Macroeconomic Fundamentals in Range-Based Volatility Models

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Abstract

The paper devises a mixed-frequency model for forecasting range-based volatility. The Parkinson range is decomposed into two components: long-run and short-run volatilities. The long-run component is described with a mixed data sampling [MiDaS] regression model and depends on low-frequency macroeconomic variables. The short-run volatility is modelled with a conditional heteroscedasticity structure. Forecast performance is assessed with the realized Parkinson range and is benchmarked and contrasted with a family of conditional heteroscedasticity models. The devised model opens a new perspective for modelling realized volatility in emerging financial markets where intra-daily data facilities are difficult to access.

I. Introduction

Uncertainty dominates financial markets as one cannot be 100% certain of the future direction of companies, governments, and individual participants in the market. Thus, the determination of uncertainty through measurement of volatility in these markets has been foundational in finance in terms of investment portfolio management, risk management, and asset pricing [6, 16, 20, 25]. To estimate volatility, a thorough understanding of statistical properties of financial time series, so-called stylized facts [20, 25] are required. These stylized facts are generally concerned with nonconstant variance in time and with nonnormality of stock return series.

As variance is nonconstant, volatility measurement should be conditional on existing information at current time that can explain or cause volatility. A family of models that target dynamic variation of returns are the family of conditional heteroscedasticity models [11, 7, 15].

In addition to the flourishing of volatility models, big financial databases have developed throughout the years, giving the ability to extract intra-daily prices of financial assets [13, 17] and to measure and model with realized volatility, which is volatility based on intra-daily observations of price movements [3, 21].

Even with the growth of modelling especially with realized volatility, two problems are found: 1) much of the growth in conditional heteroscedasticity models, specifically realized volatility models is based on non-structural approaches which does not account for possible exogenous contributors to volatility dynamics [24]; and 2) the hurdles, may it be in costs or in infrastructure, in acquiring intra-daily data for emerging markets such as the Philippines [19].

To resolve these problems, a possible framework can be constructed from the following: 1) Engle, et al. [12] introduced the GARCH-mixed frequency data sampling [GARCH-MiDaS] volatility model which combines the GARCH specification for short-run volatility while the long-run component has a MiDaS structure [14] which considers covariates collected at lower frequency than the financial time series; and 2) Mapa [19] introduced the GARCH-PARK-R model for forecasting daily volatility through the Parkinson range [22], a substitute for realized volatility but easily available from free databases.

In combining the two previous approaches, the GARCH-MIDAS-PARK-R model is devised, of which daily volatility with Parkinson range is modelled and GARCH-MIDAS methods are used to account for long-run and short-run volatility dynamics.

The flow of the paper is as follows. The first part introduces the general ideas and motivations of the paper. The background literature is expounded on the second part, which covers basic concepts in financial time series, volatility models, realized volatility, and GARCH-PARK-R [19] model. The proposed model, the GARCH-MiDaS-PARK-R, and its application in real world data is discussed in the third part, with the results discussed in the fourth. The paper concludes with its findings in the fifth part.

II. Background Literature

a. Basic Concepts in Financial Time Series

In the analysis of financial time series, a basic transformation of the price data P_t is initially done [25], which would be interpretable as the log-return:

$$r_t = [\log(P_t) - \log(P_{t-1})] \times 100\%$$

The transformation possesses nice properties of stabilizing the variance, additivity for generating cumulative log returns, directly related to the interest rate for continuous compounding accumulative models of investment, and its approximation of the percent-change return.

Even with transformed log returns, there are generally observed features, known as stylized facts, for financial return series, which are [20, 25]:

1) Nonnormality of financial returns, which may be include at least one of the two;
   i. thicker tails than the normal distribution, which means higher or positively infinite kurtosis; or
   ii. negative skewness or skewed in which tails are longer in the side of negative values, called leverage effects; and,

2) Volatility clustering, modeled by the autoregressive conditional heteroscedasticity (ARCH) specifications by Engle [11] and are extended by Bollerslev [7] through the generalized ARCH (GARCH) models.

Checking for nonnormalities may be quickly done with skewness and kurtosis measures and any normality test. In the next subsection, the development of volatility models to describe volatility clustering are discussed.

b. Volatility Models

In the family of conditional heteroscedasticity models, the ARCH model is described as follows [11]: Let r_t be the log-return of a financial asset at time t. $r_t \sim ARCH(p)$ if and only if:

$$r_t = \epsilon_t, \epsilon_t \sim (0, h_t)$$
$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2$$

In the specification above, errors should be serially uncorrelated with zero mean and variance equal to h_t. The types of distributions often used as error structure are the normal or the Student's t distribution [20, 25]. The second equation in the ARCH specification outlines the volatility dynamics characteristic of the ARCH process. The order p describes the number of past squared errors ϵ_t of which the conditional volatility h_t has dependence, of which each dependence is weighted by the parameters α_i. If large errors within the p immediate past periods are observed, this implies an increase in uncertainty reflected by the increase in variance at time t. By introducing nonconstant variation, thick tails can manifest on the return series to some limited extent by having a higher kurtosis than the normal distribution, even if the error in ARCH model is Gaussian. A typical problem with ARCH modelling is that it seems to require a large number of lags p. This was resolved with the generalized ARCH (GARCH) model [7].

For the return series r_t being a GARCH process with orders p and q, denoted as $r_t \sim GARCH(p,q)$, the variance equation h_t from the previous ARCH is replaced with [7]:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}$$

The new β_j parameters account for persistence of high volatility whilst the α_i parameters carried over from the ARCH process account for immediate response of volatility to large errors. When q = 0, the model specializes back to the ARCH specification. By this modification, low p and q are often required in financial time series modeling. A common specification would be the GARCH(1,1) model. It also leads to larger kurtosis whether one uses the Gaussian or the Student's t distribution. A shortcoming of the GARCH(1,1) is the lack of accounting for negative skewness or leverage effects, which is typically described under the GJRGARCH model [15].

A return series is described by the GJRGARCH process, denoted as $r_t \sim GJRGARCH(p,q)$, if and only if the variance equation is specified as:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \left[\alpha_i + \gamma_i I_{\{\epsilon_{t-i}<0\}}\right] \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}$$

The additional parameter in this model is the γ_i which adds more variance when the return has a negative value, reflecting more uncertainty in the direction of returns which is called the leverage effect.

In the earlier-discussed volatility models, the only inputs were the return distribution of the financial asset. There are existing methodologies that make it possible to integrate exogenous variables in the variance equation of the GARCH models if they share the same data frequency of the return series. However, macroeconomic variables rarely are collected in high frequency as financial asset prices, thus including macroeconomic time series seem to be less influential with financial returns. A remedy for the method is the GARCH-MiDaS model [12] which integrates mixed data sampling (MiDaS) modelling [14] for time series with differing frequencies.

The specification of a GARCH-MiDaS model is as follows. Let $r_{l,t}$ be the return series with high-frequency time index l, e.g. the index for daily data, and the low-frequency time index t, e.g., index for monthly data. A sample specification with $r_{l,t} \sim GARCH-MiDaS(1,1)$ is:

$$r_{l,t} = \sqrt{\tau_t}\epsilon_{l,t},$$
$$\epsilon_{l,t} \sim (0, h_{l,t})$$
$$h_{l,t} = (1 - \alpha_1 - \beta_1) + \alpha_1 \frac{\epsilon_{l-1,t}^2}{\tau_t} + \beta_1 h_{l-1,t}$$
$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \phi_k(\omega_2) X_{t-k}$$

The conditional variance of the returns under the model is $\sigma_{l,t}^2 = \tau_t h_{l,t}$. The short-run volatility is described by the structure of $h_{l,t}$, which is an adjusted form of the GARCH(1,1) specification. The long-run volatility component τ_t is specified with a MiDaS regression structure [14] with an exogenous variable X_t. The parameter m is the intercept of the regression, whilst θ is the parameter that describes whether the regressor X_t is relevant in the modelling of the underlying long-run volatility.

The function $\phi_k(\omega_2)$ describe a distributed lag structure of weights which lays out how the lagged values of X_t contribute to the volatility dynamics. The weighting used by Amendola, et al. [2] for the GARCH-MiDaS specification is the following:

$$\text{Beta Function Weights: } \phi_k(\omega_2) = \frac{(1-k/K)^{\omega_2-1}}{\sum_{s=1}^{K}(1-s/K)^{\omega_2-1}}$$

The weights sum up to 1 and are monotone decreasing with respect to k. With respect to the choice of lags K, it is often the seasonal frequency of the regressor variable, K=4 for quarterly regressors, or K=12 for monthly regressors. The model can also be expanded into the GJRGARCH-MiDaS [10] by adjusting the short-term variance equation $h_{l,t}$ with an asymmetry term:

$$h_{l,t} = (1-\alpha_1-\gamma_1/2-\beta_1) + \left[\alpha_1 + \gamma_1 I_{\{\epsilon_{l-i,t}\}}\right]\frac{\epsilon_{l-1,t}^2}{\tau_t} + \beta_1 h_{l-1,t}$$

To estimate these models, the quasi-maximum likelihood estimation (QMLE) algorithm [26,8] is utilized. For the GARCH-MiDaS and GJRGARCH-MiDaS, Conrad and Kleen [10] outlines the QMLE approach in more detail.

c. Realized Volatility

The concept of realized volatility was introduced by Andersen and Bollerslev [3] in response to critique of the forecasting capability of GARCH models.

To setup the definition of realized volatility, let $r_{n,t} = log(P_{n,t}) - log(P_{n-1,t}) \sim (0, \sigma_t^2)$ be the intra-daily return at time-point n within day t, with $P_{n,t}$ as the price of the financial asset, with $P_{0,t}$ as the opening price of the asset, $n = 1,2,\ldots,N$, where N is the number of the time points within the day t, $t = 1,2,\ldots,T$ where T is the number of days, and σ_t^2 is the population variance for day t.

In the question of estimating the unknown population variance σ_t^2, the unbiased and consistent estimator is given by [4]:

$$s_t^2 = \sum_{n=1}^{N} r_{n,t}^2$$

The quantity s_t^2 is called the realized variance at day t. This quantity is estimated when intra-daily data exists, which is typically available from databases with high subscription fees (e.g., Refinitiv®, formerly Thomson Reuters Tick History) and are never published in business broadsheets.

d. GARCH-PARK-R Model

Realized variances give insight the daily variability of stock returns, but the manner of estimation is inaccessible to many researchers since they require subscription to financial databases. As a means to estimate realized variance with available free financial data easily accessible through broadsheets and free databases, Parkinson [22] defined the Parkinson range as:

$$R_{Park,t} = \frac{log\,(P_{H,t}) - log\,(P_{L,t})}{\sqrt{4 log(2)}} \times 100\%$$

The quantity $P_{H,t}$ is the high price at day t whilst $P_{L,t}$ is the low price, for $t = 1,2, \dots, T$. The square of the Parkinson range is an unbiased estimator of σ_t^2, i.e., $E(R_{Park,t}^2) = \sigma_t^2$.

With the usability of the Parkinson range, it becomes amenable for modelling volatility clustering, of which Mapa [19] devised the GARCH(p,q)-PARK-R model, a conditional heteroscedasticity that uses the Parkinson range:

$$\begin{aligned} R_{Park,t} &= \mu_t \epsilon_t, \\ \epsilon_t | I_{t-1} &\sim iid(1, \phi\ ) \\ \mu_t &= \omega + \sum_{j=1}^{p} \alpha_j R_{Park,t-j} + \sum_{j=1}^{q} \beta_j \mu_{t-j} \end{aligned}$$

The first equation above breaks down the Parkinson range into a stochastic component with mean 1 and variance ϕ and the conditional heteroscedasticity component in which the term $\mu_t = E(R_{Park,t}|I_{t-1})$ has a GARCH structure.

It is possible to design an approach to estimate the GARCH-PARK-R model, but a re-specification below for estimation to use the QMLE [26,8] can be done:

$$\begin{aligned} \sqrt{R_{Park,t}} &= \sqrt{\mu_t} \nu_t, \\ \nu_t | I_{t-1} &\sim iid(0, 1) \\ \mu_t &= \omega + \sum_{j=1}^{p} \alpha_j R_{Park,t-j} + \sum_{j=1}^{q} \beta_j \mu_{t-j} \end{aligned}$$

The alternative specification for the QMLE procedure works because:

1) $E[\sqrt{R_{Park,t}}|I_{t-1}] = 0$,
2) $Var[\sqrt{R_{Park,t}}|I_{t-1}] = \mu_t$, and
3) The QML estimators are asymptotically normal and consistent even if the density of ν_t is misspecified [5].

Thus, estimating the GARCH-PARK-R model is similar to estimating a GARCH model on the square-root of the Parkinson range with a fixed zero error mean.

With the background knowledge of GARCH-MiDaS modelling and the Parkinson range as measure for realized volatility, combining both methods create the GARCH-MiDaS-PARK-R model devised in this paper.

III. Methodology

a. GARCH-MiDaS-PARK-R Model

Following from the work of Mapa [19] and Engle, et al. [12], the GARCH-MiDaS-PARK-R model is:

$$
\begin{aligned}
R_{Park,l,t} &= \mu_{l,t}\epsilon_{l,t}, \\
\mu_{l,t} &= \tau_t, h_{l,t}, \\
\epsilon_{l,t}|I_{l-1,t} &\sim iid(1, \phi_{l,t}) \\
\log(\tau_t) &= m + \theta \sum_{k=1}^{K} \phi_k(\omega_2) X_{t-k} \\
h_{l,t} &= (1 - \alpha_1 - \beta_1) + \alpha_1 \frac{R_{Park,l-1,t}}{\tau_t} + \beta_1 \frac{\mu_{l-1,t}}{\tau_t}
\end{aligned}
$$

In the system of equations above, $l = 1,2,\dots,L_t$, where L_t is the number of trading days in the low-frequency period t, and $t = 1,2,\dots,T$, where T is the number of low-frequency periods, e.g., weeks, months, quarters, years.

In the same manner, to simplify the estimation procedure, the re-specification of the model for the QMLE approach is also done:

$$
\begin{aligned}
\sqrt{R_{Park,l,t}} &= \sqrt{\mu_{l,t}}\nu_{l,t}, \\
\mu_{l,t} &= \tau_t, h_{l,t}, \\
\nu_{l,t}|I_{l-1,t} &\sim iid(0, 1) \\
\log(\tau_t) &= m + \theta \sum_{k=1}^{K} \phi_k(\omega_2) X_{t-k} \\
h_{l,t} &= \omega + \sum_{j=1}^{p} \alpha_j \frac{R_{Park,l-j,t}}{\tau_t} + \sum_{j=1}^{q} \beta_j \frac{\mu_{l-1,t}}{\tau_t}
\end{aligned}
$$

By having the specification above in which the square-root of the Parkinson range is used as the data for estimation with regressor X_t, any software that can do GARCH-MiDaS estimation with QMLE can estimate the model above. The program used for the paper was designed by Candila [9].

The proposed method is benchmarked with other time series models used to estimate daily volatility, namely GARCH, GJRGARCH, GARCH-MiDaS, GJRGARCH-MiDaS, and GARCH-PARK-R with real data.

b. Application to Real Data

The GARCH-MiDaS-PARK-R model is applied with real data and benchmarked with existing conditional heteroscedasticity models. The Philippine stock exchange index (PSEI) adjusted closing, high, and low prices, from January 2008 to December 2019 were used as data.

As MiDaS regressors, the following monthly variables are used: 1) the year-on-year percentage change of the volume of production index (VoPI), and 2) the monthly realized volatility [RV] of the log returns, defined as $RV_t = \frac{1}{L_t}\sum_{i=1}^{L_t}\left(r_{i,t} - \overline{r_t}\right)^2$. Current MiDaS approaches will only use 1 regressor at a time as current software can accommodate. K=12 will be the specification for the MiDaS lag structure as the regressors are monthly data.

the last 250 observations will be the designated test data set for out-of-sample evaluation while the rest will be used for model estimation.

The devised GARCH-PARK-R model is benchmarked with other models. The table below shows the list of 15 models in this paper. The last three models in the table used the

Parkinson range, with the PGAR being the original Mapa [19] model and PGMR and PGMV based on the devised methodology.

Name	GJR Term	MiDaS term	Distribution	Parkinson Range
GARN	No	No	Normal	No
GART	No	No	Student's t	No
GJRN	Yes	No	Normal	No
GJRT	Yes	No	Student's t	No
GMNV	No	VoPI	Normal	No
GMNR	No	RV	Normal	No
GMTV	No	VoPI	Student's t	No
GMTR	No	RV	Student's t	No
JMNV	Yes	VoPI	Normal	No
JMNR	Yes	RV	Normal	No
JMTV	Yes	VoPI	Student's t	No
JMTR	Yes	RV	Student's t	No
PGAR	No	No	Normal (QMLE)	Yes
PGMV	No	VoPI	Normal (QMLE)	Yes
PGMR	No	RV	Normal (QMLE)	Yes

Table 1: Conditional Heteroscedasticity Models under Consideration

For in-sample goodness-of-fit, the Akaike information criterion [1] is used, while for in-sample and out-of-sample performance, the mean-square error (MSE) based on the squared return, Parkinson range, and squared Parkinson range are used:

$$MSE\left(\hat{\underline{\sigma}}^2; r_{l,t}^2\right) = \frac{1}{\#obs}\sum_{l,t}\left(r_{l,t}^2 - \hat{\sigma}_{l,t}^2\right)^2$$

$$MSE\left(\hat{\underline{\sigma}}; R_{Park,l,t}\right) = \frac{1}{\#obs}\sum_{l,t}\left(R_{Park,l,t} - \hat{\sigma}_{l,t}\right)^2$$

$$MSE\left(\hat{\underline{\sigma}}^2; R_{Park,l,t}^2\right) = \frac{1}{\#obs}\sum_{l,t}\left(R_{Park,l,t}^2 - \hat{\sigma}_{l,t}^2\right)^2$$

IV. Results and Discussion

a. Descriptive Analysis

Some initial historical plots and summary statistics about the time series data are shown below.

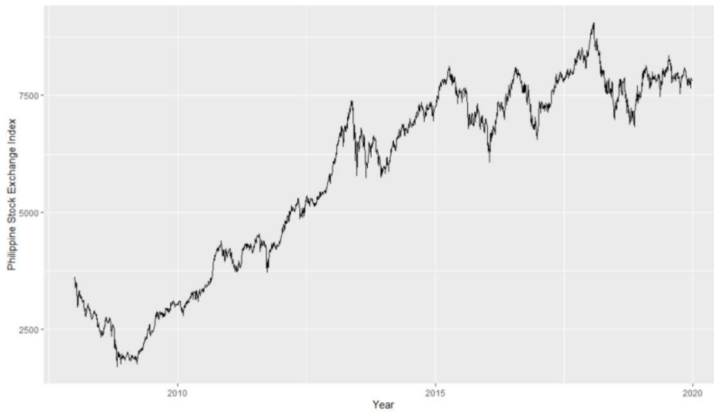

Figure 1: Historical Plot of the Philippine Stock Exchange Index, 2008-2019

Generally, the Philippine stock exchange rate has had a positive trend from 2008 to 2019. Thought starting in 2015, it has stayed stagnant with large fluctuations up to 2019.

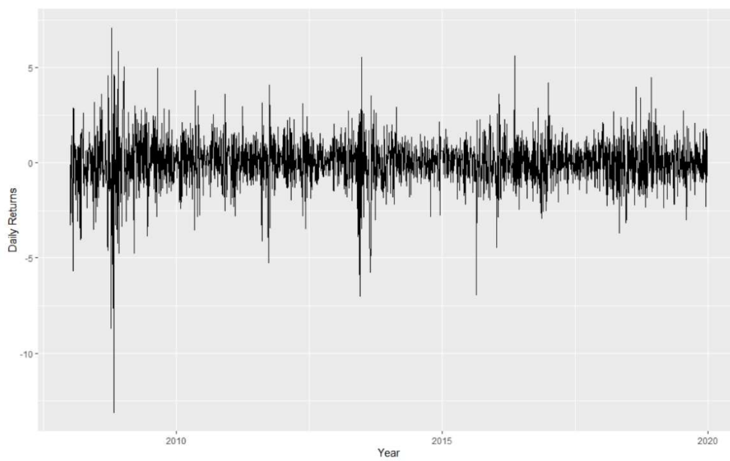

Figure 2: Daily Returns of the Philippine Stock Exchange Index, 2008-2019

For the daily returns, some volatility clusters may be noted in the early parts of the plots related to the Global Financial Crisis of 2008-2010. Some sharp negative spikes were observed in 2013-2014 and in mid-2015.

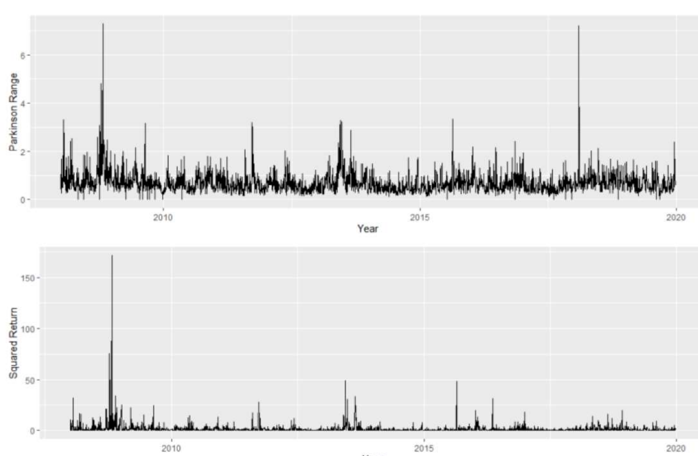

Figure 3: Parkinson Range and Squared Return of the Philippine Stock Exchange Index, 2008-2019

In observing the Parkinson range and the squared return of the PSEI, they generally have similar spikes except for the start of 2018, where a spike in the Parkinson range may be seen but not in the squared return.

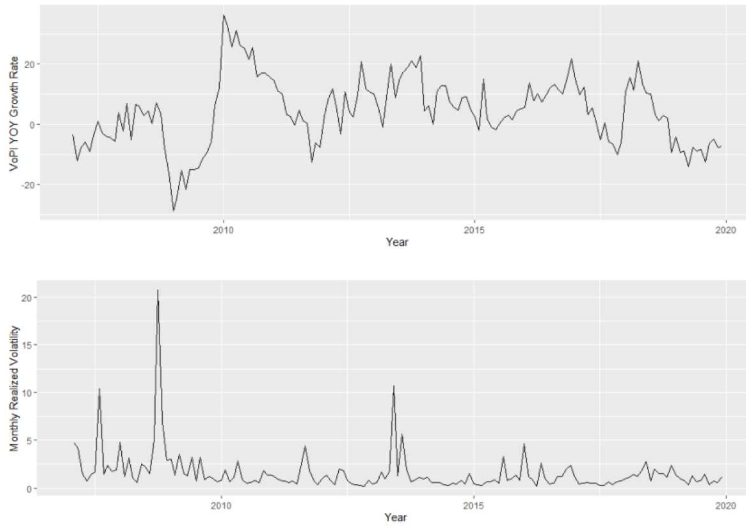

Figure 4: Monthly Regressors; VoPI Growth Rate and Monthly Realized Volatility

With the VoPI and monthly volatility regressors, some minor correspondence between the fluctuations may be linked except for the period in 2010 where large growth in production volumes were observed as reflected in the VoPI.

Summary Statistics	PSEI Returns	VoPI Growth Rate
Minimum	-13.089	-28.700
First Quartile	-0.582	-4.290
Median	0.049	4.400
Mean	0.027	4.075
Third Quartile	0.680	11.107
Maximum	7.056	36.200
Variance	1.489	128.031
Skewness	-0.770	0.039
Kurtosis (=3 means Normal)	11.536	3.145
KPSS [18] test stat (Ho: Stationary)	0.151	0.235
KPSS 10% Critical Value	0.347	0.347
KPSS 5% Critical Value	0.463	0.463

Table 2: Summary Statistics Between PSEI and VoPI Growth Rate

With the summary statistics above, PSEI returns are sufficiently stationary with the KPSS test [18]. It is best practice to have regressors to be also stationary, which is fulfilled by the VoPI growth rate. The PSEI returns are skewed to the left and heavy tailed, as indicated by the negative skewness and high kurtosis, respectively. The VoPI may be practically be normally distributed with very small skewness close to zero and kurtosis close to 3.

b. Forecasting Performance

The table below shows AIC and the MSE for squared returns, Parkinson range, and squared Parkinson range.

Model	AIC	MSE (Sq Ret)	MSE (Park R)	MSE (Sq Park R)
GARN	2.921	7.590	0.333	2.546
GART	2.870	7.611	0.332	2.542
GJRN	2.895	7.484	0.341	2.873
GJRT	2.859	7.469	0.331	2.730
GMNV	6933.384	7.598	0.347	2.639
GMNR	6924.232	7.623	0.340	2.627
GMTV	4101.440	7.610	0.340	2.590
GMTR	4096.382	7.632	0.338	2.616
JMNV	6867.086	7.498	0.356	3.002
JMNR	6851.571	7.443	0.343	2.867
JMTV	4070.364	7.449	0.339	2.776
JMTR	4059.322	7.424	0.333	2.740
PGAR	2.412	8.358	0.139	1.777
PGMV	-533.959	9.597	0.361	2.188
PGMR	-528.670	9.598	0.361	2.188

Table 3: In-Sample Statistics for Volatility Modelling

With respect to in-sample AIC, among the GARCH models not using the Parkinson range, the first 4 models which do not use the MiDaS terms seem to fit best with low AIC value. Among the Parkinson range GARCH models, the GARCH-MiDaS-PARK-R models have lower AIC.

In the in-sample MSE statistics, the non-Parkinson range models fit well with the squared returns, with the lowest being with the JMTR models which uses a GJRGARCH-MiDaS model with t distribution and monthly realized volatility regressor. The Parkinson range models fit poorly with the squared return.

With the in-sample MSEs for the Parkinson ranges, the Mapa [19] model performs well for both squared and non-squared ranges, with the PGMV and PGMR models worse for crude Parkinson range but performs second best with squared ranges.

Model	MSE (Sq Ret)	Rank	MSE (Park R)	Rank	MSE (Sq Park R)	Rank
GARN	2.480	1	0.214	3	0.609	4
GART	2.568	2	0.211	2	0.600	3
GJRN	2.788	3	0.206	1	0.569	2
GJRT	3.300	6	0.237	7	0.679	9
GMNV	3.376	12	0.281	13	0.853	15
GMNR	3.322	9	0.244	9	0.741	11
GMTV	3.340	11	0.267	10	0.799	13
GMTR	3.309	7	0.238	8	0.716	10
JMNV	3.328	10	0.275	12	0.802	14
JMNR	3.261	5	0.226	6	0.650	8
JMTV	3.310	8	0.270	11	0.771	12
JMTR	3.251	4	0.221	4	0.628	7
PGAR	3.477	13	0.221	4	0.348	1
PGMV	3.974	14	0.288	14	0.612	5
PGMR	3.980	15	0.295	15	0.615	6

Table 4: Out-of-Sample Forecasting Performance of Volatility Models

In out-of-sample forecast measures, ranks are also shown with the lowest MSE values ranked first. Similar observations from in-sample statistics wer seen as well. Generally, Parkinson-based models performed poorly with squared returns MSE, while Parkinson-based models performed well in squared Parkinson range MSEs. The GARN, GART, and GJRN models performed well in Parkinson range MSE, to be followed by PGAR by Mapa [19].

Overall, the proposed GARCH-PARK-R with VoPI and monthly volatility regressors seems to fit well with low AICs for Parkinson range. The devised model performs poorly with the squared returns MSE but has some potential with MSEs based on squared Parkinson range, which are known to be unbiased for realized variance.

V. Conclusion

The GARCH-MiDaS-PARK-R model seeks to address the scenario of forecasting volatility with a reliable proxy and when strong evidence of dependence of volatility to macroeconomic low frequency data is present. This research was devised to assess the performance of the GARCH-MiDaS-PARK-R approach when face with problems in real application and in competition with other models.

From the application of the model to the PSEI data with VoPI and RV as potential regressors for GARCH-MiDaS fitting and benchmarking with various heteroscedasticity models, the results have showed that in-sample fit has been promising and much room for improvement and steps forward for out-of-sample forecasting.

The work sets forth an idea for more creative volatility model design and contributes to the idea of expanding the potential sources of dependence of volatility to other macroeconomic or low-frequency time series data.

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References

[1] Akaike, H, A new look at the statistical model identification, IEEE Transactions on Automatic Control, vol. 19, issue 6, pp. 716-723, 1974.

[2] Amendola, A; Candila, V; and Gallo. GM, Choosing the frequency of volatility components within the Double Asymmetric GARCH–MIDAS–X model, Econometrics and Statistics, 2021.

[3] Andersen, TG; and Bollerslev, T, Answering the Skeptics: Yes, Standard Volatility Models do Provide Accurate Forecasts, International Economic Review, vol. 39, pp. 885-905, 1998.

[4] Barndorff-Nielsen, OE, and Shephard, N, Estimating Quadratic Variation Using Realized Variance, Journal of Applied Econometrics, vol. 17, no. 5, Special Issue: Modelling and Forecasting Financial Volatility, pp. 457-477, 2002.

[5] Berkes, I; Horvath, L; and Kokoszka, P, GARCH processes: structure and estimation, Bernoulli, vol. 9, no. 2, pp. 201-227, 2003.

[6] Bodie, Z; Kane, A; and Marcus, AJ, Investments,11th ed., New York, NY: McGraw-Hill Education, 2018.

[7] Bollerslev, T, Generalized Autregressive Conditional Heteroscedasticity, Journal of Econometrics, vol. 31, pp. 307-327, 1986.

[8] Bollerslev, T, and Wooldridge, JM, Quasi Maximum Likelihood Estimation and Inference in Dynamic Models with Time Varying Covariances, Economic Reviews, vol. 11, pp. 143-172, 1986.

[9] Candila, V, rumidas: Univariate GARCH-MIDAS, Double-Asymmetric GARCH-MIDAS and MEM-MIDAS models, R package version 0.1.1, 2021.

[10] Conrad, C; and Kleen, O, Two are better than one: volatility forecasting using multiplicative component GARCH-MIDAS models, Working paper, Heidelberg University.

[11] Engle, RF, Autoregressive Conditional Heteroscedastciity with Estimates of the Variance of United Kingdom Inflation, Econometrica, vol. 50, pp. 987-1008, 1982.

[12] Engle, RF, Ghysels, E; and Sohn, B, Stock market volatility and macroeconomic fundamentals, The Review of Economics and Statistics, vol. 95, no. 3, pp. 776–797, 2013.

[13] Foran, J; Hutchinson, MC; and O'Sullivan, N, The asset pricing effects of UK market liquidity shocks: Evidence from tick data, International Review of Financial Analysis, vol. 32, pp. 85-94, 2014.

[14] Ghysels, E; Santa-Clara, P; and Valkanov R, The MIDAS Touch: Mixed Data Sampling Regression Models, Working paper, UNC and UCLA.

[15] Glosten, LR; Jagannathan, R; and Runkle, DE, On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, The Journal of Finance, vol. 48, no. 5, pp. 1779-1801, 1993.

[16] Gonzalez-Rivera, G; Lee, TH; and Mishra, S, Forecasting volatility: A reality check based on option pricing, utility function, value-at-risk, and predictive likelihood International Journal of Forecasting, vol. 20, pp. 629-645, 2004.

[17] Korajczyk, RA, and Sadka, R, Pricing the commonality across alternative measures of liquidity, Journal of Financial Economics, vol. 87, issue 1, pp. 45-72, 2008.

[18] Kwiatkowski, D; Phillips, PC; Schmidt, P; and Shin, Y, Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root, Journal of Econometrics, vol. 54, pp. 159-178, 1992.

[19] Mapa, DS, A range-based GARCH model for forecasting financial volatility, Philippine Review of Economics, vol. 40, no. 2, pp. 73-90, 2003.

[20] McNeil, AJ; Frey, R and Embrechts P, Quantitative Risk Management: Concepts, Techniques, Tools, New Jersey: Princeton University Press, 2005.

[21] Ng, SL; Chin, WC; and Chong, LL, Realized volatility transmission within Islamic stock markets: A multivariate HAR-GARCH-type with nearest neighbor truncation estimator, Borsa Istanbul Review, vol. 20, supplement 1, pp. S26-S39, 2020.

[22] Parkinson, M, The Extreme Value Method for Estimating the Variance of the Rate of Return, The Journal of Business, vol. 53, no. 1, pp. 61-65, 1980.

[23] Patton, AJ, Volatility forecast comparison using imperfect volatility proxies, Journal of Econometrics, vol. 160, pp. 246–256, 2011.

[24] Schwert, GW Why Does Stock Market Volatility Change over Time?, Journal of Finance, vol. 44, pp. 1207-1239, 1989.

[25] Tsay, RS, Analysis of Financial Time Series, New York, NY: John Wiley and Sons, Inc., 2002.

[26] White, H, Maximum likelihood estimation of misspecified models, Econometrica, vol. 50, pp. 1-25, 1982.