0.1240	**1.0000**	0.0000	**0.5990**
HAR-RV-MOM	0.0030	0.0000	0.0000	**1.0000**	0.0060	**1.0000**	0.0000	**1.0000**	0.0000	0.0000	**1.0000**
	HMSE-SQ										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	**0.8340**	**1.0000**	**1.0000**	0.0100	0.0040	0.0140	**1.0000**	0.0000	0.0000	0.1210	0.0000
HAR-RV-IV	0.0050	0.0010	0.0000	0.0260	0.0040	0.0140	**0.3820**	0.0000	0.0000	**1.0000**	0.0220
HAR-RV-IS	**0.8340**	**0.3580**	0.0000	0.0030	0.0040	0.0140	0.0020	0.0040	0.0000	0.0560	0.0220
HAR-RV-IK	**1.0000**	0.0010	0.0000	**0.9670**	**1.0000**	**0.9530**	0.0000	0.0040	**1.0000**	0.0010	**1.0000**
HAR-RV-MOM	0.0020	0.0240	0.0000	**1.0000**	0.0040	**1.0000**	0.0020	**1.0000**	0.0000	0.0020	**0.7140**

The table presents p-values of models that include individual moments based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table 9: Model confidence set p-values of models that include GDP-weighted moments

	HMAE-Range(max)										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0000	0.0000	0.0000	0.0010	0.0010	0.0000	0.0000	0.0050	0.0080	0.0000	0.0000
HAR-RV-IV-GDP	0.0520	0.1200	0.0000	0.0010	0.0360	0.0740	**0.8310**	0.0050	0.0000	**0.9360**	0.0000
HAR-RV-IS-GDP	0.0000	0.0080	0.0110	0.0010	0.0020	0.0050	0.0000	0.2200	0.0080	0.0000	0.0000
HAR-RV-IK-GDP	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**0.2880**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**0.8020**	**1.0000**
HAR-RV-MOM-GDP	0.0390	**0.8680**	0.0000	0.0010	**1.0000**	**0.2950**	**0.8310**	0.0050	0.0010	**1.0000**	0.0620
	HMSE-Range(max)										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0010	0.0010	0.0000	0.0010	0.0000	0.0000	0.0000	0.0030	0.0150	0.0000	0.0000
HAR-RV-IV-GDP	0.0570	0.1050	0.0000	0.0010	0.0060	0.0190	**0.9870**	0.0030	0.0060	**0.2720**	0.0000
HAR-RV-IS-GDP	0.0010	0.0070	0.0010	0.0010	0.0000	0.0000	0.0000	0.0120	0.0150	0.0000	0.0010
HAR-RV-IK-GDP	**1.0000**	**0.7380**	**1.0000**	**1.0000**	0.2000	**1.0000**	**0.9940**	**1.0000**	**1.0000**	**0.2720**	**1.0000**
HAR-RV-MOM-GDP	0.0290	**1.0000**	0.0000	0.0010	**1.0000**	0.1420	**1.0000**	0.1220	0.0060	**1.0000**	0.0050
	HMAE-SQ										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0050	0.0020	0.0020	0.0080	0.0000	0.0030	0.0000	0.0070	0.0050	0.0000	0.0000
HAR-RV-IV-GDP	0.0390	0.0850	0.0000	0.0080	0.1080	0.0680	**0.8190**	0.0010	0.0010	**0.9420**	0.0000
HAR-RV-IS-GDP	0.0000	0.0170	0.0080	0.0080	0.0010	0.0100	0.0000	0.2110	0.0060	0.0070	0.0010
HAR-RV-IK-GDP	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**0.2890**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**0.8150**	**1.0000**
HAR-RV-MOM-GDP	0.0050	**0.8680**	0.0000	0.0080	**1.0000**	**0.2620**	**0.8190**	0.0070	0.0020	**1.0000**	0.0660
	HMSE-SQ										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0070	0.0030	0.0000	0.0060	0.0000	0.0090	0.0000	0.0020	0.0210	0.0000	0.0000
HAR-RV-IV-GDP	0.0540	0.1330	0.0000	0.0060	0.0260	0.0290	**0.9910**	0.0000	0.0040	**0.3460**	0.0000
HAR-RV-IS-GDP	0.0050	0.0120	0.0010	0.0060	0.0000	0.0110	0.0000	0.0300	0.0210	0.0030	0.0020
HAR-RV-IK-GDP	**1.0000**	**0.7350**	**1.0000**	**1.0000**	0.2130	**1.0000**	**0.9910**	**1.0000**	**1.0000**	**0.3460**	**1.0000**
HAR-RV-MOM-GDP	0.0220	**1.0000**	0.0000	0.0060	**1.0000**	0.1250	**1.0000**	0.1480	0.0060	**1.0000**	0.0070

The table presents p-values of models that include GDP-weighted moments based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table 10: Model confidence set p-values of models that include equal-weighted moments

	HMAE-Range(max)										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0000	0.0120	0.0040	0.0000	0.0000	0.0000	0.0290	**0.8640**	0.0640	0.0080	**0.2870**
HAR-RV-IV-EW	0.0000	**0.2650**	0.0000	0.0000	0.0000	0.0160	0.2040	0.0000	0.0000	0.0000	0.0060
HAR-RV-IS-EW	0.0000	0.0120	0.0040	0.0000	0.0000	0.0000	0.0020	**0.9610**	0.0640	0.0080	**0.2870**
HAR-RV-IK-EW	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**0.5540**	**1.0000**	**0.8350**	**1.0000**	**1.0000**	**0.8020**	**1.0000**
HAR-RV-MOM-EW	0.0000	**0.7690**	0.0000	0.0000	**1.0000**	**0.3330**	**1.0000**	**0.9710**	0.0020	**1.0000**	0.2400
	HMSE-Range(max)										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0000	0.1000	0.0020	0.0040	0.0020	0.0000	0.0430	0.2110	0.0750	0.0010	0.2370
HAR-RV-IV-EW	0.0000	**0.3220**	0.0010	0.0010	0.0020	0.0060	0.1270	0.0000	0.0050	0.0010	0.0110
HAR-RV-IS-EW	0.0000	0.0090	0.0020	0.0040	0.0020	0.0000	0.0020	0.2110	0.0750	0.0010	0.0880
HAR-RV-IK-EW	**1.0000**	**0.8290**	**1.0000**	**1.0000**	**0.9000**	**1.0000**	**0.7290**	**1.0000**	**1.0000**	**0.7140**	**1.0000**
HAR-RV-MOM-EW	0.0000	**1.0000**	0.0020	0.0040	**1.0000**	0.2210	**1.0000**	**0.6140**	0.0190	**1.0000**	0.0880
	HMAE-SQ										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0000	0.0540	0.0040	0.0040	0.0110	0.0010	0.0300	**0.9190**	0.0390	0.0180	**0.2530**
HAR-RV-IV-EW	0.0000	0.2190	0.0000	0.0000	0.0110	0.0040	**0.3290**	0.0040	0.0010	0.0060	0.0130
HAR-RV-IS-EW	0.0000	0.0090	0.0040	0.0040	0.0060	0.0000	0.0000	**0.9510**	0.0350	0.0130	**0.2530**
HAR-RV-IK-EW	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**0.5570**	**1.0000**	**0.8460**	**1.0000**	**1.0000**	**0.7960**	**1.0000**
HAR-RV-MOM-EW	0.0000	**0.7670**	0.0000	0.0040	**1.0000**	**0.2990**	**1.0000**	**0.9610**	0.0060	**1.0000**	**0.2530**
	HMSE-SQ										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0000	0.1690	0.0010	0.0050	0.0010	0.0010	0.0620	**0.2620**	0.0740	0.0070	**0.2540**
HAR-RV-IV-EW	0.0000	**0.4080**	0.0000	0.0000	0.0070	0.0030	**0.2540**	0.0000	0.0030	0.0030	0.0100
HAR-RV-IS-EW	0.0000	0.0460	0.0010	0.0050	0.0000	0.0000	0.0000	**0.2990**	0.0390	0.0020	0.0540
HAR-RV-IK-EW	**1.0000**	**0.8340**	**1.0000**	**1.0000**	**0.8780**	**1.0000**	**0.7210**	**1.0000**	**1.0000**	**0.7170**	**1.0000**
HAR-RV-MOM-EW	0.0010	**1.0000**	0.0000	0.0050	**1.0000**	0.2000	**1.0000**	**0.5880**	0.0130	**1.0000**	0.0770

The table presents p-values of models that include equal-weighted moments based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table 11: Model confidence set p-values of models that include PC-aggregated moments

	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HMAE-Range(max)											
HAR-RV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0540	0.0000	0.0000	0.0000
HAR-RV-IV-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0330	0.0010	0.0000	0.0000	0.0000
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0540	0.0000	0.0000	0.0000
HAR-RV-IK-PCA	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-MOM-PCA	0.0000	**0.5120**	0.0000	0.0000	**0.3580**	**0.6150**	0.2220	0.1680	0.0350	**0.5190**	0.0110
HMSE-Range(max)											
HAR-RV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HAR-RV-IV-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0180	0.0000	0.0000	0.0000	0.0000
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HAR-RV-IK-PCA	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-MOM-PCA	0.0000	**0.7810**	0.0000	0.0000	0.2110	**0.2850**	0.0960	**0.4730**	0.0190	**0.8330**	0.0010
HMAE-SQ											
HAR-RV	0.0000	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0750	0.0000	0.0000	0.0000
HAR-RV-IV-PCA	0.0000	0.0010	0.0000	0.0000	0.0000	0.0000	0.0230	0.0010	0.0000	0.0000	0.0000
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0750	0.0000	0.0000	0.0000
HAR-RV-IK-PCA	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-MOM-PCA	0.0000	**0.5020**	0.0000	0.0000	**0.3560**	**0.6480**	0.2010	0.1560	0.0270	**0.4550**	0.0160
HMSE-SQ											
HAR-RV	0.0000	0.0000	0.0000	0.0000	0.0020	0.0000	0.0000	0.0050	0.0000	0.0020	0.0010
HAR-RV-IV-PCA	0.0000	0.0000	0.0000	0.0000	0.0020	0.0000	0.0070	0.0000	0.0000	0.0020	0.0000
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0020	0.0000	0.0000	0.0000
HAR-RV-IK-PCA	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-MOM-PCA	0.0000	**0.7780**	0.0000	0.0000	0.2100	**0.3220**	0.0970	**0.4920**	0.0260	**0.8060**	0.0060

The table presents p-values of models that include PC-aggregated moments based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table 12: Model confidence set p-values of Range(max) t-statistics of the pool of models

	HMAE-Range(max)										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0300	0.0000	0.0000	0.0000
HAR-RV-IV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0300	0.0000	0.0000	0.2040
HAR-RV-IS	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**0.5060**	0.0000	0.0000	0.0080
HAR-RV-IK	0.0000	0.0000	0.0000	**0.9420**	0.0310	0.1190	0.0000	0.0790	0.0850	0.0000	**0.3950**
HAR-RV-MOM	0.0000	0.0000	0.0000	**0.9420**	0.0000	**1.0000**	0.0000	**1.0000**	0.0000	0.0000	**1.0000**
HAR-RV-IV-GDP	0.0010	0.1370	0.0000	0.0000	0.1230	0.1190	**0.7930**	0.0300	0.0000	**0.9310**	0.0000
HAR-RV-IS-GDP	0.0000	0.1130	0.0000	0.0480	0.0180	0.0000	0.0000	**0.3500**	0.0000	0.0000	0.0000
HAR-RV-IK-GDP	0.0010	**0.6790**	0.0100	**1.0000**	0.1230	**0.7230**	**0.7930**	**0.5350**	0.0080	**0.9310**	**0.9820**
HAR-RV-MOM-GDP	0.0010	**1.0000**	0.0000	0.0480	**1.0000**	**0.7030**	**0.7930**	0.0300	0.0000	**1.0000**	0.2040
HAR-RV-IV-EW	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0020	0.0000	0.0000	0.0000
HAR-RV-IS-EW	0.0000	0.0000	0.0000	0.0480	0.0000	0.0000	0.0000	0.0300	0.0000	0.0000	0.0000
HAR-RV-IK-EW	0.0010	0.1370	0.0000	**0.9420**	0.0310	**0.7030**	0.0010	0.0300	0.0000	0.0650	0.0000
HAR-RV-MOM-EW	0.0000	0.1370	0.0000	0.0480	0.1230	**0.3970**	0.0010	0.0300	0.0000	**0.3230**	0.0000
HAR-RV-IV-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0020	0.0000	0.0000	0.0000
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0300	0.0000	0.0000	0.0000
HAR-RV-IK-PCA	**1.0000**	0.1990	**1.0000**	**0.8610**	**0.4540**	**0.7040**	**1.0000**	**0.5960**	**1.0000**	**0.9310**	**0.9820**
HAR-RV-MOM-PCA	0.0010	0.1130	0.0000	0.2200	0.0310	**0.7030**	**0.6740**	**0.3500**	0.0850	0.0650	0.0080
	HMSE-Range(max)										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000	0.0000	0.0030	0.0000	0.0010	0.0000
HAR-RV-IV	0.0000	0.0000	0.0000	0.0600	0.0000	0.0060	0.0000	0.0030	0.0000	0.0010	0.1590
HAR-RV-IS	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000	0.0000	0.0410	0.0000	0.0010	0.0080
HAR-RV-IK	0.0000	0.0000	0.0000	**0.9000**	0.0060	0.0110	0.0000	0.0190	0.0540	0.0010	**0.3480**
HAR-RV-MOM	0.0000	0.0000	0.0000	**0.9290**	0.0000	**0.9290**	0.0000	**1.0000**	0.0000	0.0010	**0.5680**
HAR-RV-IV-GDP	0.0120	0.1310	0.0000	0.0010	0.0220	0.0110	**0.5230**	0.0030	0.0000	**0.3090**	0.0000
HAR-RV-IS-GDP	0.0000	0.0600	0.0000	0.0060	0.0000	0.0060	0.0000	0.0030	0.0000	0.0010	0.0000
HAR-RV-IK-GDP	0.0120	**0.6440**	0.0050	**1.0000**	**0.2530**	**1.0000**	**0.5230**	0.0700	0.0240	**0.5930**	**0.5680**
HAR-RV-MOM-GDP	0.0120	**1.0000**	0.0000	0.0770	**1.0000**	**0.6560**	**0.5230**	0.0060	0.0000	**1.0000**	0.0910
HAR-RV-IV-EW	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000
HAR-RV-IS-EW	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000	0.0000	0.0030	0.0000	0.0010	0.0000
HAR-RV-IK-EW	0.0120	0.1280	0.0000	**0.9000**	0.0220	**0.9290**	0.0010	0.0060	0.0000	0.1250	0.0000
HAR-RV-MOM-EW	0.0000	0.1280	0.0000	0.0060	0.0120	**0.4430**	0.0010	0.0030	0.0000	**0.3030**	0.0000
HAR-RV-IV-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0030	0.0000	0.0000	0.0000
HAR-RV-IK-PCA	**1.0000**	**0.3580**	**1.0000**	**0.8290**	0.0220	**0.9290**	**1.0000**	0.1070	**1.0000**	**0.3090**	**1.0000**
HAR-RV-MOM-PCA	0.0000	**0.3090**	0.0000	0.1080	0.0060	**0.6560**	0.0010	0.0990	0.0540	**0.3090**	0.0000

The table presents p-values of Range t-statistics based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table 13: Model confidence set p-values of Semi-quadratic t-statistics of the pool of models

	HMAE-SQ										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0000	0.0100	0.0000	0.0110	0.0020	0.0010	0.0000	0.0200	0.0000	0.0020	0.0000
HAR-RV-IV	0.0000	0.0000	0.0000	0.0080	0.0000	0.0210	0.0010	0.0470	0.0000	0.0100	**0.3430**
HAR-RV-IS	0.0000	0.0060	0.0000	0.0050	0.0010	0.0000	0.0000	**0.4100**	0.0000	0.0000	0.0330
HAR-RV-IK	0.0000	0.0000	0.0000	**0.9600**	0.0960	0.2290	0.0000	0.1020	0.1040	0.0000	**0.5830**
HAR-RV-MOM	0.0000	0.0000	0.0000	**0.9600**	0.0010	**1.0000**	0.0000	**1.0000**	0.0000	0.0000	**1.0000**
HAR-RV-IV-GDP	0.0010	0.1440	0.0000	0.0040	**0.2750**	0.1620	**0.6630**	0.0050	0.0000	**0.9440**	0.0000
HAR-RV-IS-GDP	0.0000	0.1160	0.0000	0.0820	0.0330	0.0120	0.0020	0.1520	0.0000	0.0470	0.0010
HAR-RV-IK-GDP	0.0010	**0.6560**	0.0030	**1.0000**	**0.2750**	**0.7170**	**0.6630**	**0.4270**	0.0110	**0.9440**	**0.9750**
HAR-RV-MOM-GDP	0.0010	**1.0000**	0.0000	0.0110	**1.0000**	**0.6790**	**0.6630**	0.0190	0.0000	**1.0000**	**0.2720**
HAR-RV-IV-EW	0.0000	0.0210	0.0000	0.0000	0.0010	0.0000	0.0050	0.0010	0.0000	0.0000	0.0000
HAR-RV-IS-EW	0.0000	0.0000	0.0000	0.0470	0.0000	0.0000	0.0000	0.0290	0.0000	0.0000	0.0000
HAR-RV-IK-EW	0.0010	0.1310	0.0000	**0.9600**	0.1270	**0.6790**	0.1310	0.0730	0.0000	0.2350	0.0010
HAR-RV-MOM-EW	0.0000	0.1410	0.0000	0.0680	**0.2750**	**0.5220**	0.1080	0.0730	0.0000	**0.5120**	0.0000
HAR-RV-IV-PCA	0.0000	0.0030	0.0000	0.0000	0.0050	0.0000	0.0210	0.0010	0.0000	0.0000	0.0000
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0270	0.0000	0.0000	0.0000
HAR-RV-IK-PCA	**1.0000**	**0.2550**	**1.0000**	**0.9010**	**0.4590**	**0.6790**	**1.0000**	**0.5940**	**1.0000**	**0.9440**	**0.9750**
HAR-RV-MOM-PCA	0.0010	0.1190	0.0000	**0.2610**	0.1110	**0.6790**	**0.5010**	**0.2770**	0.0530	0.2000	0.0060
	HMSE-SQ										
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom	United States
HAR-RV	0.0000	0.0020	0.0000	0.0040	0.0030	0.0030	0.0000	0.0010	0.0000	0.0050	0.0010
HAR-RV-IV	0.0000	0.0000	0.0000	0.0330	0.0010	0.0260	0.0000	0.0060	0.0000	0.0070	0.1320
HAR-RV-IS	0.0000	0.0070	0.0000	0.0000	0.0020	0.0000	0.0000	0.0340	0.0000	0.0070	0.0250
HAR-RV-IK	0.0010	0.0000	0.0000	**0.8820**	0.0320	0.1870	0.0000	0.0180	0.0330	0.0020	**0.3210**
HAR-RV-MOM	0.0000	0.0000	0.0000	**0.9120**	0.0020	**0.9540**	0.0000	**1.0000**	0.0000	0.0020	**0.4970**
HAR-RV-IV-GDP	0.0060	0.2200	0.0000	0.0020	0.1410	0.0890	**0.5280**	0.0000	0.0000	**0.3590**	0.0030
HAR-RV-IS-GDP	0.0000	0.0950	0.0000	0.0170	0.0120	0.0120	0.0020	0.0060	0.0000	0.0520	0.0030
HAR-RV-IK-GDP	0.0060	**0.6440**	0.0090	**1.0000**	**0.2700**	**1.0000**	**0.5280**	0.0590	0.0200	**0.5740**	**0.4970**
HAR-RV-MOM-GDP	0.0060	**1.0000**	0.0000	0.1530	**1.0000**	**0.8730**	**0.5280**	0.0070	0.0000	**1.0000**	0.0790
HAR-RV-IV-EW	0.0000	0.0170	0.0000	0.0000	0.0020	0.0000	0.0010	0.0000	0.0000	0.0040	0.0000
HAR-RV-IS-EW	0.0000	0.0000	0.0000	0.0020	0.0010	0.0000	0.0000	0.0020	0.0000	0.0040	0.0000
HAR-RV-IK-EW	0.0060	0.1700	0.0000	**0.8820**	0.1370	**0.9540**	0.0690	0.0070	0.0000	**0.2620**	0.0050
HAR-RV-MOM-EW	0.0060	0.1700	0.0000	0.0170	0.0810	**0.6010**	0.0500	0.0060	0.0000	**0.3450**	0.0000
HAR-RV-IV-PCA	0.0000	0.0000	0.0000	0.0000	0.0020	0.0000	0.0100	0.0000	0.0000	0.0040	0.0000
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000	0.0010	0.0000	0.0020	0.0000
HAR-RV-IK-PCA	**1.0000**	**0.3870**	**1.0000**	**0.8820**	0.1410	**0.9540**	**1.0000**	0.1000	**1.0000**	**0.3590**	**1.0000**
HAR-RV-MOM-PCA	0.0010	**0.3080**	0.0000	0.0660	0.0470	**0.8070**	0.0690	0.0920	0.0330	**0.3450**	0.0040

The table presents p-values of Semi-quadratic t-statistics based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table 14: Predictive power of risk-neutral moments of SPY toward volatility of individual location

Location	VOL			$SKEW$			$KURT$		
	β	$Adj.R^2$	R^2_{OS}	β	$Adj.R^2$	R^2_{OS}	β	$Adj.R^2$	R^2_{OS}
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Australia	0.1845***	0.4031	0.3150***	0.0057**	0.3705	0.2808***	-0.0026***	0.3733	0.2859***
	(6.33)		(9.29)	(2.35)		(8.80)	(-4.23)		(9.04)
Brazil	0.1015***	0.4256	0.4457***	0.0049	0.4185	0.4413***	-0.0018**	0.4192	0.4422***
	(4.04)		(9.15)	(1.47)		(8.72)	(-2.22)		(8.73)
Canada	0.3161***	0.4958	0.6607***	0.0067***	0.4646	0.6852***	-0.0023***	0.4657	0.6869***
	(5.48)		(11.22)	(2.60)		(10.65)	(-4.02)		(10.65)
Germany	0.2520***	0.6375	0.6190***	0.0030	0.6225	0.6069***	-0.0021***	0.6232	0.6079***
	(6.76)		(10.06)	(1.13)		(9.50)	(-3.28)		(9.46)
Hong Kong	0.1460***	0.3976	0.3485***	0.0042*	0.3756	0.3188***	-0.0018***	0.3769	0.3178***
	(4.68)		(7.87)	(1.75)		(8.13)	(-2.72)		(8.22)
Japan	0.1250***	0.4454	0.4060***	0.0158***	0.4387	0.3944***	-0.0042***	0.4395	0.3980***
	(4.55)		(7.75)	(4.54)		(7.68)	(-5.66)		(7.78)
Mexico	0.2099***	0.2811	0.2515***	0.0060**	0.2567	0.2540***	-0.0024***	0.2580	0.2574***
	(4.91)		(6.11)	(2.00)		(5.15)	(-3.38)		(5.33)
South Korea	0.1784***	0.5517	0.4119***	0.0026	0.5305	0.3801***	-0.0012***	0.5312	0.3795***
	(5.29)		(7.82)	(1.37)		(7.44)	(-2.80)		(7.55)
Spain	0.2740***	0.5461	0.5381***	0.0098***	0.5292	0.5467***	-0.0038***	0.5304	0.5486***
	(5.29)		(9.90)	(2.72)		(9.85)	(-4.11)		(9.95)
United Kingdom	0.5284***	0.5016	0.3042***	0.0085**	0.4380	0.2480***	-0.0040***	0.4407	0.2551***
	(11.08)		(7.96)	(2.36)		(5.41)	(-4.18)		(5.80)

The second, fifth and eighth columns present coefficients of the PCA-aggregated VOL, $SKEW$ and $KURT$ of all the location embedded within the local HAR-RV model from the in-sample test, where we named them as HAR-RV-IV-SPY, HAR-RV-IS-SPY, HAR-RV-IK-SPY in this paper. The third, sixth and ninth columns present the adjusted R squared of the regression from the in-sample test. The fourth, seventh and tenth columns are the R^2_{OS} from the out-of-sample test. Newey and West (1986) t-statistics are reported in the parentheses. *, ** and *** indicate the significance level at 0.10, 0.05 and 0.01, respectively.

Table 15: Model confidence set p-values of models that include moments of SPY

	HMAE-Range(max)									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV	0.0360	0.0020	0.0050	0.0790	0.0070	0.0070	0.0000	0.0010	0.0470	0.0000
HAR-RV-IV-SPY	0.0360	0.0020	0.0000	0.0790	**<u>1.0000</u>**	0.0060	**<u>1.0000</u>**	**<u>0.5520</u>**	0.0000	**<u>1.0000</u>**
HAR-RV-IS-SPY	0.0360	0.0020	0.0050	0.0790	0.1660	**<u>0.4600</u>**	0.0010	0.0130	0.0510	0.0000
HAR-RV-IK-SPY	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>0.7590</u>**	**<u>1.0000</u>**	**<u>0.2990</u>**	0.0310	**<u>1.0000</u>**	**<u>0.3260</u>**
HAR-RV-MOM-SPY	0.0270	0.0020	0.0000	0.0040	**<u>0.7590</u>**	0.0320	0.0010	**<u>1.0000</u>**	0.0000	0.0500
	HMSE-Range(max)									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV	0.0200	0.0060	0.0160	0.0220	0.0010	0.0130	0.0000	0.0020	0.1160	0.0000
HAR-RV-IV-SPY	0.0200	0.0060	0.0000	0.0220	**<u>1.0000</u>**	0.0020	**<u>1.0000</u>**	**<u>0.9460</u>**	0.0040	**<u>1.0000</u>**
HAR-RV-IS-SPY	0.0200	0.0060	0.0190	0.0220	0.0130	**<u>0.4790</u>**	0.0000	0.0030	0.1160	0.0000
HAR-RV-IK-SPY	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>0.8560</u>**	**<u>1.0000</u>**	0.1750	0.0050	**<u>1.0000</u>**	**<u>0.6990</u>**
HAR-RV-MOM-SPY	0.0200	0.0060	0.0000	0.0220	**<u>0.7290</u>**	0.0130	0.0000	**<u>1.0000</u>**	0.0040	**<u>0.2900</u>**
	HMAE-SQ									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV	0.0280	0.0020	0.0050	0.0970	0.0120	0.0030	0.0000	0.0000	0.0290	0.0000
HAR-RV-IV-SPY	0.0280	0.0030	0.0000	0.0970	**<u>1.0000</u>**	0.0020	**<u>1.0000</u>**	**<u>0.5450</u>**	0.0000	**<u>1.0000</u>**
HAR-RV-IS-SPY	0.0280	0.0030	0.0050	0.0970	**<u>0.2840</u>**	**<u>0.4430</u>**	0.0030	0.0060	0.0670	0.0060
HAR-RV-IK-SPY	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>0.7910</u>**	**<u>1.0000</u>**	**<u>0.2840</u>**	0.0210	**<u>1.0000</u>**	**<u>0.3360</u>**
HAR-RV-MOM-SPY	0.0130	0.0030	0.0000	0.0100	**<u>0.7910</u>**	0.0240	0.0150	**<u>1.0000</u>**	0.0000	0.1170
	HMSE-SQ									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV	0.0740	0.0030	0.0030	0.0220	0.0030	0.0040	0.0000	0.0010	0.0750	0.0040
HAR-RV-IV-SPY	0.0740	0.0050	0.0000	0.0220	**<u>1.0000</u>**	0.0010	**<u>1.0000</u>**	**<u>0.9510</u>**	0.0040	**<u>1.0000</u>**
HAR-RV-IS-SPY	0.0740	0.0050	0.0100	0.0220	0.1160	**<u>0.4910</u>**	0.0020	0.0010	0.1100	0.0150
HAR-RV-IK-SPY	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>0.8630</u>**	**<u>1.0000</u>**	0.1780	0.0030	**<u>1.0000</u>**	**<u>0.6950</u>**
HAR-RV-MOM-SPY	0.0740	0.0050	0.0000	0.0070	**<u>0.8040</u>**	0.0040	0.0050	**<u>1.0000</u>**	0.0080	**<u>0.4530</u>**

The table presents p-values of Semi-quadratic t-statistics based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table 16: Model confidence set p-values among models incorporating weighted VOLs and VOL of SPY

	HMAE-Range(max)									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IV-GDP	**1.0000**	**1.0000**	**0.5440**	**0.9280**	**0.8690**	**1.0000**	**0.6460**	0.0000	**1.0000**	**0.8560**
HAR-RV-IV-EW	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HAR-RV-IV-SPY	0.0960	0.0040	**1.0000**	**1.0000**	**1.0000**	0.0000	**1.0000**	**1.0000**	0.0730	**1.0000**
	HMSE-Range(max)									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IV-GDP	**1.0000**	**1.0000**	0.1520	**0.8180**	**1.0000**	**1.0000**	**0.6520**	0.0000	**1.0000**	**1.0000**
HAR-RV-IV-EW	0.0000	0.0000	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HAR-RV-IV-SPY	0.0990	0.0070	**1.0000**	**1.0000**	**0.9610**	0.0000	**1.0000**	**1.0000**	0.0920	**0.7270**
	HMAE-SQ									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IV-GDP	**1.0000**	**1.0000**	**0.5550**	**0.9130**	**0.8920**	**1.0000**	**0.6550**	0.0000	**1.0000**	**0.8640**
HAR-RV-IV-EW	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000
HAR-RV-IV-SPY	0.0670	0.0060	**1.0000**	**1.0000**	**1.0000**	0.0000	**1.0000**	**1.0000**	0.0820	**1.0000**
	HMSE-SQ									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IV-GDP	**1.0000**	**1.0000**	0.1680	**0.8190**	**1.0000**	**1.0000**	**0.6340**	0.0000	**1.0000**	**1.0000**
HAR-RV-IV-EW	0.0000	0.0000	0.0080	0.0010	0.0000	0.0000	0.0000	0.0000	0.0140	0.0000
HAR-RV-IV-SPY	0.1270	0.0100	**1.0000**	**1.0000**	**0.9670**	0.0000	**1.0000**	**1.0000**	0.0990	**0.7080**

The table presents p-values of Semi-quadratic t-statistics based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table 17: Model confidence set p-values among models incorporating weighted $SKEW$ and $SKEW$ of SPY

	HMAE-Range(max)									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IS-GDP	0.0030	**0.4340**	**0.4140**	**1.0000**	0.0060	0.0030	0.0010	0.1340	0.0310	**0.4030**
HAR-RV-IS-EW	0.0000	0.0000	0.0000	0.0590	0.0000	0.0000	0.0000	0.0030	0.0290	0.0000
HAR-RV-IS-SPY	**1.0000**	**1.0000**	**1.0000**	0.2500	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
	HMSE-Range(max)									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IS-GDP	0.0230	0.1750	0.0840	**1.0000**	0.0000	0.0040	0.0010	0.0030	0.0540	0.0920
HAR-RV-IS-EW	0.0000	0.0000	0.0000	0.0060	0.0000	0.0000	0.0000	0.0000	0.0450	0.0010
HAR-RV-IS-SPY	**1.0000**	**1.0000**	**1.0000**	**0.6620**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
	HMAE-SQ									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IS-GDP	0.0060	**0.4480**	**0.4120**	**1.0000**	0.0070	0.0050	0.0000	0.0990	0.0480	**0.4050**
HAR-RV-IS-EW	0.0000	0.0000	0.0030	0.1340	0.0000	0.0000	0.0000	0.0100	0.0210	0.0000
HAR-RV-IS-SPY	**1.0000**	**1.0000**	**1.0000**	0.2140	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
	HMSE-SQ									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IS-GDP	0.0380	0.1690	0.1040	**1.0000**	0.0010	0.0040	0.0020	0.0110	0.0550	0.1130
HAR-RV-IS-EW	0.0000	0.0000	0.0000	0.0320	0.0000	0.0000	0.0000	0.0000	0.0280	0.0000
HAR-RV-IS-SPY	**1.0000**	**1.0000**	**1.0000**	**0.6450**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**

The table presents p-values of Semi-quadratic t-statistics based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table 18: Model confidence set p-values among models incorporating weighted $KURT$ and $KURT$ of SPY

	HMAE-Range(max)									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IK-GDP	0.1830	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**
HAR-RV-IK-EW	**<u>1.0000</u>**	0.0860	**<u>0.3640</u>**	**<u>0.8640</u>**	0.1410	**<u>0.5560</u>**	0.0480	0.2300	**<u>0.4700</u>**	0.0240
HAR-RV-IK-SPY	0.0080	**<u>0.8640</u>**	0.1780	0.0070	**<u>0.7190</u>**	**<u>0.5560</u>**	0.0480	**<u>0.8710</u>**	**<u>0.4700</u>**	0.2340
	HMSE-Range(max)									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IK-GDP	0.0420	**<u>0.6690</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**
HAR-RV-IK-EW	**<u>1.0000</u>**	0.1000	**<u>0.3110</u>**	**<u>0.4350</u>**	0.1710	**<u>0.6640</u>**	0.0150	**<u>0.2670</u>**	**<u>0.3820</u>**	0.0060
HAR-RV-IK-SPY	0.0040	**<u>1.0000</u>**	0.0280	0.0130	**<u>0.5080</u>**	0.2100	0.0150	**<u>0.2670</u>**	**<u>0.3820</u>**	0.1310
	HMAE-SQ									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IK-GDP	0.1650	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**
HAR-RV-IK-EW	**<u>1.0000</u>**	0.1450	**<u>0.3730</u>**	**<u>0.8590</u>**	0.2170	**<u>0.5820</u>**	0.0390	**<u>0.2850</u>**	**<u>0.3980</u>**	0.0580
HAR-RV-IK-SPY	0.0120	**<u>0.8520</u>**	**<u>0.3100</u>**	0.0250	**<u>0.7400</u>**	**<u>0.5820</u>**	0.0420	**<u>0.8500</u>**	**<u>0.3980</u>**	0.2300
	HMSE-SQ									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV-IK-GDP	0.0380	**<u>0.6590</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**
HAR-RV-IK-EW	**<u>1.0000</u>**	0.1290	**<u>0.3380</u>**	**<u>0.4210</u>**	0.2440	**<u>0.6280</u>**	0.0140	**<u>0.3430</u>**	**<u>0.4130</u>**	0.0290
HAR-RV-IK-SPY	0.0000	**<u>1.0000</u>**	0.0910	0.0460	**<u>0.5210</u>**	**<u>0.3540</u>**	0.0140	**<u>0.3430</u>**	**<u>0.4130</u>**	0.1190

The table presents p-values of Semi-quadratic t-statistics based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table 19: Model confidence set p-values of Range(max) t-statistics of the pool of models including models with moments of SPY

	HMAE-Range(max)									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0110	0.0000	0.0000
HAR-RV-IV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0110	0.0000	0.0000
HAR-RV-IS	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1330	0.0000	0.0000
HAR-RV-IK	0.0000	0.0000	0.0000	**0.9420**	0.0560	0.1680	0.0000	0.0120	0.0850	0.0000
HAR-RV-MOM	0.0000	0.0000	0.0000	**0.9420**	0.0000	**1.0000**	0.0000	**0.5720**	0.0000	0.0000
HAR-RV-IV-GDP	0.0000	0.1690	0.0000	0.0000	0.2180	0.1680	**0.8960**	0.0010	0.0000	**0.9780**
HAR-RV-IS-GDP	0.0000	0.0090	0.0000	0.0510	0.0280	0.0000	0.0000	0.0120	0.0000	0.0000
HAR-RV-IK-GDP	0.0000	**0.9010**	0.0100	**1.0000**	0.2180	**0.7430**	**0.8960**	0.1330	0.0120	**0.9780**
HAR-RV-MOM-GDP	0.0000	**1.0000**	0.0000	0.0510	**1.0000**	**0.7430**	**0.8960**	0.0010	0.0000	**0.9780**
HAR-RV-IV-EW	0.0000	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HAR-RV-IS-EW	0.0000	0.0000	0.0000	0.0510	0.0000	0.0000	0.0000	0.0110	0.0000	0.0000
HAR-RV-IK-EW	0.0000	0.1690	0.0000	**0.9420**	0.0560	**0.7430**	0.0030	0.0120	0.0000	0.0810
HAR-RV-MOM-EW	0.0000	0.1690	0.0000	0.0510	0.2180	**0.5070**	0.0030	0.0120	0.0000	0.0810
HAR-RV-IV-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0110	0.0000	0.0000
HAR-RV-IK-PCA	**1.0000**	**0.3000**	**1.0000**	**0.8610**	**0.4540**	**0.7430**	**1.0000**	**0.4150**	**1.0000**	**0.9780**
HAR-RV-MOM-PCA	0.0000	0.1010	0.0000	0.0510	0.0560	**0.6540**	**0.6700**	0.0120	0.0850	0.0810
HAR-RV-IV-SPY	0.0000	0.0090	0.0000	0.0000	0.2180	0.0000	**0.8960**	**0.6750**	0.0000	**1.0000**
HAR-RV-IS-SPY	0.0000	0.0090	0.0000	0.0000	0.0560	**0.6540**	0.0030	0.0120	0.0000	0.0000
HAR-RV-IK-SPY	0.0000	**0.9010**	0.0000	0.0510	0.2180	**0.7430**	**0.6700**	0.1330	0.0120	**0.9160**
HAR-RV-MOM-SPY	0.0000	0.0090	0.0000	0.0000	0.2180	0.1680	0.0030	**1.0000**	0.0000	0.0810

	HMSE-Range(max)									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000	0.0000	0.0010	0.0000	0.0010
HAR-RV-IV	0.0000	0.0000	0.0000	0.0500	0.0000	0.0070	0.0000	0.0010	0.0000	0.0010
HAR-RV-IS	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000	0.0000	0.0630	0.0000	0.0010
HAR-RV-IK	0.0000	0.0000	0.0000	**0.9000**	0.0130	0.0160	0.0000	0.0290	0.0540	0.0010
HAR-RV-MOM	0.0000	0.0000	0.0000	**0.9290**	0.0000	**0.9290**	0.0000	**0.9930**	0.0000	0.0010
HAR-RV-IV-GDP	0.0110	0.1700	0.0000	0.0010	0.0340	0.0160	**0.6470**	0.0010	0.0000	**0.4480**
HAR-RV-IS-GDP	0.0000	0.0160	0.0000	0.0070	0.0010	0.0070	0.0000	0.0010	0.0000	0.0010
HAR-RV-IK-GDP	0.0110	**0.7860**	0.0050	**1.0000**	**0.2530**	**1.0000**	**0.6470**	0.0630	0.0300	**0.5930**
HAR-RV-MOM-GDP	0.0020	**1.0000**	0.0000	0.0500	**1.0000**	**0.5840**	**0.6470**	0.0010	0.0000	**1.0000**
HAR-RV-IV-EW	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010
HAR-RV-IS-EW	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000	0.0000	0.0010	0.0000	0.0010
HAR-RV-IK-EW	0.0110	0.1520	0.0000	**0.9000**	0.0340	**0.9290**	0.0010	0.0070	0.0000	0.1830
HAR-RV-MOM-EW	0.0020	0.1520	0.0000	0.0500	0.0200	**0.2670**	0.0010	0.0010	0.0000	**0.4480**
HAR-RV-IV-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000
HAR-RV-IK-PCA	**1.0000**	**0.5080**	**1.0000**	**0.8290**	0.0340	**0.9290**	**1.0000**	**0.3230**	**1.0000**	**0.4480**
HAR-RV-MOM-PCA	0.0000	**0.3990**	0.0000	0.0500	0.0130	**0.3380**	0.0010	0.0630	0.0540	**0.4480**
HAR-RV-IV-SPY	0.0020	0.0170	0.0000	0.0070	0.0340	0.0040	**0.6470**	**1.0000**	0.0000	**0.4480**
HAR-RV-IS-SPY	0.0000	0.0170	0.0000	0.0010	0.0200	**0.2670**	0.0010	0.0010	0.0000	0.0010
HAR-RV-IK-SPY	0.0020	**0.9420**	0.0000	0.0500	0.0340	**0.3380**	0.0060	0.0630	0.0300	**0.4480**
HAR-RV-MOM-SPY	0.0020	0.0160	0.0000	0.0010	0.0340	0.0160	0.0060	**0.9930**	0.0000	**0.4480**

The table presents p-values of Range t-statistics based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table 20: Model confidence set p-values of Semi-quadratic t-statistics of the pool of models including models with moments of SPY

	HMAE-SQ									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV	0.0000	0.0060	0.0000	0.0130	0.0090	0.0030	0.0000	0.0020	0.0000	0.0040
HAR-RV-IV	0.0000	0.0000	0.0000	0.0040	0.0000	0.0190	0.0050	0.0060	0.0000	0.0110
HAR-RV-IS	0.0000	0.0080	0.0000	0.0030	0.0020	0.0010	0.0000	0.0940	0.0000	0.0000
HAR-RV-IK	0.0000	0.0000	0.0000	**0.9600**	0.2470	0.2330	0.0000	0.0240	0.1040	0.0000
HAR-RV-MOM	0.0000	0.0000	0.0000	**0.9600**	0.0470	**1.0000**	0.0000	**0.5780**	0.0000	0.0000
HAR-RV-IV-GDP	0.0020	0.1530	0.0000	0.0030	**0.5650**	0.1780	**0.8260**	0.0020	0.0000	**0.9460**
HAR-RV-IS-GDP	0.0000	0.0540	0.0000	0.0630	0.1020	0.0140	0.0030	0.0150	0.0000	0.0340
HAR-RV-IK-GDP	0.0020	**0.8630**	0.0030	**1.0000**	**0.5650**	**0.7500**	**0.8260**	0.1400	0.0120	**0.9460**
HAR-RV-MOM-GDP	0.0020	**1.0000**	0.0000	0.0120	**1.0000**	**0.7500**	**0.8260**	0.0020	0.0000	**0.9460**
HAR-RV-IV-EW	0.0000	0.0090	0.0000	0.0000	0.0010	0.0010	0.0120	0.0010	0.0000	0.0000
HAR-RV-IS-EW	0.0000	0.0040	0.0000	0.0470	0.0010	0.0000	0.0000	0.0040	0.0000	0.0010
HAR-RV-IK-EW	0.0020	0.1280	0.0000	**0.9600**	**0.3660**	**0.7500**	**0.2890**	0.0150	0.0000	**0.3580**
HAR-RV-MOM-EW	0.0000	0.2000	0.0000	0.1120	**0.5650**	**0.6240**	0.1980	0.0140	0.0000	**0.5160**
HAR-RV-IV-PCA	0.0000	0.0000	0.0000	0.0000	0.0050	0.0000	0.0290	0.0010	0.0000	0.0000
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0030	0.0000	0.0000
HAR-RV-IK-PCA	**1.0000**	**0.3590**	**1.0000**	**0.9010**	**0.5650**	**0.7500**	**1.0000**	**0.3900**	**1.0000**	**0.9460**
HAR-RV-MOM-PCA	0.0010	0.1190	0.0000	0.1700	**0.3130**	**0.7500**	**0.6280**	0.0320	0.0530	**0.3200**
HAR-RV-IV-SPY	0.0020	0.0180	0.0000	0.0050	**0.5650**	0.0660	**0.8260**	**0.7430**	0.0000	**1.0000**
HAR-RV-IS-SPY	0.0000	0.0660	0.0000	0.0070	0.2240	**0.7500**	0.0770	0.0240	0.0000	0.0900
HAR-RV-IK-SPY	0.0020	**0.8630**	0.0000	**0.4280**	**0.5650**	**0.7500**	**0.6910**	0.0760	0.0120	**0.9260**
HAR-RV-MOM-SPY	0.0000	0.0260	0.0000	0.0010	**0.5650**	**0.3720**	0.2280	**1.0000**	0.0000	**0.5990**
	HMSE-SQ									
	Australia	Brazil	Canada	Germany	Hong Kong	Japan	Mexico	South Korea	Spain	United Kingdom
HAR-RV	0.0000	0.0030	0.0000	0.0030	0.0110	0.0010	0.0000	0.0000	0.0000	0.0090
HAR-RV-IV	0.0000	0.0000	0.0000	0.0310	0.0020	0.0390	0.0120	0.0010	0.0000	0.0120
HAR-RV-IS	0.0000	0.0110	0.0000	0.0010	0.0050	0.0000	0.0000	0.0180	0.0000	0.0070
HAR-RV-IK	0.0010	0.0000	0.0000	**0.8820**	0.0860	**0.2930**	0.0000	0.0090	0.0330	0.0020
HAR-RV-MOM	0.0000	0.0000	0.0000	**0.9120**	0.0080	**0.9540**	0.0000	**0.9760**	0.0000	0.0020
HAR-RV-IV-GDP	0.0090	0.2090	0.0000	0.0010	**0.4080**	0.0880	**0.7280**	0.0000	0.0000	**0.6010**
HAR-RV-IS-GDP	0.0000	0.0310	0.0000	0.0130	0.0250	0.0130	0.0000	0.0010	0.0000	0.0390
HAR-RV-IK-GDP	0.0090	**0.7910**	0.0090	**1.0000**	**0.4080**	**1.0000**	**0.7280**	0.0160	0.0210	**0.6010**
HAR-RV-MOM-GDP	0.0090	**1.0000**	0.0000	0.1120	**1.0000**	**0.8730**	**0.7280**	0.0030	0.0000	**1.0000**
HAR-RV-IV-EW	0.0000	0.0040	0.0000	0.0000	0.0040	0.0000	0.0020	0.0000	0.0000	0.0080
HAR-RV-IS-EW	0.0000	0.0000	0.0000	0.0010	0.0020	0.0000	0.0000	0.0010	0.0000	0.0040
HAR-RV-IK-EW	0.0090	0.1590	0.0000	**0.8820**	**0.3650**	**0.9540**	0.0950	0.0040	0.0000	**0.4820**
HAR-RV-MOM-EW	0.0090	0.1550	0.0000	0.0270	**0.2840**	**0.6170**	0.0770	0.0010	0.0000	**0.5780**
HAR-RV-IV-PCA	0.0000	0.0000	0.0000	0.0000	0.0040	0.0000	0.0030	0.0000	0.0000	0.0040
HAR-RV-IS-PCA	0.0000	0.0000	0.0000	0.0000	0.0020	0.0000	0.0000	0.0000	0.0000	0.0020
HAR-RV-IK-PCA	**1.0000**	**0.4810**	**1.0000**	**0.8820**	**0.4080**	**0.9540**	**1.0000**	**0.2600**	**1.0000**	**0.6010**
HAR-RV-MOM-PCA	0.0000	**0.3400**	0.0000	0.0530	0.1180	**0.7640**	0.0950	0.0500	0.0330	**0.5620**
HAR-RV-IV-SPY	0.0090	0.0430	0.0000	0.0060	**0.4080**	0.0080	**0.7280**	**1.0000**	0.0000	**0.6010**
HAR-RV-IS-SPY	0.0000	0.0920	0.0000	0.0010	0.1680	**0.6860**	0.0300	0.0020	0.0000	0.1200
HAR-RV-IK-SPY	0.0090	**0.9340**	0.0000	**0.3960**	**0.4080**	**0.7650**	0.1500	0.0120	0.0210	**0.6010**
HAR-RV-MOM-SPY	0.0090	0.0180	0.0000	0.0010	**0.4080**	0.1430	0.2060	**0.9760**	0.0000	**0.5580**

The table presents p-values of Semi-quadratic t-statistics based on loss functions of HMAE and HMSE from the MCS test. All p-values larger than 0.25 are marked in bold and underlined. The higher the p-value, the more significant prediction.

Table A.1: Eigenvalues for moments

	Eigenvalues	Explained variance ratio(%)	Cumulative explained ratio (%)
		VOL	
PC1	5.9	53.6	53.6
PC2	1.0	9.4	63.0
PC3	0.9	8.6	71.6
PC4	0.8	7.3	78.9
PC5	0.7	5.9	84.8
PC6	0.5	4.6	89.4
PC7	0.4	3.5	92.9
PC8	0.3	3.2	96.1
PC9	0.2	1.8	97.9
PC10	0.1	1.2	99.1
PC11	0.1	0.9	100.0
		SKEW	
	Eigenvalues	Explained variance ratio	Cumulative explained ratio
PC1	2.7	24.3	24.3
PC2	1.5	13.4	37.7
PC3	1.4	12.4	50.1
PC4	0.9	8.5	58.6
PC5	0.8	7.2	65.8
PC6	0.8	6.9	72.7
PC7	0.7	6.7	79.4
PC8	0.6	5.6	85.0
PC9	0.6	5.3	90.3
PC10	0.6	5.2	95.5
PC11	0.5	4.4	99.9
		KURT	
	Eigenvalues	Explained variance ratio	Cumulative explained ratio
PC1	3.5	31.7	31.7
PC2	1.7	15.6	47.3
PC3	1.4	12.6	59.9
PC4	0.9	8.6	68.5
PC5	0.7	6.8	75.3
PC6	0.6	5.3	80.6
PC7	0.5	4.7	85.3
PC8	0.5	4.3	89.6
PC9	0.4	4.0	93.6
PC10	0.4	3.4	97.0
PC11	0.3	3.0	100.0

Table A.2: PCA loading scores

					VOL						
location	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
Australia	0.292266	0.182819	0.273815	0.429864	-0.2195	0.192024	-0.45408	0.561036	0.079836	-0.08321	0.045763
Brazil	0.254015	0.179511	-0.20243	0.357109	0.754338	-0.3305	-0.17964	-0.09294	-0.10699	-0.0009	0.064286
Canada	0.290273	0.472604	0.090754	0.136514	-0.01402	0.165521	0.760829	0.125146	-0.17006	0.065094	0.101195
Germany	0.360477	-0.31293	-0.03355	-0.08243	-0.02988	0.141815	-0.10597	0.031396	-0.48153	0.687861	-0.16115
Hong Kong	0.250835	0.516613	-0.05961	-0.1947	-0.44168	-0.53894	-0.219	-0.26097	0.016306	0.138226	-0.08803
Japan	0.244183	-0.4102	0.258582	0.560015	-0.26674	-0.14853	0.156924	-0.5042	0.049935	-0.12401	0.041291
Mexico	0.352528	-0.18316	-0.28538	-0.03767	0.045592	-0.04673	0.19174	0.181404	0.743356	0.19455	-0.30815
South Korea	0.356021	-0.23396	-0.26336	-0.26028	-0.09874	-0.07047	-0.00956	0.109608	0.004239	-0.14378	0.796181
Spain	0.306237	0.230232	0.119118	-0.21312	0.155684	0.631528	-0.23955	-0.51896	0.195607	-0.06796	0.0309
United Kingdom	0.176413	-0.12701	0.776797	-0.39673	0.27905	-0.29647	0.061647	0.119285	0.087731	-0.02131	-0.00059
United States	0.370649	-0.14317	-0.18938	-0.19688	-0.03917	0.001558	0.02861	0.095717	-0.34652	-0.64623	-0.46722

					SKEW						
location	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
Australia	0.377691	-0.02582	-0.26977	-0.27995	-0.32451	-0.22419	-0.21709	-0.36909	0.100573	0.538744	0.257397
Brazil	0.376326	-0.13292	0.303376	0.334302	-0.14579	-0.32272	-0.02632	-0.28164	0.282957	-0.1489	-0.57382
Canada	0.299991	0.058403	-0.38719	-0.57054	0.082497	-0.12461	-0.03403	0.031817	-0.2509	-0.49504	-0.31408
Germany	0.397538	0.048988	0.16328	-0.10295	-0.14058	0.331928	-0.36367	0.664662	0.293851	0.089458	-0.06309
Hong Kong	0.194229	-0.00514	0.566956	-0.33895	0.472441	0.077711	0.081575	-0.11567	-0.33989	0.374444	-0.14462
Japan	0.079826	0.511987	0.361333	-0.28989	-0.27968	0.0755	0.413374	-0.16352	0.305215	-0.26757	0.265735
Mexico	0.381794	-0.22801	0.192545	0.239944	-0.30021	-0.20039	0.173352	0.219089	-0.56025	-0.18331	0.389584
South Korea	0.223525	0.478485	-0.01294	0.287956	0.496254	-0.24913	-0.42399	-0.07969	0.027066	-0.18367	0.330271
Spain	0.314668	0.10364	-0.3555	0.174315	0.309261	-0.13215	0.653853	0.280496	0.19387	0.272007	-0.05093
United Kingdom	0.350637	-0.05665	-0.18713	0.245821	0.057041	0.765243	0.051193	-0.40635	-0.08891	-0.11509	0.025606
United States	-0.07686	0.647157	-0.08927	0.208656	-0.3319	0.053533	-0.03552	0.05831	-0.43787	0.261047	-0.38238

					KURT						
location	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
Australia	0.325441	0.420762	-0.03619	0.143739	0.168244	0.383272	-0.34539	0.043083	0.215618	0.018991	0.593184
Brazil	-0.28703	-0.09509	0.466165	0.399256	0.078567	0.246935	-0.24126	-0.48519	0.05854	-0.385	-0.13941
Canada	0.339342	0.454422	0.018054	0.027404	-0.02288	0.258251	-0.10733	0.010852	0.026015	0.176156	-0.7528
Germany	0.348462	-0.22094	0.29813	-0.20988	0.252653	0.180018	-0.02627	-0.17609	-0.72099	0.197711	0.099853
Hong Kong	0.312554	-0.03723	-0.17265	0.615553	-0.12521	0.128849	0.655352	-0.1125	-0.09916	-0.04852	0.074855
Japan	0.297001	-0.29283	0.202586	-0.07599	0.669109	-0.10537	0.214324	0.05844	0.508783	-0.00426	-0.11041
Mexico	-0.16049	0.257698	0.597747	0.283367	0.042546	-0.17917	0.109655	0.627522	-0.15386	0.066776	0.048826
South Korea	0.347445	-0.18272	0.221446	0.255763	-0.35729	-0.48271	-0.31632	-0.22484	0.186415	0.427144	0.054461
Spain	0.426093	-0.01564	-0.12423	0.04903	-0.0123	-0.35631	-0.25681	0.190972	-0.19524	-0.72573	-0.07763
United Kingdom	0.075872	0.528569	0.295554	-0.38032	-0.09154	-0.30184	0.376973	-0.43052	0.06452	-0.1732	0.147492
United States	0.235448	-0.30339	0.334961	-0.31256	-0.54752	0.426786	0.12134	0.222223	0.245309	-0.18793	0.033106