ASIAN ACADEMY *of*
MANAGEMENT JOURNAL
of ACCOUNTING
and FINANCE

AAMJAF Vol. 18, No. 2, 241–269, 2022

FORECASTING THE HIGH-FREQUENCY EXCHANGE RATE VOLATILITY WITH SMOOTH TRANSITION EXPONENTIAL SMOOTHING

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ABSTRACT

Smooth Transition Exponential Smoothing (STES) is a popular exponential smoothing method for volatility forecasting; whereby the success of the STES model lies in the choice of the transition variable. In this paper, three realized variance (RV), daily, weekly and monthly RV were used as the transition variables in STES methods to evaluate the performance of intraday data. While daily squared return is a noisy series, squared residual and daily RV were employed as the proxy for actual volatilities in this study. With five series of exchange rates, a comparative analysis was conducted for Ad Hoc methods, Generalised Autoregressive Conditional Heteroscedastic (GARCH) models, and STES methods using various RV combinations. The empirical results showed that when daily RV was used as proxy for actual volatility, the traditional STES models and STES models with RV as the transition variables outperformed Ad Hoc methods and GARCH models under the RMSE evaluation criteria. Similar promising results were also observed for traditional STES models and STES models with RV as the transition variables under MAE evaluation. The MCS results generally reaffirmed the results from both the MAE and RMSE evaluation criteria.

Publication date: 30 December 2022

To cite this article: Ho, J. S., Choo, W. C., Zhangyu, R., Yee, C. L., & Lau, W. T. (2022). Forecasting the high-frequency exchange rate volatility with smooth transition exponential smoothing. *Asian Academy of Management Journal of Accounting and Finance, 18*(2), 241–269. https://doi.org/10.21315/aamjaf2022.18.2.10

To link to this article: https://doi.org/10.21315/aamjaf2022.18.2.10

Keywords: Volatility forecast, realised variance, Smooth Transition Exponential Smoothing, STES

INTRODUCTION

The foreign exchange market is one of the most liquid, globally integrated and highly decentralised financial markets (Kinyo, 2020). Since the fall of the Bretton Woods agreement of fixed exchange rates in 1973, there has been an increase in the number of studies on the exchange rate volatility. Exchange rates are widely exposed to global shocks, market sentiments, and speculations, and the review of literature has shown evidence that the foreign exchange rate volatility significantly affects the trade flow that might weaken the economic growth and increase the risk of inflation, impacts of production and transaction costs and global welfare (Chan et al., 2013; Bahmani-Oskooee & Gelan, 2018; Sugiharti et al., 2020). Many studies have shown that the volatility of exchange rate affects the stock prices asymmetrically (Habibi & Lee, 2019). However, the effect of volatility of exchange rate on a country performance only lasts for short term (Lock et al., 2019).

As volatility is latent, non-normal, clustering, persistent, and heavy-tailed, the modelling and forecasting of the exchange rate volatility has become very challenging. Numerous models have been developed to explain the exchange rate volatility over different time horizons and regions. Among them are two well-known models, the Autoregressive Conditional Heteroscedastic (ARCH) model by Engle (1982) and the Generalised Autoregressive Conditional Heteroscedastic (GARCH) model by Bollerslev (1986). Other models include the stochastic volatility models, *Ad Hoc* time series methods and option implied methods (Poon & Granger, 2003; Bollerslev et al., 2006; Sulliman, 2012; Julianto & Ekaputra, 2019). Another pragmatic approach for volatility forecasting is using the exponential smoothing method. Taylor (2004a) introduced an adaptive exponential smoothing method, the Smooth Transition Exponential Smoothing (STES) that allows the smoothing parameters to change over time, which has proved its robustness in dealing with outliers (Liu et al., 2020). While numerous theories and models were proposed, no consensus was reached on the best model for volatility forecasting (Poon & Granger, 2003; Taylor, 2005; Andersen et al., 2006; Benavides & Capistran, 2012).

In recent years, the advent of high-frequency data has triggered numerous studies to use realized measures of volatility. Realized volatility, proposed by Andersen and Bollerslev (1998), is defined as the sum of intraday returns, which allows volatility to be treated as an observed estimator rather than a latent process.

The RV is more accurate and reliable than the squared daily return, which is widely known as a notoriously noisy estimator (see, for example, Andersen & Bollerslev, 1998; Martens, 2011; Zhu et al., 2017). Furthermore, RV can capture the fluctuation of the day although the return of the previous trading day is zero.

Taylor (2004a) applied weekly realized volatility constructed from daily returns in STES for volatility prediction and showed that the approach produced encouraging results compared to other exponential smoothing approaches and GARCH family models. Ung et al. (2014) applied STES method to evaluate the role of asymmetry volatility model in portfolio formation. The results concluded that STES method can help to optimally allocate the fund in portfolio risk management. Liu et al. (2020) further explored the robustness of the STES method in handling the outliers by using daily returns. Their results also demonstrated that the STES, with appropriate transition variables such as the sign and size of past shocks, outperformed other volatility forecasts models. This study extends the works of Taylor (2004a) and Liu et al. (2020) by introducing three realized variances (daily RV, weekly RV, and monthly RV constructed from daily returns and 60-minute returns) into the STES models and GARCH models to evaluate the performance of these models.

LITERATURE REVIEW

Volatility is a measure of risk in asset pricing and is important in various risk management activities. Nonetheless, volatility is usually seen as a latent and unobservable variable, thereby, making the prediction of volatility very complicated.

The earliest popular volatility model is the ARCH model proposed by Engle (1982) which describes conditional variance as a linear function of lagged squared error terms whereby the error term denotes the price shock. Bollerslev (1986) extended the ARCH model to the GARCH model where the conditional variance is represented by a linear function of lagged squared error terms and lagged conditional variance terms. Subsequently, another area of study has emerged on the development of non-linear GARCH models such as Exponential GARCH and GJRGARCH (Glosten, Jagannathan and Runkle GARCH). The EGARCH proposed by Nelson (1991) is capable in capturing asymmetric effect while the GJRGARCH model proposed by Glosten et al. (1993) is a powerful model which can effectively capture the leverage effect by switching between the sign of the previous period's shock. Hagerud (1997) further added value to the GJRGARCH by smoothing the coefficient of the lagged squared error terms using the logistic smooth transition approach (LSTGARCH). Other GARCH models applying the smooth transition approach include exponential smooth transition GARCH (ESTGARCH) and Anderson, Nam and Vahid GARCH (ANSTGARCH).

The smoothing method is a pragmatic approach where it enables the parameter to change over time as a continuous function of a transition variable. There are two common transition variables, sign of past shocks (ε_t) and size of past shocks (ε_t^2). The former is used to model the asymmetry in stock return volatility while the latter is for modelling the dynamics of conditional variance. Taylor (2004a) introduced the STES method for forecasting the volatility in financial returns. The STES uses a logistic function of a user-specified transition variable as an adaptive in time varying smoothing parameter. Taylor (2004a) further tested the STES method using realized weekly volatility calculated from daily data for stock volatility prediction. The results were very promising compared to other GARCH models and fixed parameter exponential smoothing models. Taylor (2004b) conducted another empirical study using the monthly time series from the M3 and proved that the STES method produced encouraging results in comparison to other methods. Next, Gooi et al. (2018) applied the STES method for forecasting the volatility of Malaysian real estate stocks. The findings showed that the STES method outperformed all the other methods such as GARCH family models and standard models. Liu et al. (2020) used STES in forecasting eight main stock indices has also demonstrated that the STES method performed well, regardless of the magnitude of the outliers, compared to other standard methods such as the ES (Exponential Smoothing) and GARCH methods. A recent work by Wan et al. (2021) applying STES methods on Malaysia Mutual Fund Indices has showed that the STES method outperformed GARCH model.

With the evolution of technology, high-frequency data have been made available. Andersen and Bollerslev (1998) introduced the use of high-frequency data or also known as realised volatility in forecasting and the results generally outperformed those of the models with a conventional volatility measure. The RV, a measure of the sum of the squared intra-daily returns, has the merits of containing more information, being less noisy, and being able to generate unbiased and more stable results. Martens (2001) in his study on using the intraday returns in forecasting daily exchange rates concluded that the higher the frequency of realized volatility as the explanatory variable, the better the performance of intraday GARCH (1,1). This finding concurred with the study by Blair et al. (2001) where they showed that intraday returns gave more accurate results compared to daily returns. Meanwhile, Koopman et al. (2005) proved that the predictive power improved by incorporating RV into stochastic volatility (SV) and GARCH models. Taylor (2004a) applied weekly realised volatility derived from the summation of five daily squared residuals to estimate the STES parameters as well as to evaluate the performance compared to other models. The results revealed that the STES models outperformed the DAILY-GARCH and AR (Autoregressive) with realised measures. Ekaputra (2014) used daily realized volatility to examine the impact of order imbalance on return and volatility – volume relation in the Indonesian stock market. However, the results indicated that the order imbalance failed to explain the realized volatility variations.

Patton (2011) has indicated that the use of different volatility proxies can result in unexpected outcomes. In volatility forecasting, daily squared return is always used as the closest proxy to the actual volatility, but the measure is not without flaw. It is widely known that the squared return has microstructure noise, which is one of the main reasons causing the prediction process to become tedious and have low accuracy. Andersen and Bollerslev (1998) have pointed out that the is not suitable to be used as a proxy for standard deviation because it is a biased estimator. Furthermore, the availability of RV has prompted many researchers to use RV as a volatility proxy which is proved to be a better proxy for true variance than the daily squared returns (Day & Lewis, 1992; Taylor, 2004a; Hansen & Lund, 2005). Moreover, Liu et al. (2015) have pointed out that the use of a more noisy proxy can decrease the ability to discriminate the estimators without influencing the consistency of the procedure. Nevertheless, it has also been revealed that the use of RV as the proxy does not increase the predictive performance of the RV measures.

The robustness of the STES method has been tested in stock markets (Taylor, 2004a; 2004b; Ung et al., 2014; Liu et al., 2020), Malaysian real estate stocks (Gooi et al., 2018) and Malaysia Mutual Fund Indices (Wan et al., 2021). This present study extends previous research (where Taylor (2004a) used realised weekly volatility as the estimator and proxy while Liu et al. (2020), Gooi et al. (2018) and Wan et al. (2021) focused on daily returns as the estimator) by applying the STES methods on the exchange rate series using daily RV, weekly RV, and monthly RV. The hourly returns are used to construct the RV as other higher frequency data are not available. Besides, the performance of the volatility forecasts is evaluated using two proxies namely squared residual and daily RV where the RV is widely known to be more accurate than the squared residual.

METHODOLOGY AND ESTIMATION MODELS

Volatility is a measure of risk and varies over time with a latency characteristic. The estimation models used in this study were divided into three categories, namely *Ad Hoc* methods, GARCH models, and STES models. These methods are briefly described in the following subsections.

Ad Hoc Methods

Random walk

Fama (1965) applied the random walk theory as an approach to evaluate the weak form efficiency within a series of asset returns. The weak form efficiency suggests that the future value of a stock is random and independent of each other's movement. Fama (1965) generalised that the best forecast for today's volatility $\left(\sigma_t^2\right)$ is yesterday's volatility $\left(\sigma_{t-1}^2\right)$. The equation is expressed by:

$$\sigma_t^2 = \sigma_{t-1}^2 = \varepsilon_{t-1}^2 \tag{1}$$

and σ_t^2 is the forecast variance and ε_{t-1}^2 is the squared error or past shock.

Naïve forecast method

The naïve forecast method is also known as the historical average method. This method works well if there is no discernible pattern in the actual historical data series. The last period's actual is used as this period's forecast and the method can only forecast up to one period in the future. This model is expressed by:

$$\sigma_t^2 = \frac{\varepsilon_{t-1}^2 + \varepsilon_{t-2}^2 + \ldots + \varepsilon_1^2}{t-1} \tag{2}$$

and ε_{t-1}^2 is the squared error.

Moving average model (MA30)

In contrast to the historical average method in which all the past observations receive equal weight, the moving average method assigns the more recent observations with more weight. The simple moving average method is a simple and popular approach to volatility forecasting, which can be written as:

$$\hat{\sigma}_t^2 = \left(\varepsilon_{t-1}^2 + \varepsilon_{t-2}^2 + \varepsilon_{t-\tau}^2\right)/\tau \tag{3}$$

where τ is the size of the moving frame and in this current study, it was 30 days and ε_{t-1}^2 is the squared error.

Exponentially weighted moving average (EWMA) model

The exponentially weighted moving average (EWMA) is essentially an extension of the simple moving average volatility measure, which allows more recent observations to have a stronger impact on the forecast of volatility than older points and could be written as:

$$\hat{\sigma}_t^2 = \alpha\varepsilon_{t-1}^2 + (1-\alpha)\hat{\sigma}_{t-1}^2 \tag{4}$$

and is the forecast variance and ε_{t-1}^2 is the squared error.

The parameter (1 – α) is seen as a 'decay' factor, which determines how much weight is given to recent versus older observations. As recommended by RiskMetrics (1996), the decay factor could be set at 0.94 for daily data.

GARCH Models

Linear GARCH and non-linear GARCH models were considered in this study. The GARCH model proposed by Bollerslev (1986) was extended from the ARCH models which allows a longer lag-length and is more parsimonious. The GARCH (q, p) model is expressed as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \tag{5}$$

where $\sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2$ represents the ARCH component while $\sum_{j=1}^{p}\beta_j\sigma_{t-j}^2$ represents the GARCH component. The parameters $\omega > 0, \alpha > 0$, and $\beta > 0$ must be estimated. The α coefficient refers to the impact of news shock i.e. a larger α means that volatility responds intensely to the market movements. On the other hand, the β coefficient indicates the volatility clustering. σ_t^2 is dependent not only on the past shock ε_{t-i}^2, but also past conditional variance σ_{t-j}^2. The parameters are optimised using maximum likelihood and assumed to follow the student-t error term distribution.

Nonetheless, it is very common to observe that negative returns tend to be followed by periods of greater volatility than positive returns in financial time series. Black (1976) explains that this asymmetry of the positive and negative shocks leads to different values for the leverage of a firm and thus results in different volatilities. Nelson (1991) first proposed the asymmetric formulation, the exponential GARCH or EGARCH model to model asymmetric variance effects. The general EGARCH (1,1) model is given as:

$$ln\,\sigma_t^2 = \omega + \alpha_1\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma_1\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1\,ln\left(\sigma_{t-1}^2\right) \tag{6}$$

Where, $\varepsilon_{t-1}$is the error term and γ_1 is the parameter of the asymmetric effect. There are three asymmetric effects of γ_1: i) if γ_1, there is no asymmetric effect; ii) if $\gamma_1 > 0$, the volatility increases along with a positive past shock which implies that volatility is more sensitive to good news than bad news; and iii) if $\gamma_1 < 0$, the volatility increases along with a negative past shock or bad news. In other words, leverage effects occur.

Glosten et al. (1993) proposed the GJRGARCH model to accommodate the asymmetry and leverage effects. The GJRGARCH model is shown as:

$$\sigma_t^2 = \omega + \left(1 - I\left[\varepsilon_{t-1} > 0\right]\right)\alpha_1 \varepsilon_{t-1}^2 + \left(I\left[\varepsilon_{t-1} > 0\right]\right)\gamma_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (7)$$

where $I\left[\varepsilon_{t-1} > 0\right]$ is the indicator function, taking a value of 1 if $\varepsilon_{t-1} > 0$ or 0 otherwise. In general, if there is a leverage effect, then, $\alpha_1 > \gamma_1$.

Smooth transition exponential smoothing (STES)

STES was proposed by Taylor in 2004 where a logistic function of a user-specified variable is used as an adaptive smoothing parameter. The formula is written as:

$$\sigma_t^2 = \alpha_{t-1}\varepsilon_{t-1}^2 + \left(1 - \alpha_{t-1}\right)\sigma_{t-1}^2 \qquad (8)$$

where the smoothing parameter is:

$$\alpha_{t-1} = \frac{1}{1 + \exp\left(\beta + \gamma v_{t-1}\right)} \text{ for a single transition variable} \qquad (9)$$

Or $\alpha_{t-1} = \dfrac{1}{1 + \exp\left(\beta + \gamma_1 v_{a(t-1)} + \gamma_2 v_{b(t-1)} + \gamma_3 v_{c(t-1)}\right)}$ for three transition variables (10)

Where $\beta, \gamma_1, \gamma_2, \gamma_3$ are the parameters in the logistic function; $v_{a(t-1)}, v_{b(t-1)}, v_{c(t-1)}$ are the transition variables.

The smoothing parameter varies between 0 and 1 and adapts according to the changes in the transition variable, v_{t-1}. The v_{t-1} in this study was represented by a series of transition variables such as $\varepsilon_{t-1}, \varepsilon_{t-1}^2, |\varepsilon_{t-1}|$, daily RV (RVd), weekly RV (RVw), and monthly RV (RVm). STES is not guided by any statistical theory in the choice of parameter optimisation. Thereby, it is recommended to minimise the sum of in sample one-step-ahead prediction errors, shown as follows:

$$min \sum\nolimits_{t=1}^{T} \left(\varepsilon_t^2 - \hat{\sigma}_t^2\right)^2 (11)$$

where ε_t^2 is the size of past shocks which is used to model the dynamics of the conditional variance while ε_t (sign of past shock) is used in modelling the asymmetry in stock return volatility. According to Taylor (2004a), the STES model with $|\varepsilon_{t-1}|$ or ε_{t-1}^2 as the transition variable would perform better when the estimation sample and evaluation sample contain a level shift or an outlier. By using 1,428 real-time series from the M3-Competition, Taylor (2004b) showed that the STES method with ε_{t-1}^2 as the transition variable could outperform constant parameter exponential smoothing in terms of one-step-ahead post-sample prediction. Although the optimised parameter allows standard simple exponential smoothing to be reasonably robust to outliers, there is still a noticeable rise in the forecast function following each outlier. On the other hand, the success of STES can be attributed to the adaptive nature of the time-varying parameter, which decreases around the outlier to put a reduced weight on the outlier. All in all, the robustness of the STES models relies on their ability of smoothly weighting down the outlying observations in accordance with the time varying transition variable.

Model confidence set procedure

The Model Confidence Set (MCS) procedure was proposed by Hansen et al. (2003; 2011) for model comparative evaluation. This method has advantages over the Diebold and Mariano (DM) test by Diebold and Mariano (1995) and Harvey et al. (1997) in three perspectives. First, a benchmark model is not needed in the MCS test. Second, the MCS test considers the limitations of the data sets and finally, the MCS procedure can generate more than one best model. Based on the work by Hansen et al. (2011), this study adopted the 90% confidence level and set the bootstrap replications at 5,000 times to acquire the Tmax statistics. The MCS test was performed using the RStudio software.

The loss function has the following expression:

$$L_{i,t} = L\left(Y_t, \hat{Y}_{i,t}\right) \tag{12}$$

where, $L_{i,t}$ denotes the loss function associated with i^{th} model in time t; Y_t denotes the actual observation in time t; $\hat{Y}_{i,t}$ denotes the forecasts obtained from i^{th} model in time t.

The loss differential between two models is shown as:

$$d_{ij,t} = L_{i,t} - L_{j,t}, \text{for all } i,j \in M_0 \tag{13}$$

The set of superior model is defined by

$$M^* = \left\{ i \in M^0 : \mu_{ij} \leq 0 \ \textit{for all} \ j \in M^0 \right\} \tag{14}$$

where $\mu_{ij} = E\left[L_{i,t} - L_{j,t}\right] \forall i,j \in M^0$ with M^0 the universe of model.

DATA

Every day, trillions of dollars are traded around the world. The top traded currencies are the US Dollar, the Euro, the Japanese Yen, the Great British Pound, and the Canadian Dollar. In this study, the top five series of exchange rates, i.e., the Australian Dollar (AUD), the Euro (EUR), the British Pound (GBP), the Canadian Dollar (CAD), and the Japanese Yen (JPY) against the US Dollar (USD), were studied. These intraday exchange rate data were obtained from the Dukascopy – SWFX – Swiss Foreign Exchange Marketplace and the forex directory.

For this study, the sample period spanned approximately 6 years, from 1 January 2011 to 29 December 2017. This sample period delivered 2,000 daily observation data. For simplicity, in this initial study, the focus was on the one-step-ahead forecasting of volatility. The first 1,500 log returns were used to estimate the parameters of the various volatility forecasting methods and the remaining 500 observations were the holdout sample for post-sample forecast evaluation.

Daily return of a series, r_t on day t is obtained by:

$$r_t = \text{In}\left(\frac{p_t}{p_{t-1}}\right) \tag{15}$$

where p_t is the closing price on day t and p_{t-1} is the closing price on day t–1.

Intraday daily return constructed from hourly data, r_t on day t is obtained by:

$$r_{t,n} = \text{In}\left(\frac{p_{t,n}}{p_{t-1,n}}\right) \tag{16}$$

where $p_{t,n}$ is the closing price of the n^{th} interval in day t and $r_{t,n}$ is the return of the interval in day t. In this study, for the intraday daily returns derived from the hourly or 60-min returns, n is equal to 24. Thus, a total of 48,000 (2,000 × 24) samples for intraday daily returns were obtained.

Realized Volatility

Realized volatility, as proposed by Andersen and Bollerslev (1998), is generally known to be more accurate than squared daily return. In this study, there were two types of daily RV. The first daily RV was derived from the squared daily return and the second daily RV was the summation of squared intraday returns, which in this study was the hourly returns. The daily realised measures were then used to construct the weekly RV (RVw) and monthly RV (RVm) as shown in the following equations. The three RV were then used as transition variables to formulate various STES models. Table 1 lists the formation of different STES methods using the daily, weekly, and monthly RV.

$$\text{Weekly RV: } RV_w = \textit{sum of } 5 \textit{ previous squared errors for the week} = \sum_{j=1}^{5} \varepsilon^2_{1-1+\frac{j}{5}} \quad (17)$$

$$\text{Monthly RV: } RV_m = \textit{sum of } 22 \textit{ previous squared errors for the month} = \sum_{k=1}^{22} \varepsilon^2_{1-1+\frac{k}{22}} \quad (18)$$

The daily, weekly and monthly RV were then used as transition variables in the STES models.

Table 1
Types of transition variables used in the STES models

Variables	Type of transition
STES Method applied on Squared Residual	
STES-E	STES with ε_{t-1} as the transition variable
STES-AE	STES with $\lvert\varepsilon_{t-1}\rvert$ as the transition variable
STES-SE	STES with ε^2_{t-1} as the transition variable
STES-EAE	STES with ε_{t-1} and $\lvert\varepsilon_{t-1}\rvert$ as the transition variables
STES-ESE	STES with ε_{t-1} and ε^2_{t-1} as the transition variables
STES-RVd	STES with daily RV as the transition variable
STES-RVw	STES with weekly RV as the transition variable
STES-RVm	STES with monthly RV as the transition variable
STES-RVdw	STES with daily and weekly RV as the transition variables
STES-RVdm	STES with daily and monthly RV as the transition variables
STES-RVwm	STES with weekly and monthly RV as the transition variables
STES-RVdwm	STES with daily, weekly, and monthly RV as the transition variables
STES Method applied on daily RV (obtained using hourly data)	
RVSTES-RVd	RVSTES with daily RV as the transition variable
RVSTES-RVw	RVSTES with weekly RV as the transition variable
RVSTES-RVm	RVSTES with monthly RV as the transition variable
RVSTES-RVdw	RVSTES with daily and weekly RV as the transition variables
RVSTES-RVdm	RVSTES with daily and monthly RV as the transition variables
RVSTES-RVwm	RVSTES with weekly and monthly RV as the transition variables
RVSTES-RVdwm	RVSTES with daily, weekly, and monthly RV as the transition variables

Post-sample evaluation and loss functions

As mentioned earlier, the first 1,500 observations were used to conduct in-sample estimation and the remaining 500 observations were used for post-sample forecasting. Two volatility proxies namely squared residual and daily RV as actual proxies were used. The forecasted error was obtained from the difference between the proxy for actual volatility (squared residual or daily RV) and the forecasted variance of each model.

Two popular evaluation criteria, MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error), were employed to compare the performance of the models. The two loss functions are given by:

$$MAE = \frac{1}{n}\sum_{t=1}^{N}\left|\hat{\sigma}_t^2 - \sigma_t^2\right| \quad (14)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\hat{\sigma}_t^2 - \sigma_t^2\right)^2} \quad (15)$$

where N is the post-sample size, σ_t^2 is the squared residual or daily RV, and $\hat{\sigma}_t^2$ is the predicted volatility.

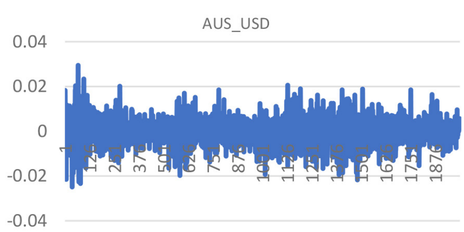
To ease the comparison of the performances for the five series, the mean value of a Theil-U measure was calculated for each series as the ratio of the MAE/RMSE for that method with respect to the MAE/RMSE for the GJRGARCH method. This Theil-U measure was proposed by Poon and Granger (2003) as a measure to summarise the relative performances of methods. The lowest value of Theil-U indicates the best performing model. The values in bold in each column of the table indicate the best performing method for each series.

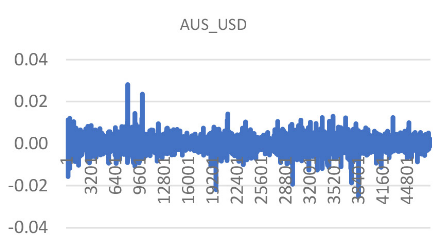
EMPIRICAL RESULTS

This section discusses the results of this study. To ease the discussion, the models are categorised into Standard methods and STES methods.

Figure 1 presents the patterns of daily log returns and hourly log returns for the AUD, EUR, GBP, CAD, and JPY against the USD.

Daily Log Returns	Hourly Log Returns





(*Continue on next page*)

Figure 1 (*Continued*)

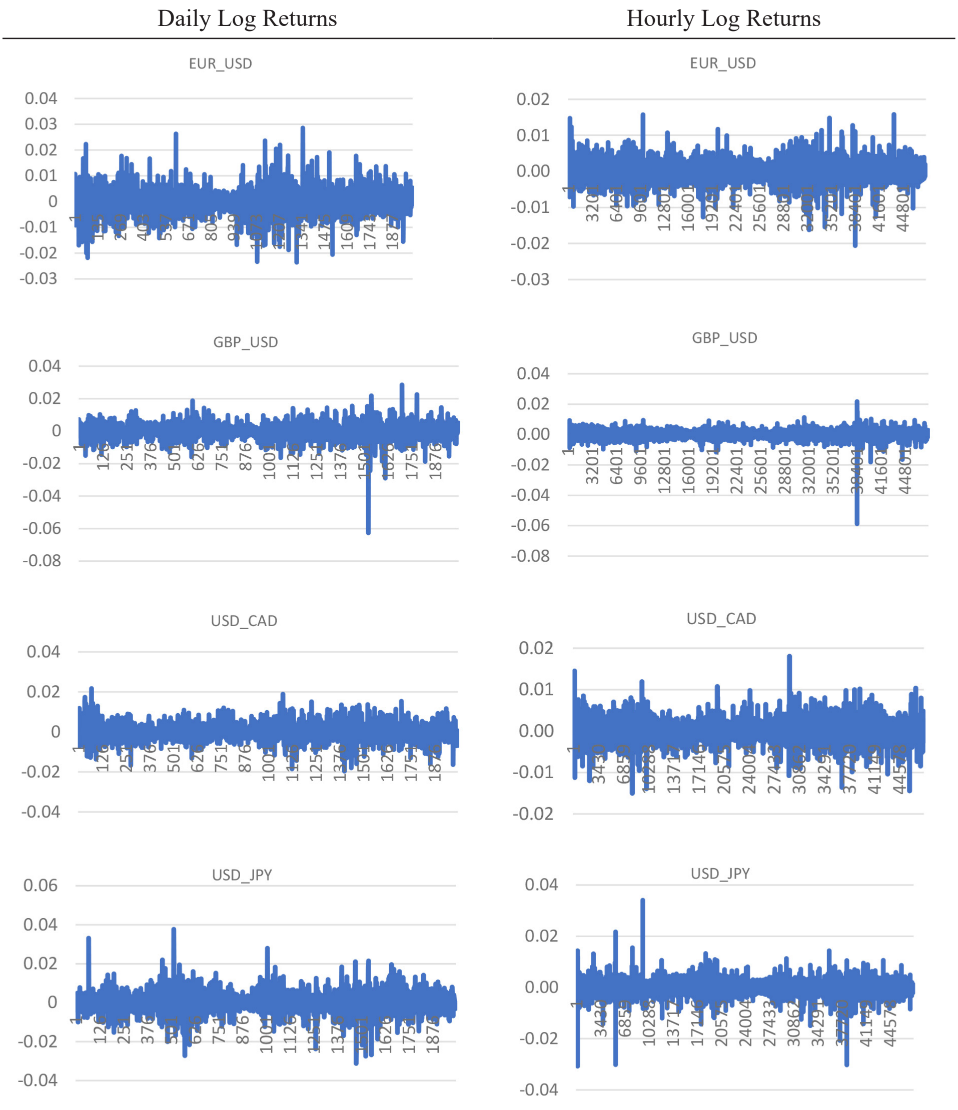


Figure 1 Plots of daily log returns and hourly log returns

Post-Sample Forecasting Performance with Squared Residual as Actual Volatility

Tables 2 and 3 present the post-sample results with squared residual as actual volatility. The MAE values were generally smaller than the RMSE values. Under the MAE evaluation criteria, the Theil-U rankings showed that the STES-

SE, STES-AE, STES-EAE, and STES-ESE models emerged as the best models compared to the other models. STES-RVd had the same Theil-U results as STES-ESE. The intraday hourly (60mRV) applied in GARCH models appeared to be inferior among all the models.

On the other hand, opposite results were observed under the RMSE evaluation criteria. The performance of the STES models, except STES-E, did not seem to be better than the STES models with the weekly and monthly RV measures derived from squared residuals as transition variables. Other equally good performing models included the EWMA, GARCH, IGARCH, and EGARCH models. The Random Walk model was the worst model followed by the 60mRV_GARCH, 60mRV_EGARCH, and 60mRV_GJRGARCH models.

Table 2
MAE for 500 post-sample daily variance forecasts using squared residual as actual volatility

Model	AUS_USD	EUR_USD	GBP_USD	USD_ CAD	USD_JPY	Mean Theil-U
Standard Method						
RW	33.68	29.18	61.78	26.97	47.36	1.18
Naïve forecast	32.40	25.20	40.55	72.47	34.96	1.22
MA30	25.21	21.65	52.14	72.47	38.12	1.25
EWMA (0.06)	25.47	21.84	50.72	21.27	37.94	0.94
GARCH	26.43	22.19	48.61	21.24	37.73	0.93
GJRGARCH	25.89	20.99	62.02	21.08	37.95	1.00
IGARCH	25.56	21.72	51.23	21.33	38.03	0.94
EGARCH	25.94	21.37	44.29	21.04	37.83	0.90
60mRV_GARCH	35.70	32.37	60.09	30.48	43.69	1.28
60mRV_GJRGARCH	36.50	32.44	60.18	30.47	44.38	1.27
60mRV_IGARCH	34.81	26.76	61.56	27.05	44.43	1.23
60mRV_EGARCH	34.53	32.92	53.09	34.92	42.02	1.25
STES Method						
STES-E	25.51	21.92	40.55	20.79	34.96	0.86
STES-AE	22.82	18.88	39.02	18.15	32.64	0.78
STES-SE	21.99	18.84	39.35	18.14	31.41	**0.77**
STES-EAE	23.39	19.37	39.38	18.74	33.36	**0.80**
STES-ESE	23.17	19.13	39.24	18.49	33.01	**0.79**
60mRV_STES-E	35.18	26.26	43.52	28.03	38.00	1.02
60mRV_STES-AE	22.64	25.67	43.52	27.86	38.00	0.94

(*continue on next page*)

Table 2 (*Continued*)

Model	AUS_USD	EUR_USD	GBP_USD	USD_ CAD	USD_JPY	Mean Theil-U
STES-RVd	23.21	19.82	40.67	18.16	31.39	**0.79**
STES-RVw	23.36	21.98	40.68	20.79	38.43	0.86
STES-RVm	25.51	22.72	40.67	19.85	38.20	0.88
STES-RVdw	23.21	19.82	40.67	19.46	32.97	0.81
STES-RVdm	23.21	19.82	40.67	19.46	32.97	0.81
STES-RVwm	26.67	21.98	40.68	20.79	39.23	0.89
STES-RVdwm	23.21	19.82	40.56	19.46	33.21	0.81
RVSTES-RVd	31.81	23.03	43.36	24.17	35.90	0.94
RVSTES-RVw	34.62	25.65	43.37	25.81	37.58	0.99
RVSTES-RVm	34.94	24.00	43.33	27.04	42.97	1.03
RVSTES-RVdw	31.81	23.03	43.35	25.60	37.79	0.96
RVSTES-RVdm	31.81	23.03	43.33	25.60	37.79	0.96
RVSTES-RVwm	34.62	25.65	43.36	26.71	41.06	1.02
RVSTES-RVdwm	31.81	23.03	43.17	25.60	37.79	0.96

Table 3

RMSE for 500 post-sample daily variance forecasts using squared residual as actual volatility

Model	AUD_USD	EUR_USD	GBP_USD	CAD_USD	JPY_USD	Mean Theil-U
Standard Method						
RW	58.60	58.01	259.47	47.31	99.64	1.35
Naïve forecast	43.11	41.45	196.41	75.38	71.14	1.11
MA30	41.28	41.16	196.92	75.38	70.81	1.10
EWMA (0.06)	41.45	41.30	195.45	34.61	70.96	**0.99**
GARCH	41.33	41.03	194.59	34.41	70.75	**0.99**
GJRGARCH	41.16	41.19	198.73	34.50	70.87	1.00
IGARCH	41.24	41.02	194.98	34.39	70.66	**0.99**
EGARCH	41.28	40.86	195.60	34.45	70.73	**0.99**
60mRV_GARCH	49.06	53.16	244.02	41.75	82.37	1.23
60mRV_GJRGARCH	51.28	53.11	244.94	41.73	86.99	1.21
60mRV_IGARCH	48.48	44.77	208.45	36.57	78.74	1.09
60mRV_EGARCH	46.33	63.57	203.80	80.43	74.75	1.23
STES Method						
STES-E	41.22	41.46	196.41	33.86	71.14	**0.99**
STES-AE	46.83	44.78	197.20	38.17	77.92	1.05
STES-SE	45.83	41.52	196.49	34.56	72.66	1.01

(*Continue on next page*)

Table 3 (*Continued*)

Model	AUD_USD	EUR_USD	GBP_USD	CAD_USD	JPY_USD	Mean Theil-U
STES-EAE	47.31	45.15	196.74	38.66	78.39	1.05
STES-ESE	47.14	44.99	196.86	38.47	72.33	1.03
60mRV_STES-E	46.65	42.85	195.62	41.87	71.01	1.03
60mRV_STES-AE	46.66	42.53	195.62	41.70	71.01	1.03
STES-RVd	41.23	41.09	196.39	34.70	72.62	1.00
STES-RVw	41.35	41.14	196.39	33.86	70.72	**0.99**
STES-RVm	41.30	41.06	196.39	33.99	70.63	**0.99**
STES-RVdw	41.23	41.09	196.39	34.36	71.26	**0.99**
STES-RVdm	41.23	41.09	196.39	34.36	71.26	**0.99**
STES-RVwm	41.34	41.14	196.39	33.86	70.88	**0.99**
STES-RVdwm	41.23	41.09	196.42	34.36	71.10	**0.99**
RVSTES-RVd	43.37	41.27	195.68	34.94	70.74	1.00
RVSTES-RVw	45.33	42.20	195.68	35.34	71.29	1.01
RVSTES-RVm	46.24	41.22	195.68	36.32	73.02	1.02
RVSTES-RVdw	43.37	41.27	195.68	35.57	70.67	1.00
RVSTES-RVdm	43.37	41.27	195.68	35.57	70.67	1.00
RVSTES-RVwm	45.33	42.20	195.68	35.94	71.86	1.01
RVSTES-RVdwm	43.37	41.27	195.69	35.57	70.67	1.00

Post-Sample Forecasting Performance with Daily RV as Actual Volatility

When using daily RV as actual volatility, the STES models, i.e., STES-ESE, STES-SE, STES-AE and STES-EAE were the best performers under the MAE evaluation criteria. The RV derived from hourly data (RVSTES-RVd, RVSTES-RVdw, RVSTES-RVdm and RVSTES-RVdwm) played a little role in improving the accuracy.

Under the RMSE evaluation criteria, the mean Theil-U values for most of the models (either the daily return or RV as estimators) were rather close to each other. Among the models, EWMA, the STES models (STES-E, STES-AE, STES-SE, STES-EAE, and STES-ESE), and the RVSTES models produced the best results. Under both the MAE and RMSE evaluation criteria, the use of RVs derived from hourly returns did not improve the accuracy in the GARCH models.

Table 4

MAE for 500 post-sample daily variance forecasts using daily RV as actual volatility

Model	AUD_USD	EUR_USD	GBP_USD	CAD_USD	JPY_USD	Mean Theil-U
Standard Method						
RW	36.79	22.44	64.01	20.97	35.03	1.41
Naïve forecast	22.39	25.49	34.76	60.95	27.47	1.34
MA30	20.31	18.26	43.93	60.95	28.28	1.35
EWMA (0.06)	21.03	17.91	41.63	16.23	28.04	0.98
GARCH	19.44	16.21	38.45	15.69	26.80	0.91
GJRGARCH	19.60	16.07	49.28	15.64	26.86	1.00
IGARCH	19.53	15.83	39.66	15.43	26.86	0.92
EGARCH	19.53	15.93	32.03	15.61	26.28	0.86
60mRV_GARCH	22.72	25.07	43.50	19.70	27.41	1.09
60mRV_GJRGARCH	23.49	25.13	43.57	19.69	28.93	1.10
60mRV_IGARCH	22.22	18.13	42.83	16.33	29.26	1.01
60mRV_EGARCH	21.30	25.49	36.92	24.11	26.64	1.06
STES Method						
STES-E	21.12	17.89	32.15	17.16	27.47	0.91
STES-AE	18.88	15.13	31.55	14.95	25.59	**0.83**
STES-SE	18.43	14.73	31.09	14.98	25.26	**0.82**
STES-EAE	18.84	15.15	31.47	14.84	25.37	**0.83**
STES-ESE	18.67	14.85	30.63	14.95	24.27	**0.81**
60mRV_STES-E	21.42	18.48	33.14	19.81	27.53	0.94
60mRV_STES-AE	37.69	17.95	33.14	19.68	27.54	1.07
STES-RVd	22.21	15.72	34.62	17.90	28.07	0.93
STES-RVw	18.76	16.21	34.61	16.15	26.15	0.88
STES-RVm	19.75	16.52	34.63	16.76	26.93	0.90
STES-RVdw	22.21	15.72	34.63	16.25	25.57	0.90
STES-RVdm	22.21	15.72	34.62	16.25	25.57	0.90
STES-RVwm	18.82	16.21	34.61	16.15	27.28	0.89
STES-RVdwm	22.21	15.72	34.75	16.25	25.33	0.90
RVSTES-RVd	19.17	15.95	33.19	14.93	24.67	**0.85**
RVSTES-RVw	21.03	17.95	33.19	16.47	26.18	0.90
RVSTES-RVm	21.08	17.37	33.19	16.28	28.24	0.91
RVSTES-RVdw	19.17	15.95	33.19	15.45	25.05	**0.85**
RVSTES-RVdm	19.17	15.95	33.19	15.45	25.05	**0.85**
RVSTES-RVwm	21.03	17.95	33.20	16.46	27.37	0.91
RVSTES-RVdwm	19.17	15.95	33.17	15.45	25.05	**0.85**

Table 5
RMSE for 500 post-sample daily variance forecasts using daily RV as actual volatility

Model	AUD_USD	EUR_USD	GBP_USD	CAD_USD	JPY_USD	Mean Theil-U
Standard Method						
RW	67.69	64.28	312.72	35.95	108.36	1.30
Naïve forecast	51.01	50.08	245.39	63.97	81.66	1.08
MA30	51.43	49.17	248.40	63.97	81.17	1.09
EWMA (0.06)	48.97	48.77	244.28	26.71	80.84	**0.99**
GARCH	50.92	48.90	244.56	28.70	81.27	1.00
GJRGARCH	51.20	49.28	244.09	28.76	81.24	1.00
IGARCH	51.09	48.95	243.99	28.45	81.05	1.00
EGARCH	51.24	49.18	243.89	28.78	81.10	1.00
60mRV_GARCH	51.57	56.73	276.38	30.46	71.51	1.07
60mRV_GJRGARCH	52.95	56.73	277.13	30.43	80.64	1.10
60mRV_IGARCH	51.34	49.50	250.62	27.00	82.47	1.01
60mRV_EGARCH	49.85	66.79	246.17	73.68	77.78	1.13
STES Method						
STES-E	48.86	48.79	244.58	28.09	81.66	**0.99**
STES-AE	48.81	48.78	240.44	27.31	82.94	**0.99**
STES-SE	49.28	48.86	243.48	27.02	81.80	**0.99**
STES-EAE	48.86	48.53	241.31	27.00	82.77	0.99
STES-ESE	48.92	49.30	242.93	26.67	80.18	**0.99**
60mRV_STES-E	63.32	48.83	244.50	32.42	81.63	1.01
60mRV_STES-AE	49.33	48.93	244.50	32.83	81.63	1.04
STES-RVd	53.37	49.95	245.35	31.83	85.00	1.02
STES-RVw	50.27	49.04	245.34	29.18	79.99	1.00
STES-RVm	51.23	48.77	245.35	30.16	80.98	1.00
STES-RVdw	53.37	49.95	245.35	30.04	83.01	1.02
STES-RVdm	53.37	49.95	245.35	30.04	83.01	1.02
STES-RVwm	53.35	49.04	245.34	29.18	80.33	1.01
STES-RVdwm	53.37	49.95	245.39	30.04	82.71	1.02
RVSTES-RVd	48.50	48.50	244.56	26.66	81.51	**0.99**
RVSTES-RVw	48.72	48.55	244.56	27.12	81.30	**0.99**
RVSTES-RVm	48.89	48.68	244.57	26.65	80.69	**0.99**
RVSTES-RVdw	48.50	48.50	244.56	26.50	80.75	**0.99**
RVSTES-RVdm	48.50	48.50	244.57	26.50	80.75	**0.99**
RVSTES-RVwm	48.72	48.55	244.56	26.77	80.46	**0.99**
RVSTES-RVdwm	48.50	48.50	244.59	26.50	80.75	**0.99**

Figure 2 displays the plots of mean MAE and RMSE for all the methods with respect to the squared residual and daily RV as actual volatilities. Opposite results were observed for squared residual and daily RV. In terms of MAE evaluation, the forecasted errors with daily RV as actual proxy were smaller compared to the forecast errors with squared residual as actual volatility. Based on the profiles, the biggest gaps between the two proxies were observed for the 60mRV GARCH family models.

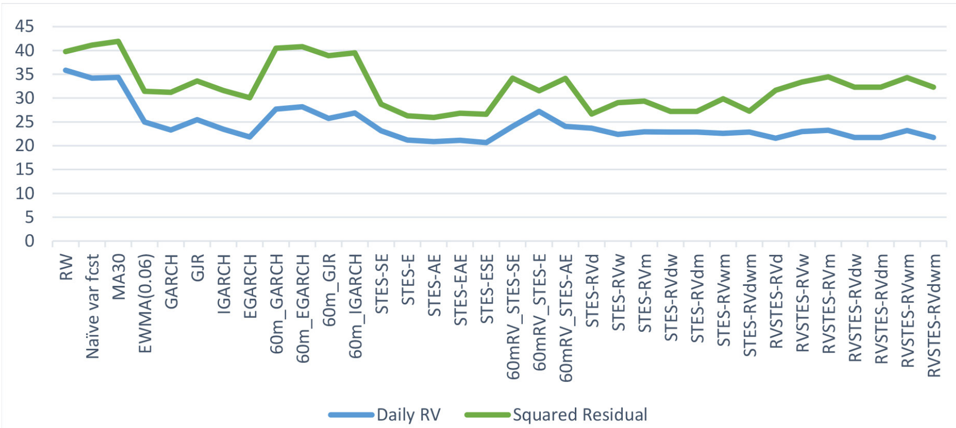


Figure 2. Plot of mean MAE for 500 post-sample results

In contrast to the results for the MAE evaluation criteria, the RMSE values with daily RV as actual proxy were higher than the values with squared residual as actual volatility (as shown in Figure 3). The smallest gaps were observed for the 60mRV GARCH models.

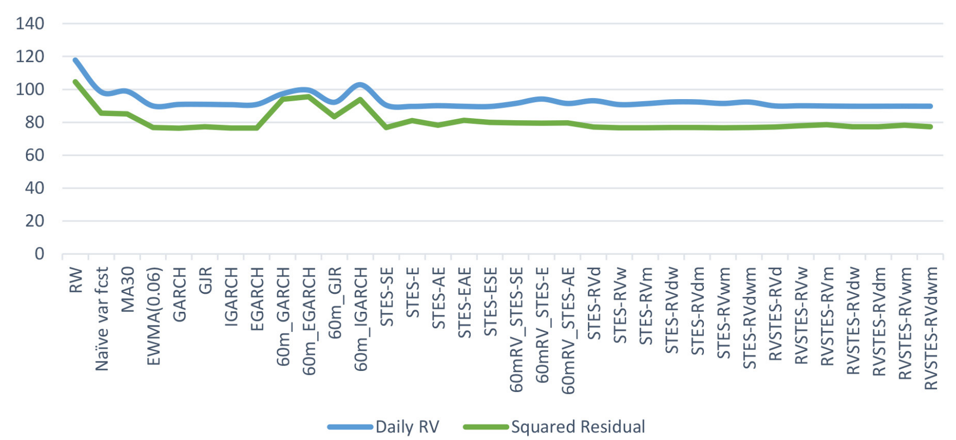


Figure 3. Plot of mean RMSE for 500 post-sample results

Tables 6 and 7 present the results of the MCS tests using squared residual and daily RV as actual volatilities, respectively. The values in the tables denote the scores of the models that survived the elimination process. The Tmax statistics of the models are shown in the Appendices. Based on Table 6, the STES-AE and STES-SE models have significantly outperformed all the other models across all five series. Meanwhile, as shown in Table 7, STES-AE, STES-SE, STES-EAE, and STES-ESE models are significantly better than the other models when using daily RV as actual proxy. Standard GARCH models and STES-RVdm and STES-RVdwm performed significantly well in four of the series. Overall, the MCS tests revealed that the STES methods were superior to the other methods and RV played a small role in improving the accuracy of the models.

Table 6
MCS test for 500 post-sample daily variance forecasts using squared residual as actual volatility

Model	AUS_USD	EUR_USD	GBP_USD	USD_CAD	USD_JPY	Total
Standard Method						
RW						0
Naïve forecast						0
MA30						0
EWMA (0.06)						0
GARCH			1			1
GJRGARCH						0
IGARCH						0
EGARCH			1			1
60mRV_GARCH			1			1
60mRV_GJRGARCH			1			1
60mRV_IGARCH			1			1
60mRV_EGARCH			0			0
STES Method						
STES-E			1			1
STES-AE	1	1	1	1	1	**5**
STES-SE	1	1	1	1	1	**5**
STES-EAE	1		1		1	3
STES-ESE	1	1	1		1	**4**
60mRV_STES-E			1			1
60mRV_STES-AE	1					1

(*Continue on next page*)

Table 6 (*Continued*)

Model	AUS_USD	EUR_USD	GBP_USD	USD_CAD	USD_JPY	Total
60mRV_STES-SE			1			1
STES-RVd	1		1		1	3
STES-RVw			1			1
STES-RVm			1			1
STES-RVdw	1		1		1	3
STES-RVdm	1		1		1	3
STES-RVwm	1		1			2
STES-RVdwm			1		1	2
RVSTES-RVd			1			1
RVSTES-RVw			1			1
RVSTES-RVm						0
RVSTES-RVdw			1			1
RVSTES-RVdm			1			1
RVSTES-RVwm						0
RVSTES-RVdwm						0

Table 7
MCS test for 500 post-sample daily variance forecasts using daily RV as actual volatility

Model	AUS_USD	EUR_USD	GBP_USD	USD_CAD	USD_JPY	Total
Standard Method						
RW						0
Naïve forecast			1		1	2
MA30			1		1	2
EWMA (0.06)			1		1	2
GARCH	1		1	1	1	**4**
GJRGARCH	1		1	1	1	**4**
IGARCH	1		1	1	1	**4**
EGARCH	1		1	1	1	**4**
60mRV_GARCH			1		1	2
60mRV_GJRGARCH			1		1	2
60mRV_IGARCH			1		1	2
60mRV_EGARCH			1		1	2

(*Continue on next page*)

Table 7 (*Continued*)

Model	AUS_USD	EUR_USD	GBP_USD	USD_CAD	USD_JPY	Total
STES Method						
STES-E			1		1	2
STES-AE	1	1	1	1	1	**5**
STES-SE	1	1	1	1	1	**5**
STES-EAE	1	1	1	1	1	**5**
STES-ESE	1	1	1	1	1	**5**
60mRV_STES-E			1		1	2
60mRV_STES-AE			1		1	2
60mRV_STES-SE			1		1	2
STES-RVd		1	1		1	3
STES-RVw	1		1		1	3
STES-RVm			1		1	2
STES-RVdw		1	1		1	3
STES-RVdm	1	1	1		1	**4**
STES-RVwm			1		1	2
STES-RVdwm	1	1	1		1	4
RVSTES-RVd			1	1	1	3
RVSTES-RVw			1		1	2
RVSTES-RVm			1		1	2
RVSTES-RVdw			1	1	1	3
RVSTES-RVdm			1	1	1	3
RVSTES-RVwm			1		1	2
RVSTES-RVdwm			1	1	1	3

In general, this empirical study investigated the robustness of the STES methods by applying the RV derived from hourly data as transition variables and compared them with daily returns as transition variables. The results showed that the traditional STES models emerged as the best performers when daily RV was used as the actual proxy (except STES-E with a slightly poorer performance under the MAE evaluation criteria). While Liu et al. (2015) in their study applying various RV measures in the HAR (Heterogeneous Autoregressive) model noted that the use of RV as the proxy did not favour the RV measure, in this study, the models with RV measures performed relatively well with RV as the actual proxy. For instance, the results of this present study revealed that the STES models with RV performed well with RV as the actual volatility proxy. This suggests that the intraday high-frequency realised volatility 60-min, as the measure of "true volatility", leads to modest improvements in forecasting performance. The findings also demonstrated that more variables in a STES model had little effect in increasing the accuracy. On the other hand, the RV GARCH models did not seem to outperform the standard GARCH models across the five series of exchange rates, which contradicted the findings of Martens (2001). Furthermore, the results were consistent with the earlier findings of Taylor (2004a) where the forecasted errors were smaller when daily RV was used as the actual proxy under the MAE evaluation criteria.

CONCLUSION

The classic STES models use ε_{t-1}, $|\varepsilon_{t-1}|$, and ε_{t-1}^2, which are the sign and size of past shocks as the transition variables. Nevertheless, as the closing price is not enough to capture the price fluctuations during the day, the use of high-frequency returns can build the 'true volatility' that can significantly improve the longer run volatility forecasts. This study has introduced daily RV, weekly RV, and monthly RV constructed from hourly data as transition variables in STES models. The analysis of five exchange rate series has shown that the results of the STES models with RV as the transition variable are very encouraging compared to other *Ad Hoc* models and GARCH family models. The findings have also indicated that the RV with additional intraday information is another practical alternative and beneficial measure in volatility forecasting. It has shown that regardless of using the squared residual or daily RV as actual volatility, the forecast accuracy improves with data frequency. The findings add values to the existing volatility forecasting models and contributes to the improvement of the predictive accuracy in risk management, asset pricing and portfolio analysis.

ACKNOWLEDGEMENTS

The authors are grateful to the Editor-in-Chief, Professor Chee-Wooi Hooy, and anonymous referees for substantive comments that have significantly improved this manuscript.

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APPENDICES

Appendix A

Forecasting performance based on the MCS Test with the Tmax for 500 post sample daily variance forecasts using squared residual as actual volatility

Model	AUS_USD	EUR_USD	GBP_USD	USD_CAD	USD_JPY	Total Acceptance
Standard Method						
RW	0.00	0.00	0.00	0.00	0.00	0
Naïve forecast	0.00	0.00	0.00	0.00	0.00	0
MA30	0.00	0.00	0.00	0.00	0.00	0
EWMA (0.06)	0.00	0.00	0.00	0.00	0.00	0
GARCH	0.00	0.00	0.23	0.00	0.00	1
GJRGARCH	0.00	0.00	0.00	0.00	0.00	0
IGARCH	0.00	0.00	0.00	0.00	0.00	0
EGARCH	0.00	0.00	1.00	0.00	0.00	1
60mRV_GARCH	0.00	0.00	0.19	0.00	0.00	1
60mRV_GJRGARCH	0.00	0.00	0.20	0.00	0.00	1
60mRV_IGARCH	0.00	0.00	0.20	0.00	0.00	1

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Appendix A (*Continued*)

Model	AUS_USD	EUR_USD	GBP_USD	USD_CAD	USD_JPY	Total Acceptance
60mRV_EGARCH	0.00	0.00	0.00	0.00	0.00	0
STES Method						
STES-E	0.00	0.00	1.00	0.00	0.00	1
STES-AE	1.00	1.00	1.00	1.00	1.00	**5**
STES-SE	1.00	1.00	1.00	1.00	1.00	**5**
STES-EAE	0.16	0.00	1.00	0.00	0.39	3
STES-ESE	0.55	0.17	1.00	0.00	0.27	4
60mRV_STES-E	0.00	0.00	1.00	0.00	0.00	1
60mRV_STES-AE	1.00	0.00	0.00	0.00	0.00	1
60mRV_STES-SE	0.00	0.00	1.00	0.00	0.00	1
STES-RVd	0.53	0.00	1.00	0.00	1.00	3
STES-RVw	0.00	0.00	1.00	0.00	0.00	1
STES-RVm	0.00	0.00	1.00	0.00	0.00	1
STES-RVdw	0.53	0.00	1.00	0.00	0.43	3
STES-RVdm	0.53	0.00	1.00	0.00	0.43	3
STES-RVwm	0.53	0.00	1.00	0.00	0.00	2
STES-RVdwm	0.00	0.00	1.00	0.00	0.16	2
RVSTES-RVd	0.00	0.00	0.89	0.00	0.00	1
RVSTES-RVw	0.00	0.00	0.72	0.00	0.00	1
RVSTES-RVm	0.00	0.00	0.00	0.00	0.00	0
RVSTES-RVdw	0.00	0.00	0.24	0.00	0.00	1
RVSTES-RVdm	0.00	0.00	0.37	0.00	0.00	1
RVSTES-RVwm	0.00	0.00	0.00	0.00	0.00	0
RVSTES-RVdwm	0.00	0.00	0.00	0.00	0.00	0

Appendix B

Forecasting performance based on the MCS Test with the Tmax for 500 post sample daily variance forecasts using daily RV as actual volatility

Model	AUS_USD	EUR_USD	GBP_USD	USD_CAD	USD_JPY	Total Acceptance
Standard Method						
RW	0.00	0.00	0.00	0.00	0.00	0
Naïve forecast	0.00	0.00	1.00	0.00	0.99	2
MA30	0.00	0.00	0.76	0.00	0.62	2
EWMA (0.06)	0.00	0.00	0.71	0.00	0.73	2
GARCH	0.67	0.00	0.96	0.53	1.00	4
GJRGARCH	0.30	0.00	0.22	0.64	1.00	4
IGARCH	0.31	0.00	0.88	0.96	1.00	4
EGARCH	0.35	0.00	1.00	0.70	1.00	4
60mRV_GARCH	0.00	0.00	0.75	0.00	0.96	2
60mRV_GJRGARCH	0.00	0.00	0.75	0.00	0.44	2
60mRV_IGARCH	0.00	0.00	0.81	0.00	0.81	2
60mRV_EGARCH	0.00	0.00	0.95	0.00	1.00	2
STES Method						
STES-E	0.00	0.00	1.00	0.00	1.00	2
STES-AE	1.00	1.00	1.00	1.00	1.00	**5**
STES-SE	1.00	1.00	1.00	1.00	1.00	**5**
STES-EAE	1.00	0.39	1.00	1.00	1.00	**5**
STES-ESE	1.00	0.26	1.00	1.00	1.00	**5**
60mRV_STES-E	0.00	0.00	1.00	0.00	0.99	2
60mRV_STES-AE	0.00	0.00	1.00	0.00	0.99	2
60mRV_STES-SE	0.00	0.00	1.00	0.00	0.99	2
STES-RVd	0.00	1.00	1.00	0.00	0.87	3
STES-RVw	1.00	0.00	1.00	0.00	0.87	3
STES-RVm	0.00	0.00	1.00	0.00	1.00	2
STES-RVdw	0.00	0.44	1.00	0.00	1.00	3
STES-RVdm	0.99	0.44	1.00	0.00	1.00	**4**
STES-RVwm	1.00	0.00	1.00	0.00	0.99	3
STES-RVdwm	0.00	0.18	1.00	0.00	1.00	3
RVSTES-RVd	1.00	0.00	1.00	1.00	1.00	4

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Appendix B (*Continued*)

Model	AUS_USD	EUR_USD	GBP_USD	USD_CAD	USD_JPY	Total Acceptance
RVSTES-RVw	0.00	0.00	1.00	0.00	1.00	2
RVSTES-RVm	0.00	0.00	0.43	0.00	0.53	2
RVSTES-RVdw	0.99	0.00	1.00	0.88	1.00	**4**
RVSTES-RVdm	0.99	0.00	1.00	0.88	1.00	**4**
RVSTES-RVwm	0.00	0.00	1.00	0.00	0.99	2
RVSTES-RVdwm	0.92	0.00	1.00	0.55	1.00	**4**