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Supremacy of Realized Variance MIDAS Regression in Volatility Forecasting of Mutual Funds: Empirical Evidence From Malaysia*

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Abstract

Combining the strength of both Mixed Data Sampling (MIDAS) Regression and realized variance measures, this paper seeks to investigate two objectives: (1) evaluate the post-sample performance of the proposed weekly Realized Variance-MIDAS (RVar-MIDAS) in one-week ahead volatility forecasting against the established Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the less explored but robust STES (Smooth Transition Exponential Smoothing) methods. (2) comparing forecast error performance between realized variance and squared residuals measures as a proxy for actual volatility. Data of seven private equity mutual fund indices (generated from 57 individual funds) from two different time periods (with and without financial crisis) are applied to 21 models. Robustness of the post-sample volatility forecasting of all models is validated by the Model Confidence Set (MCS) Procedures and revealed: (1) The weekly RVar-MIDAS model emerged as the best model, outperformed the robust DAILY-STES methods, and the weekly DAILY-GARCH models, particularly during a volatile period. (2) models with realized variance measured in estimation and as a proxy for actual volatility outperformed those using squared residual. This study contributes an empirical approach to one-week ahead volatility forecasting of mutual funds return, which is less explored in past literature on financial volatility forecasting compared to stocks volatility.

Keywords: Mixed Data Sampling, Realized Variance, Volatility Forecasting, Smooth Transition Exponential Smoothing, Mutual Funds

JEL Classification Code: C22, C52, C53

1. Introduction

Volatility forecasting has been an area extensively researched in managing risk, optimizing return of investment portfolio, option pricing in derivatives trading as well as macroeconomic policy management. Volatility, the quantified measurement of risk that arises due to uncertainty, has been a subject of great interest among investors, fund managers, and academicians. A highly volatile financial asset is often regarded as risky. Risk can be caused by either upside or downside risk. Upside risk occurs during a market uptrend and can result in a "missed opportunity" of gaining, while downside risk often occurs during a market downtrend resulting in a loss. Thus, risk assessment of a financial asset must commence with the ability to forecast the volatility of its return (Poon & Granger, 2003).

The introduction of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH hereafter) framework has enabled volatility to be forecasted (Engle, 1982; Bollerslev, 1986). The symmetric GARCH model has evolved into asymmetric GARCH models such as Exponential GARCH (E-GARCH) (Nelson, 1991) and

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GJR-GARCH (Glosten et al., 1993). These asymmetric models can capture both the asymmetric and leverage effect of the news shock. The GARCH family models have been widely adopted, particularly in stocks volatility studies (Chou, 1988; Poon & Taylor, 1992; Choo et al., 1999; McMillan & Speight, 2004; Sahadudheen, 2015; Rahmi et al., 2016; Nguyen & Nguyen, 2019; Golder et al., 2022). GARCH model further evolved into a non-linear GARCH model, namely, ST-GARCH (Gonzalez-Rivera, 1998), LST-GARCH (Logistic Smooth Transition GARCH), and EST-GARCH (Exponential Smooth Transition GARCH), which has indirectly led to the introduction of Smooth Transition Exponential Smoothing (STES hereafter) method of volatility forecasting introduced by Taylor (2004a), capable of handling changing characteristics of time series over time.

Time-varying conditional variance (volatility), though unobservable and latent, it persists over time (Mandelbrot, 1963), and hence, is forecastable. Therefore, a proxy for actual volatility is required as a comparison against forecasted variance to obtain the forecast error of an estimated volatility forecasting model. The daily squared return has been widely adopted as the closest proxy to actual volatility. However, since daily squared return innovation possesses microstructure noise, its reliability is subjected to an appropriately specified volatility model. This means the noise in the daily squared return series reduces the ability of a model to capture the latent volatility process resulting in forecasting inaccuracy. The emergence of high-frequency data has enabled the measurement of realized variance (RVar hereafter). Mcaleer and Rotterdam (2008) pointed out that actual volatility could be fairly proxied by the variance within a fixed interval, provided the data within the fixed interval is of very high frequency through the process of sum squared realization which produces a realized variance measurement for conditional variance.

In short, realized variance measurement is the summation of squared returns of higher frequency data within a stipulated interval; for instance, intraday with either a 5-minutes or hourly data frequency, is regarded as a better proxy for actual volatility compared to daily squared return (Bollerslev & Andersen, 1998). Higher frequency data contains more information about the volatility of a financial asset, is less noisy, and is capable of producing better post-sample forecasting accuracy (Hansen & Lunde, 2005). Past empirical study has documented a tenfold improvement in post-sample forecasting accuracy attributed to the application of realized variance measures of 5-minutes (288 observations per day) sampling frequency on foreign exchange volatility study by Bollerslev and Andersen (1998) using the GARCH (1, 1) model.

Data of different frequencies often pose great challenges to many researchers. However, the introduction of the Mixed Data Sampling (MIDAS hereafter) Regression by Ghysels et al. (2004) has resolved this concern. While the Ordinary Least Square regression model requires data of both dependent and independent variables to be of similar frequency, the MIDAS Regression model allows simultaneous regression between dependent and independent variables of different frequencies, particularly in many macroeconomic studies where most economic data are sampled at a lower frequency (Breitung & Roling, 2015; Li et al., 2015; Jiang et al., 2017; Tsui et al., 2018; Gorgi et al., 2019) of monthly, quarterly or annually. Supremacy of the MIDAS model lies in its distinctive parsimoniously parameterized lag polynomial function where the high frequency daily realized volatility (attributed to greater shocks, particularly during the "stress" period) to mean revert faster than a GARCH model where greater shock tend to persist longer (Alper et al., 2012).

Motivated by the strength of MIDAS Regression and realized variance measures that improve volatility forecasting, this study contributes in three ways. First, it combines the strength of MIDAS Regression with realized variance measures and proposes the Realized Variance-MIDAS (RVar-MIDAS model hereafter) model to examine one-week ahead volatility forecasting of private equity mutual funds indices in Malaysia. The aim is to empirically verify the superiority of the RVar-MIDAS model through a one-week-ahead volatility forecast accuracy comparison between the GARCH (1, 1) models and STES methods (with five different transition variables).

Second, this study employed both the realized variance and the squared residuals measures in both estimations of competing models as well as proxies for actual volatility in forecast error evaluation, following Taylor's (2004a, 2004b) approach. The aim is to verify if realized variance or squared residuals approach provides better post-sample performance of a one-week-ahead volatility forecasting.

Third, while many past studies applied the realized variance measures to examine stocks or exchange rate volatility, this study examines the risk of seven mutual funds indices in Malaysia from different risk categories (generated from 57 individual mutual funds), which has never existed in Malaysia. Mutual fund adopts a daily single pricing mechanism known as Net Asset Value (NAV), representing the daily value of a fund.

Since mutual funds' daily trading (investing and repurchasing) is based on a daily single pricing mechanism determined at the end of each business day, there are no intraday prices, unlike stocks or exchange rates where the intraday value in minutes or hourly frequency are generally available. As such, the application of realized variance measures is only possible for a one-week ahead volatility forecasting instead of a one-day ahead in the case of mutual funds. The remainder of this paper is organized as follows. Section 2 presents the literature reviews, while Section 3 presents the descriptive statistics of the data set. Section 3 explains the models examined and the methodology adopted.

Section 4 discusses the empirical results, and the final Section 5 concludes this study.

2. Literature Review

MIDAS Regression model has been widely applied to macroeconomic forecasting (Jiang et al., 2017; Tsui et al., 2018) and financial volatility forecasting (Xu et al., 2020; Xiong et al., 2020). This is attributed to its salient feature which enables regression between data of different frequencies using a parsimoniously parameterized lag polynomial function. Past studies have revealed the supremacy of MIDAS Regression over the popular GARCH (1, 1) model. Alper et al. (2012) applied MIDAS Regression to forecast weekly and bi-weekly stock volatility in emerging markets under two sub-periods of "stress" (with financial crisis) and "tranquil" (without financial crisis) using daily realized volatility measures. His results revealed the supremacy of MIDAS Regression over the benchmark GARCH model, particularly during the "stress" period. Körs and Karan (2021) applied MIDAS Regression to eight stock indices of developed countries for a one-month ahead volatility forecast and concluded the superiority of MIDAS over GARCH.

Unlike the popular GARCH model, the STES method application in volatility studies is relatively low despite its capability of handling changing characteristics of time series. Though lesser-known, its resilience to outliers has enabled it to outperform GARCH models and the exponential smoothing methods (see Taylor, 2004b; Choo, 2008; Gooi et al., 2018; Liu et al., 2020; Wan et al., 2021) in one-step-ahead volatility forecasting. In a comparative study of weekly volatility forecasting of eight stock indices to verify the superiority of the Smooth Transition Exponential Smoothing (STES) method against several fixed parameters exponential smoothing methods, several GARCH and autoregressive models, Taylor (2004a) applied realized variance measures not only to obtain forecast error but also in estimating parameters of exponential smoothing method. The weekly realized volatility is obtained from the summation of the daily squared residual of the respective five trading days of a week. Models (DAILY-GARCH Autoregressive model and STES methods) employing the realized measures in both estimation and forecast evaluation outperformed other models in terms of a one-week ahead post-sample volatility forecasting. The STES method with "error" and "absolute error" as transition variables emerged as the best performing model, outperforming both the DAILY-GARCH and Autoregressive model with realized measures.

Meanwhile, Koopman et al. (2005) found models using daily realized variance to be superior to models using daily squared return and implied volatility in one-day ahead stocks volatility forecasting. Hansen et al. (2011) introduced the Realized GARCH model, which allowed the incorporation of realized measures of volatility (realized variance) and applied to forecast volatility of the Dow Jones Industrial Average, which outperformed the standard GARCH in post-sample volatility forecasting. In the Turkish stock market volatility study by Çelik and Ergin (2014), both the MIDAS Regression and the HAR-Realized Volatility model emerged as joint best models, beating the standard GARCH, Realized GARCH, and two other HAR-Realized Volatility models. Huang et al. (2016) further extended the works of literature and found a newly derived Realized GARCH with HAR specification outperformed the classic Realized GARCH introduced by Hansen et al. (2011). However, Sharma and Vipul (2016) found that the forecasting ability of Realized GARCH model is subjected to the loss criterion used and found exponential weighted moving average method is superior. Nevertheless, various realized measures of volatility comprising realized variance, bi-power variation, realized kernel, and other similar measures are superior over squared return as realized measures utilize higher frequency data which generally contain more information about volatility (Hansen et al., 2011).

This study attempts to apply both realized variance and squared residual measures in both estimation as well as a proxy for actual volatility (to calculate forecast error) across the MIDAS Regression, GARCH models, and STES methods to answer the following hypotheses:

H1: *RVar-MIDAS has superiority over both the STES method and GARCH (1, 1) in one-week ahead volatility forecasting of mutual funds.*

H2: *Realized Variance (RVar) measure is the superior choice of proxy for actual volatility over the Squared Residual (RSQ) measure.*

3. Research Methods and Materials

3.1. Data

The data set is sourced from DATASTREAM, which comprises seven fund indices daily return time series made up of 57 private equity mutual funds managed by seven top private funds management companies in Malaysia, managing close to 93% of total private mutual funds in Malaysia. The 57 funds are selected based on the availability of data within the stipulated analysis period of the study. From the sample of 57 funds, funds of similar investment objectives (or same risk profile) are clustered together into one group to reflect a unique risk-return profile of those mutual funds within the group. The clustering exercise led to the creation of seven fund indices of different investment objectives, corresponding to their respective risk-return characteristics. Name of the seven fund indices, with the first being the riskiest to the seventh being the lowest risk, are as follows - Growth Fund, Growth & Income, Income, Balanced Growth, Balanced Growth & Income, Balanced Income, and Mixed Asset Growth (Table 1).

Each fund index daily return series is created using the same approach as in the Dow Jones Average Industrial Index (DJIA) (Corielli & Marcellino, 2006; Parasuraman & Ramudu, 2014) as follows: (Mutual Fund Index under specific fund objective) t = (sum of all funds NAV) t/ divisor, where the divisor of each fund index is calculated by dividing the sum of NAV of all funds within a specific fund objective at a specific base date, by 100. Each fund index will have its respective divisor value. The daily fund index is then obtained by dividing the sum of daily Net Asset Value (NAV) across all funds under a similar investment objective against the divisor. The full sample period covers from 3rd Jan 2005 to 31st Dec 2019 and is divided into two sub-periods with financial crisis (2005–2011) and without financial crisis (2012–2019) to examine if the respective model's forecasting performance is influenced by different market volatility condition. Descriptive statistics for both sub-periods are provided in Table 1. Negative skewness and higher kurtosis (leptokurtic distribution) in the sub-period compared to the sub-period without financial crises implies higher risk in the volatile sub-period with the financial crisis.

The daily return of each fund series is generated as follows:

$$R_t = \ln\left[\frac{\text{Fund Index}_t}{\text{Fund Index}_{t-1}}\right]$$

where R_t = daily return of respective fund index, Fund Index t is the fund index on day t while Fund Index t–1 is the fund index on day t–1. The plot of the daily return of each mutual fund index series in both sub-period with and without financial crisis is shown in Figure 1. The volatility clustering pattern is visible from the return series plot for all seven fund indices. Data stationarity is determined by Augmented Dickey-Fuller (ADF) Unit Root Test. The ADF statistics for all seven fund indices (see Table 2) in both sub-periods are significant at a 1% significance level, thus rejecting the null hypothesis of unit root existence. Hence, data in all seven fund indices is stationary.

3.2. Research Models

This study aims to provide empirical evidence of the supremacy of MIDAS Regression by comparing both realized variance and squared residuals measures for estimating conditional variance in a one–week ahead volatility forecasting of seven private equity mutual fund indices in Malaysia under two sub-periods of different economic conditions. 21 Models comprised of two GARCH models, ten STES methods, eight MIDAS models, and an Autoregressive model are compared for their post-sample forecasting ability.

3.2.1. Mixed Data Sampling (MIDAS) Regression Model

The strength of the MIDAS regression framework lies in its parsimoniously parameterized weighting function, which

Table 1: Descriptive Statistics of Fund Indices Return in Both Sub-Periods

Fund Index	Sub-period	Obs	Mean (10^{-4})	Max	Min	Std. Dev.	Skew	Kurt.	Jarque-Bera
Growth	2005–2011	1824	1.890	0.040	–0.082	0.007	–1.452	15.79	13067.3***
	2012–2019	2086	0.649	0.027	–0.025	0.004	–0.756	7.229	1753.0***
Growth & Income	2005–2011	1824	2.490	0.033	–0.074	0.007	–1.341	15.21	11881.0***
	2012–2019	2086	0.664	0.024	–0.023	0.004	–0.749	6.719	1397.3***
Income	2005–2011	1824	1.030	0.033	–0.070	0.007	–1.308	12.59	7504.9***
	2012–2019	2086	0.322	0.020	–0.028	0.005	–1.191	7.806	2501.1***
Balanced Growth	2005–2011	1824	0.904	0.031	–0.081	0.007	–2.371	24.71	37544.8***
	2012–2019	2086	0.046	0.021	–0.028	0.004	–1.820	14.07	11794.6***
Balanced Growth & Income	2005–2011	1824	0.292	0.025	–0.055	0.005	–1.427	14.41	10510.6***
	2012–2019	2086	0.064	0.015	–0.017	0.003	–0.855	6.660	1418.4***
Balanced Income	2005–2011	1824	2.740	0.028	–0.056	0.005	–1.195	15.45	12206.3***
	2012–2019	2086	1.930	0.018	–0.035	0.004	–0.793	9.312	3682.2***
Mixed Asset Growth	2005–2011	1824	2.190	0.036	–0.066	0.006	–1.821	19.36	21341.0***
	2012–2019	2086	0.000	0.070	–0.032	0.006	–0.005	19.41	23408.4***

Note: ***, ** and * denotes significant at level of significance of 1%, 5% and 10% based on t-statistics.

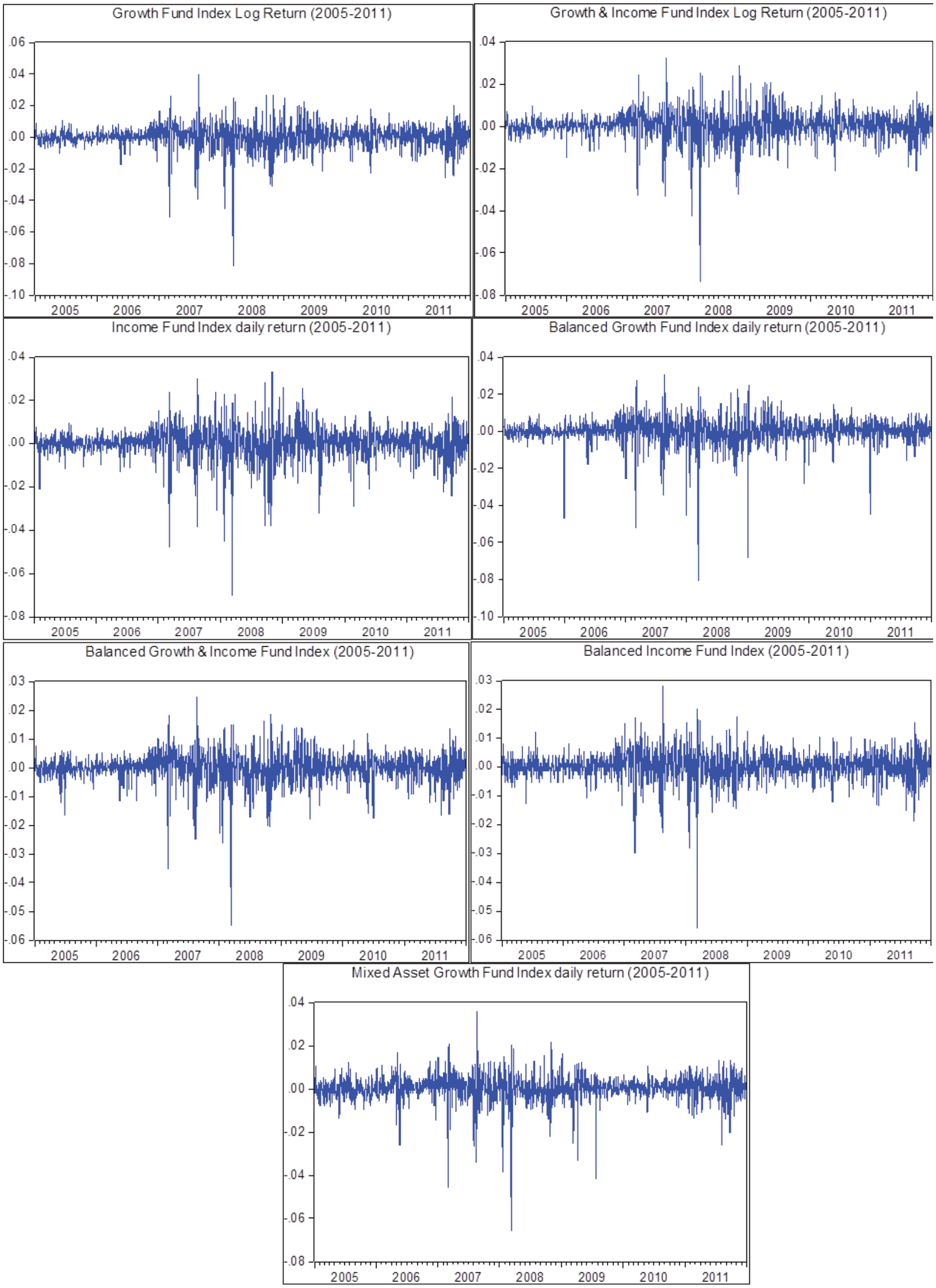

Figure 1: Return Sseries for all Seven Fund Indices Both Sub-Period 2005–2011 and 2012–2019

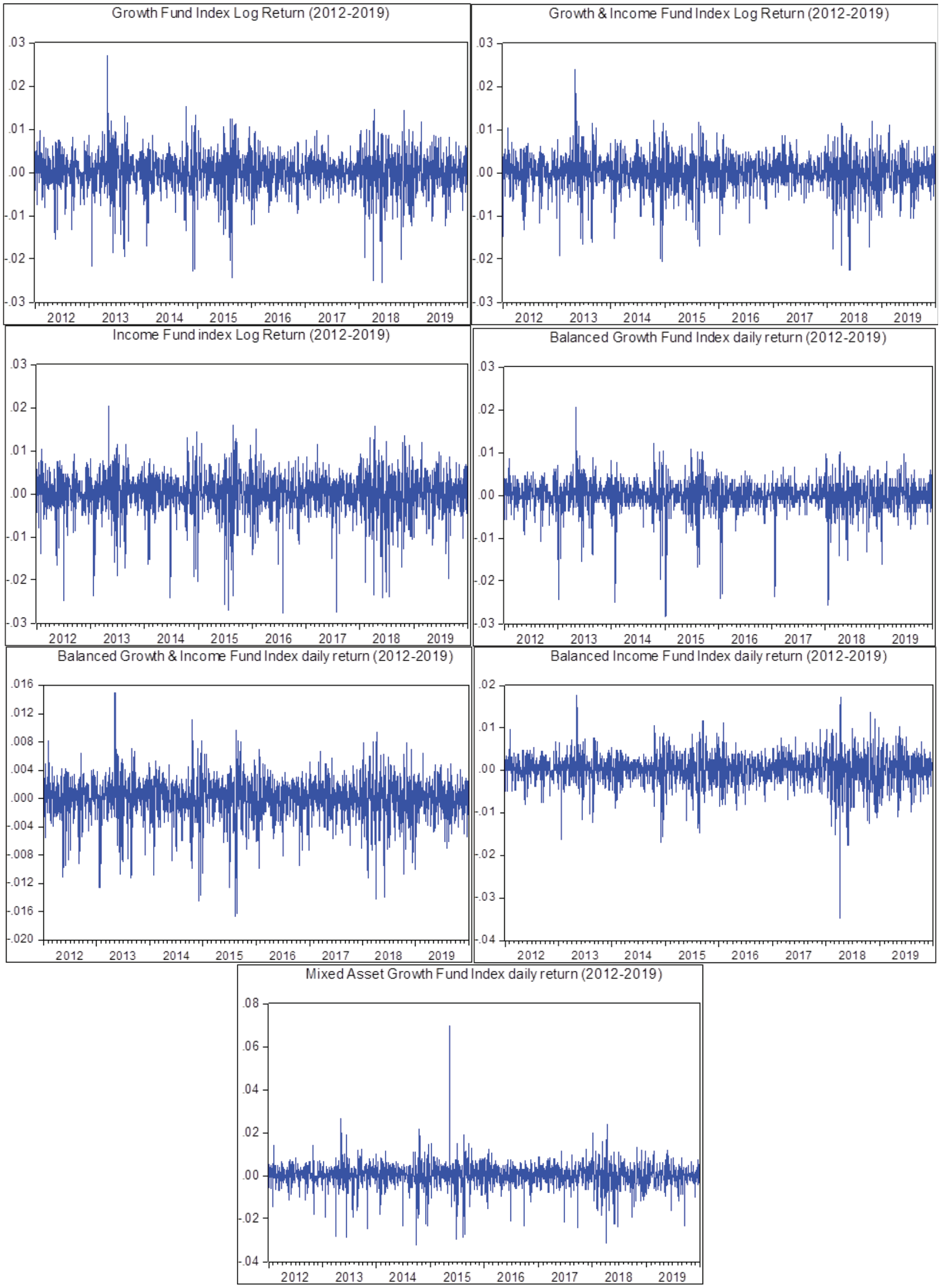

Figure 1: (Continued)

Table 2: Data Stationarity, Autocorrelation, and ARCH Effect Test for all Seven Fund Indices Return in Both Sub-Periods

Fund Index	Sub-Period 2005–2011			Sub-Period 2012–2019		
	ADF (*t*-stat)	Ljung-Box Q-stat (12)	ARCH LM-Test (Obs* *R*-squared)	ADF (*t*-stat)	Ljung-Box Q-stat (12)	ARCH LM-Test (Obs* *R*-squared)
Growth	–36.04***	90.75***	79.33***	–40.39***	40.29***	59.98***
Growth & Income	–35.91***	84.97***	77.94***	–41.62***	28.82***	58.25***
Income	–36.63***	69.60***	66.94***	–42.02***	25.53***	17.07***
Balanced Growth	–38.66***	32.99***	20.97***	–41.87***	32.98***	10.08***
Balanced Growth & Income	–37.21***	69.61***	47.94***	–41.03***	32.15***	57.10***
Balanced Income	–38.67***	46.01***	68.97***	–41.11***	46.02***	137.72***
Mixed Asset Growth	–38.45***	48.04***	51.96***	–42.19***	31.55***	6.92***

Note: ***, ** and * denotes significant at 10%, 5% and 1% level of significance based on *t*-statistics.

allows data of different frequencies to be regressed together (Ghysels et al., 2004). The MIDAS regression model is generally specified as:

$$Y_t = \alpha_0 + \alpha_1 \sum_{k=0}^{k\,Max} B\left(k,\theta\right) X_{t-k/m}^{m} + \varepsilon_t \tag{1}$$

where Y_t denotes weekly variance of respective fund index, $B\left(k,\theta\right)$ is a polynomial weighting function which depends on both elapsed time of $k < k^{Max}$ and the parameter θ, X_t^m is sampled m times ($m = 5$ in this study, denoting a five-day week) more than Y_t, as X_t is the daily residuals of a 5-day week (Monday to Friday) for the respective fund index.

Although a squared daily return of an asset is a noisy series, the squared innovations measures provide an unbiased estimate of latent and unobservable actual volatility (Bollerslev & Andersen, 1998), implying that higher frequency data contains more information. Adopting the idea of a one-week ahead volatility forecasting using the MIDAS Regression model from the work of Alper et al. (2012), this study employs MIDAS regression methodology, which allows the daily squared residuals to be regressed against weekly realized variance (lower frequency dependent variable) of each seven fund indices against their respective daily squared residual for a 5-day week in both sub-periods of analysis. Weekly realized variance (RVar) is calculated as:

$$\mathrm{RVar}_t = \sum_{i=1}^{5} \varepsilon_{i,t}^2 \tag{2}$$

where realized variance of week t is the sum of the squared residual of the day $i = 1$ to 5. This model is denoted as the weekly Realized Variance MIDAS (RVar-MIDAS). As squared residual is often taken as a proxy to actual volatility to determine forecast error, we introduce another competing weekly MIDAS model with weekly squared residuals, denoted as weekly RSQ-MIDAS, to compare against the RVar-MIDAS model. The weekly squared residual of the RSQ-MIDAS model is generated by the squared residual of the weekly return on each week's Friday. Both RVar-MIDAS and RSQ-MIDAS are estimated separately using four different polynomial weighting schemes namely, Step, Almon PDL, end-restricted Beta, and Unrestricted-MIDAS. This gives a total of eight different MIDAS models to be examined.

3.2.2. Weekly GARCH (1, 1) Model

DAILYGARCH and WEEKLYGARCH are derived based on the basic GARCH (1, 1) model specified by a mean equation (Equation 3):

$$r_t = m_t + {}_t \tag{3}$$

where $\varepsilon_t = \sqrt{v_t h_t}$ where $v_t \sim t\left(0,1\right)$ and h_t is the conditional variance (Equation 4) defined as:

$$h_t = \omega_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{4}$$

where r_t is return, m_t is mean return, ε_t is the error term, h_t = conditional variance of the respective fund index return, $\omega > 0$, $\alpha \geq 0$, and $\beta \geq 0$ are parameters to be estimated, and time subscript "t" is weekly. The α coefficient represents the impact of news shock on volatility (a larger α indicates volatility reacts strongly to news shock), while β coefficient represents the impact of past volatility on present volatility (volatility clustering). Equation 1 is the mean equation, while equation 2 is the variance equation.

The Student-t error term distribution assumption is applied to both DAILYGARCH and WEEKLY GARCH models. The weekly forecasted variance for DAILY-GARCH is obtained by summing up the daily forecasted variance of a 5-day week. As for WEEKLY-GARCH, the weekly variance is obtained from the residual of each Friday of a week in both sub-periods analyzed. Before the application of the GARCH model, the existence of the ARCH (autoregressive conditional heteroskedasticity) effect must be ascertained. Ljung-Box *Q*-statistics Test (LBQ Test) is administered (see Table 2 earlier), and the *p*-values of *Q*-statistics up to a high order of twelve lags are significant at 1% for all fund indices in both sub-periods, implying the existence of autocorrelation, thus rejecting the null hypothesis of data randomness. The significant *p*-values from the ARCH LM (Lagrange-multiplier) Test signify existence of ARCH effect, hence application of the GARCH model is appropriate.

3.2.3. Weekly Realized Variance Autoregressive (RVar-AR) model

The realized variance autoregressive model is specified as:

$$\mathrm{RVar}_t = \omega_0 + \sum_{i=1}^{q} \alpha_i \mathrm{RVar}_{t-i} \quad (5)$$

where q is the lag and RVar_t is weekly realized variance regressed on lagged RVar_t. Realized Variance (RVar) is constructed from the sum of the daily squared residual of a 5-day week (Mon to Friday) in both sub-periods analyzed. The model estimation is simulated with various numbers of lags with final lag order determined based on the significance of parameters estimated, Log-Likelihood, AIC (Akaike-Information Criterion), and SIC (Schwarz Information Criterion) value obtained from conditional least squared regression.

3.2.4. Weekly Smooth Transition Exponential Smoothing (STES)

Two models, DAILY-STES and WEEKLY-STES are generated based on the following standard STES method specification:

$$\hat{\sigma}_t^2 = \alpha_{t-1}\varepsilon_{t-1}^2 + (1-\alpha_{t-1})\hat{\sigma}_{t-1}^2 \quad (6)$$

where "t" subscript denotes week t, ε_t^2 is residual squared, $\alpha_{t-1} = \dfrac{1}{1+exp\left(\beta + \gamma V_{t-1}\right)}$ is the "adaptive or smooth transition" parameter in the form of a logistic function with a value $0 < \alpha_{t-1} < 1$ based on type of user-specified "transition variable" V_{t-1} employed. The conditional variance is a function of calibration of the adaptive smoothing parameter α_{t-1} that depends on the choice of the transition variable V_{t-1} and the optimization (using solver) of parameters β and γ (coefficient of transition variable concerned). Summation of a 5-day week daily residuals generates weekly forecasted variance for DAILY-STES, following Taylor (2004b). Meanwhile, WEEKLY-STES, weekly variance is obtained from the weekly Friday residuals in both sub-periods analyzed. Both the DAILY-STES and WEEKLY-STES are estimated using five different types of transition variables namely Squared Error (SE), Error (E), Absolute Error (AE), Error, and Absolute Error (E & AE), and Error and Squared Error (E & SE). This produces a total of 10 different STES methods. STES parameters are optimized by minimizing the sum of squared in-sample prediction errors (differences between the actual volatility σ_{Vi} proxied by either weekly squared residual or weekly realized variance and forecasted variance $\hat{\sigma}_i$) written as min $\sum_i \left(\sigma_{Vi} - \hat{\sigma}_i\right)^2$.

3.3. Post Sample Forecasting Evaluation Criteria

Approximately a 70:30 ratio is apportioned between number of weekly observations for both in-sample and post-sample of both sub-periods analysed. The sub-period with financial crisis runs from Jan 3rd, 2005 to Dec 30th, 2011, giving a total of 365 weekly returns, where 260 and 105 weekly returns are used for in-sample estimation and post-sample forecast performance evaluation, respectively. While the sub-period without financial crisis runs from Jan 2nd, 2012, to Dec 31st, 2019), giving a total of 417 weekly returns, of which 291 and 126 are reserved for in-sample estimation and post-sample forecast performance evaluation, respectively.

Weekly forecasting errors of all models and methods are obtained by taking the difference between the proxy for actual volatility (weekly residual squared or weekly realized variance) and weekly forecasted variance. The weekly absolute forecasting errors of each model and method are evaluated using two loss functions, MAE (mean absolute error) and RMSE (root mean square error). While RMSE is often a preferred evaluation criterion by virtue of its quadratic loss function (Brooks, 1998), it tends to produce biased inferences in presence of outliers (Franses & Ghijsels, 1999). Hence, a commonly adopted alternative evaluation criterion, MAE, is included alongside RMSE. Smaller MAE and RMSE values signify a better model. Model Confidence Set (MCS) procedure is applied to validate the robustness of empirical results that determine the set of best forecasting models (Hansen et al., 2011).

4. Results and Discussion

The parameters estimation results of all 21 models are not shown here as the key focus of this study is on post-sample volatility forecasting performance. The full post-sample volatility performance of the respective model and method of each fund index evaluated under MAE and RMSE criteria is summarized by the Mean Theil-U ranking of all 21 models shown in Table 3. A lower value Mean Theil-U implies a better post-sample forecasting performance of the model concerned.

4.1. Post Sample Forecasting Performance With Squared Residual (RSQ) as Proxy for Actual Volatility

Under MAE evaluation criteria with RSQ as a proxy for actual volatility, RVar-MIDAS (Step) emerged the best model in 4 out of 7 fund indices (sub-period without crisis), while RVar-MIDAS (Beta) ranked second with 3 out of 7 fund indices (sub-period with crisis). However, under RMSE criteria, RVar-MIDAS (Beta) emerged top in 4 out of 7 fund indices (sub-period without crisis), followed by RVar-MIDAS (U). All four RVar-MIDAS models secured top 4 rankings, while the RSQ-MIDAS model secured 5th to 8th ranking (see Table 3) consistently under both MAE and RMSE loss criteria. This means all 8 MIDAS models secured the top eight rankings out of 21 models examined.

The supremacy of post-sample results of MIDAS models over the GARCH is consistent with Alper et al. (2012). Meanwhile, under both MAE and RMSE criteria, the DAILYGARCH outperformed the WEEKLY-GARCH is consistent with findings of Taylor (2004b) while DAILY-STES outperformed the WEEKLY-STES under both MAE and RMSE criteria as daily residuals of a 5-day week contain more information about volatility compared to weekly residual. However, the RVar-AR, WEEKLY-GARCH, and WEEKLY-STES are among the poorer performers, with WEEKLY-GARCH being the worst in both MAE and RMSE criteria.

4.2. Post Sample Forecasting Performance with Realized Variance (RVar) as Proxy For Actual Volatility

The post-sample results with Realized Variance (RVar) as a proxy for actual volatility closely resemble the results of Squared Residual as a proxy. For both MAE and RMSE criteria, RVar-MIDAS models emerged as the best models by clinching the top four ranking across all seven fund indices under sub-periods without crisis and 6 out of 7 fund indices in sub-period with the financial crisis. Interestingly, under both MAE and RMSE criteria, the five DAILY-STES methods with different transition variables took the 5th to 9th ranking in sub-period with crisis, just behind the top four ranked RVar-MIDAS models. This is attributed to its resilience to outliers which exist particularly during a volatile period. Meanwhile, the four RSQ-MIDAS models took the 5th to 9th ranking under both MAE and RMSE criteria in the sub-period without crisis.

Similarly, the DAILY-GARCH outperformed WEEKLY-GARCH models which is consistent with findings of Taylor (2004b) while the DAILY-STES likewise outperformed the WEEKLY-STES methods. This implies that the incorporation of the daily residual of a 5-day week (which contains more information about volatility) into a DAILY-GARCH and DAILY-STES to forecast weekly volatility help to improve the forecasting ability of both models. WEEKLY-GARCH is the worst performing model evaluated under both MAE and RMSE criteria. Contrary to the findings of Taylor (2004), the performance of the RVar-AR model is not impressive and is even worse off than the DAILY-STES methods under both MAE and RMSE evaluation criteria. WEEKLY-STES is the worst performing model under both loss criteria.

4.3. Discussion

The Mean Theil-U ranking in Table 3 clearly indicates all four RVar-MIDAS models secured the top four rankings where RVar-MIDAS (with end-restricted Beta weighting function) emerged as the best post-sample volatility forecasting model, particularly during the sub-period with the financial crisis, beating all four RSQ-MIDAS models. In addition, the four RVar-MIDAS models even outperformed the five DAILY-STES methods of different transition variables, known for their resilience to outliers (Taylor, 2004a), particularly under volatile periods. While both the RVar-MIDAS models and the DAILY-STES methods are better performers during volatile periods than the RSQ-MIDAS models, the overall supremacy of all eight MIDAS Regression models in post-sample volatility forecasting concurred with the findings of both Alper et al. (2012) and Körs and Karan (2021).

The superb results are strongly attributed to the salient feature of the MIDAS Regression model combined with Realized Variance measure employed in both model estimation and forecast error evaluation. The parsimonious parameterization process of MIDAS Regression (RVar-MIDAS particularly) where the polynomial weighting function allows information contained in higher frequency daily squared residuals to be incorporated directly (via regression) into lower frequency weekly realized variance obtained from summation of five daily squared residuals in a five-day week horizon, adopting the approach applied by Taylor (2004b).

Table 3: Summary of Mean Theil-U ranking Across Models all 21 Models

Model	Sub-period	Squared Residual as Actual Volatility		Realized Variance as Actual Volatility	
		MAE	RMSE	MAE	RMSE
RSQ-MIDAS (Beta)	With crisis	13	12	17	20
	Without crisis	7	6	7	6
RSQ-MIDAS (U)	With crisis	14	13	18	21
	Without crisis	8	8	8	8
RSQ-MIDAS (Almon)	With crisis	15	8	16	17
	Without crisis	6	7	6	7
RSQ-MIDAS (Step)	With crisis	19	19	19	16
	Without crisis	5	5	5	5
RVar-MIDAS (Beta)	With crisis	2	1	1	1
	Without crisis	2	1	3	3
RVar-MIDAS (U)	With crisis	3	2	3	2
	Without crisis	3	2	2	2
RVar-MIDAS (Almon)	With crisis	4	3	2	3
	Without crisis	4	3	1	1
RVar-MIDAS (Step)	With crisis	1	4	4	4
	Without crisis	1	4	4	4
RVar_AR	With crisis	21	15	21	14
	Without crisis	15	15	15	15
DAILYGARCH (1, 1)	With crisis	12	9	10	9
	Without crisis	10	9	9	9
WEEKLYGARCH (1, 1)	With crisis	20	21	20	19
	Without crisis	21	21	21	21
DAILY STES-SE	With crisis	7	6	7	6
	Without crisis	12	12	12	12
DAILY STES-E	With crisis	8	5	8	7
	Without crisis	14	14	14	14
DAILY STES-AbsE	With crisis	6	7	5	5
	Without crisis	11	11	11	11
DAILY STES-E + AbsE	With crisis	5	11	6	8
	Without crisis	9	10	10	10
DAILY STES-E + SE	With crisis	9	10	9	10
	Without crisis	13	13	13	13
WEEKLY STES-SE	With crisis	11	17	11	11
	Without crisis	19	16	17	17
WEEKLY STES-E	With crisis	17	18	15	15
	Without crisis	18	19	19	19

Table 3: (Continued)

Model	Sub-period	Squared Residual as Actual Volatility		Realized Variance as Actual Volatility	
		MAE	RMSE	MAE	RMSE
WEEKLY STES-AbsE	With crisis	10	20	12	18
	Without crisis	20	20	20	20
WEEKLY STES-E + AbsE	With crisis	16	16	13	12
	Without crisis	16	17	16	16
WEEKLY STES-E + SE	With crisis	18	14	14	13
	Without crisis	17	18	18	18

Note: Figures shown are Mean Theil-U rank. A smaller value implies the model is superior.

The robustness of the RVar-MIDAS model's post-sample forecasting capability is further validated by the Model Confidence Set (MCS) Procedures using both Squared Forecast Error (SE) and Absolute Forecast Error (AE) criteria shown in Table 4. Regardless of using Squared Forecast Error (SE) criteria or Absolute Forecast Error (AE) in the MCS Test procedures, the weekly RVar-MIDAS models under both squared residual and realized variance as a proxy for actual volatility in both sub-periods emerged as the least eliminated models across all seven fund indices as indicated by the highest count of remaining models of equal predictive ability in the Superior Set Models (SSM). Therefore, the alternative hypothesis H1 stating MIDAS Regression with Realized Variance measures outperformed both GARCH (1, 1) models and STES methods is supported.

Although the STES method has been empirically proven for its one-day ahead forecasting ability due to its unique adaptive smoothing parameter which allows the faster reaction to outliers of higher magnitude in reverting to its previous volatility level compared to GARCH (Liu et al., 2020; Wan et al., 2021), STES may not be an appropriate model for a longer lead time of one-week ahead volatility forecasting as empirically proven by the unimpressive results of the DAILY-STES models compared to the RVar-MIDAS models. MIDAS models claim their superiority in the longer horizon (one week ahead) volatility forecasting. The DAILY-GARCH model performance is likewise relatively poor because the shocks exerting volatility tend to persist longer the higher the magnitude of shock. This impedes the capability of the GARCH model in volatility forecasting (Alper et al., 2012).

The extremely poor performance of the RVar-AR model is expected. Based on the Quadratic Variation Theory, realized volatility can be regarded as an unbiased and highly reliable estimator for the volatility of asset return (Barndorff-Nielsen & Shepard, 2002; Andersen et al., 2003). Although the realized variance enhances the forecasting ability of the MIDAS Regression framework as seen in the performance of the RVar-MIDAS models, it does not strengthen the capability of Realized Variance Autoregressive model (RVar-AR) model in post-sample volatility forecasting. The reason being the weekly realized variance data is constructed from only five daily squared residuals and the long memory AR model works more efficiently with longer time series (this study only has 365 weekly for sub-period with the financial crisis and 417 weekly data for sub-period without financial crisis) and higher frequency data like intraday data (Taylor, 2004b).

The DAILY-GARCH model, though it outperformed the WEEKLY-GARCH, the weekly variance constructed from the summation of five daily conditional variances of a five-day week horizon does not enable GARCH models to outperform the RVar-MIDAS regression models. Although the standard GARCH family model is known for its capability in shorter lead-time of one-day ahead forecasting as found in many past and even more recent studies (Nguyen & Nguyen, 2019; Golder et al., 2022), it fails to perform in longer lead time forecasting like one-week ahead (as in this study) or one-month ahead horizon. This implies that forecasting the performance of a model relies greatly on its specification besides the post-sample evaluation criteria. In this regard, Andersen et al. (2003) assert the following:

"It has become apparent that standard volatility models used for forecasting at a daily level cannot readily accommodate the information in intraday data, and models specified directly for the intraday data generally fail to capture the longer inter-daily volatility movements sufficiently well. As a result, standard practice is still to produce forecasts of daily volatility from daily return observations, even when higher frequency data are available (Andersen et al., 2003, p. 580)."

The MAE and RMSE values are observed to be relatively smaller across all seven fund indices when

Table 4: MCS Procedure Summarized Results

Models	Squared Error Criteria				Absolute Error Criteria			
	Squared Residual as a Volatility Proxy		Realized Variance as a Volatility Proxy		Squared Residual as a Volatility Proxy		Realized Variance as a Volatility Proxy	
	Crisis	Non-crisis	Crisis	Non-crisis	Crisis	Non-crisis	Crisis	Non-crisis
RSQMIDAS-Beta	3	5			4	2		
RSQMIDAS-U	3	3		1	4	1		
RSQMIDAS-APDL	2	5		1	4	1	1	
RSQMIDAS-Step	2	3			3	1		
RVarMIDAS-Beta	6	6	3	4	4	5	3	4
RVarMIDAS-U	5	6	1	3	4	3	2	3
RVarMIDAS-APDL	4	5	3	4	4	2	3	4
RVarMIDAS-Step	4	4	2	2	4	4	4	1
RVar-AR	2							
DAILYGARCH (1, 1)	4	2						
WEEKLYGARCH (1, 1)	1	0						
DAILYSTES-SE	4	1	1		2			
DAILYSTES-E	4	1	1		2			
DAILYSTES-AE	3	2	1		2		1	
DAILYSTES-E&AE	3	1			2			
DAILYSTES-E&SE	3	1						
WEEKLYSTES-SE	2				1			
WEEKLYSTES-E	2							
WEEKLYSTES-AE	2				3			
WEEKLYSTES-E&AE	2							
WEEKLYSTES-E&SE	2							

Note: Numbers denote the number of remaining models (based on *p*-values of Tmax statistics) in the Superior Set Models bootstrap elimination of models with equal predictive ability at a significance level of $\alpha = 0.75$.

forecast variance is evaluated using the realized variance as a proxy for actual volatility compared to the squared residual (values of MAE and RMSE of each fund index are not shown but available if need be). This is particularly observed in the case of RVar-MIDAS models with realized variance as a proxy to actual volatility where MAE and RMSE values, regardless of sub-periods, are smallest compared to DAILY-STES methods and RSQ-MIDAS models. The results empirically validated realized variance (RVar) measures as a better proxy for actual volatility compared to squared residual (RSQ) hence alternative hypothesis H2 stating realized variance measures outperformed squared residual measures as a proxy to actual volatility is supported.

5. Conclusion

This study seeks to answer two key objectives. First, to empirically verify the supremacy of the MIDAS Regression combined with realized variance measures in a one-week ahead volatility forecasting over the GARCH model, Smooth Transition Exponential Smoothing (STES) method with five different transition variables, and the Autoregressive model. Second, to verify if realized variance measures outperform residual squared measures as a proxy to actual volatility which is often unobservable and latent. The Weekly realized variance measure is obtained from the summation of daily squared residual for a 5-day week, while the weekly squared residual measure is obtained from weekly Friday residual.

While most past studies predominantly focus on applying MIDAS Regression to studies related to forecasting macroeconomic variables as well as stock volatility, to our best knowledge, none has applied MIDAS Regression to mutual funds. Daily return data of seven private equity mutual fund indices of different investment objectives (clustered as Growth, Growth & Income, Income, Balanced Growth, Balanced Growth & Income, Balanced Income, and Mixed Asset Growth Fund Index) were generated from 57 selected individual mutual funds in Malaysia. A total of 21 model specifications comprised Realized Variance MIDAS (RVar-MIDAS) and Squared Residual MIDAS (RSQ-MIDAS) with four different weighting schemes, respectively; DAILY-GARCH, WEEKLY-GARCH; DAILY-STES, and WEEKLY-STES with five different transition variables respectively, and a Realized Variance Autoregressive (RVar-AR) model were examined. The full analysis period is divided into two sub-periods with the financial crisis and without the financial crisis.

The empirical findings of this study revealed the RVar-MIDAS model as the best post-sample volatility forecasting model by securing the top four rankings (measured by Mean Theil-U), regardless of sub-periods, loss functions (MAE or RMSE) used for forecast evaluation, as well as two different choices of proxy for actual volatility (namely realized variance or squared residual) to obtain forecast error. The robust DAILY-STES is known for its resilience to outliers and only managed to secure between 5^{th} to 9^{th} ranking in the sub-period with the financial crisis, while RSQ-MIDAS took the 5^{th} to 8^{th} ranking on average during sub-period without a financial crisis, regardless of the choice of proxy for actual volatility.

The weekly RVar-AR model, WEEKLY-GARCH, and WEEKLY-STES are the poorer performers, with WEEKLY-GARCH being the worst performer. Thus, the post-sample volatility forecasting results support the supremacy of MIDAS Regression in longer lead time (one week ahead as in this study) volatility forecasting largely due to its parsimoniously parameterized polynomial weighting function allowing daily data to be regressed on weekly data directly. In addition, the results also show that both MAE and RMSE values are smaller when realized variance (RVar) is used as a proxy to actual volatility in obtaining forecast error compared to squared residual (RSQ) as a proxy, implying realized variance measure outperformed squared residual measure.

The present study can be extended into a multivariate analysis employing multivariate MIDAS and GARCH to explore volatility forecasting between mutual funds in comparison to other financial assets. Additionally, a larger database comprising more countries under developing and developed clusters will be an interesting comparative study. We leave this to future research.

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