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Modified Hinich and Brooks Window Tests in Exchange Rate Forecasting

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ABSTRACT
The study integrates Hinich's and Brooks' tests for forecasting exchange rates. These two researchers conducted these tests individually; the Hinich test (H-test) interacts with the non-linear components of the series, while the Brooks test (C-test) handles the linear components. The study's unique feature is that these two models were integrated to create a new model termed "modified Hinich and Brooks window tests" (modified H and C tests). The developed model was applied to the monthly currencies of a few selected countries vis-a-vis the Japanese Yen, British Pound, Nigerian Naira, and Botswana Pula from January 1982 to December 2019. The developed and developing economies were represented by these currencies. The analysis was carried out using the Statistical Package for Social Sciences, Melvin J. Hinich's T23 programs, and a set of programs built by the author. Unlike Hinich and Brooks' individual method, the newly constructed models succeeded in capturing both qualities (linear and non-linear properties) concurrently. The newly formed model (modified H and C tests) excelled in the Hinich (H) and Brooks (C) tests, indicating that the newly formed model has the advantage of taking less time and producing more accurate forecasting results.

Key words: Exchange rate, Forecasting, window test, H and C tests, Currency, developed and developing economies.

I. INTRODUCTION

Engle developed the ARCH model in 1982, and Bollerslev improved on it in 1986, culminating in the GARCH model. The GARCH model is an incredibly valuable tool for modeling and forecasting non-linear time series. According to Hall et al. (1989), these models have proven quite useful in terms of revealing the homoscedastic structure of particular series. The challenge of the appropriateness (or otherwise) of these models in forecasting financial series has been addressed seriously by statisticians, time series analysts, and econometricians (ARCH/GARCH). The reality remains that until the appropriateness or inadequacy of these models is addressed, academics, policymakers, and other potential users of the model risk incorrect formulation, which could lead to model misspecification and poor policy outcomes. If the processes for analyzing financial and economic data that are commonly employed are inadequate, forecasts based on them will almost certainly be erroneous and ineffective. Several contemporary literatures that used nonlinearity tests established in the last four or five decades or so strongly demonstrated evidence of nonlinearities in financial and economic data. The shortcomings of the ARCH and GARCH formulations in financial and economic data have been well documented.Two components of the GARCH model are being examined: the assumption of rigorous stationarity and the existence of conditional heteroscedasticity of series over a long time. The Hinich third-order portmanteau test can be used to examine the former, whereas Engle's LM (Lagrange Multiplier) test can be used to investigate the latter. A report on the GARCH model's appropriateness for modeling financial and economic data has been published as a result of several studies. Akintunde et al. (2013) confirmed the inadequacy of the GARCH model by using exchange rate data from the developed economies of the United Kingdom (pound) and Japan (yen) on the one hand, and the developing economies of Nigeria (naira) and Botswana (pula) on the other, in relation to the United States dollar. The findings demonstrate that the Garch model was grossly inadequate. Claudio A. B. and Jean S. (2011) investigated the suitability of using GARCH type expressions for modeling stock market indices in 13 emerging economies: seven from Latin America, three from Eastern Europe, and three from Asia. The findings revealed that the GARCH expression could not reveal the statistical architecture of the stock market return series for all of the countries studied. Anson Wong, Loganathan, et al. (2010) used the GARCH model to evaluate and conceptualize asymmetries in stock market volatility, using Hong Kong as a case study, noting that the approach was inadequate. Wong, J., and Fung, L. (2002) investigated how stock returns and volatility fluctuations are related to the degree of financial leverage in a company's capital structure, which is evidence of volatility regime alterations. They also discovered that the Hong Kong stock market has an unbalanced influence. The results of an asymmetric effect on the Hang Seng's daily return are clearly solved by the news impact curve. In a study of ten daily Sterling exchange rates, Kong Brooks and Hinich (1998) revealed that GARCH type models are unable to reveal the statistical architecture contained in the data. After analyzing different exchange rates for Asian economies, Lee, J., and Kang, S. (2008) and Lim et al. (2004) found that the GARCH model is insufficient in representing the behavior of exchange in those nations.After studying the key Latin American exchange rate returns series, Bonilla et al. (2006) discovered that the GARCH model was insufficient. Starica (2004) found insufficient the hypothesis that a GARCH (1,1) process is the genuine data-generating process of the S&P 500 stock market index returns between 1957 and 2003.Brooks and Hinich (1998) determined that the GARCH model is not a good fit for a number of European stock indices. After studying Asian stock markets, Lim et al. (2005) concluded that GARCH could not be used sufficiently to characterize the underlying mechanism. According to Bonilla et al. (2005) and Romero-Meza et al. (2007), the GARCH model cannot be used to characterize emerging stock markets in Latin American countries, citing political and financial instability as the cause. Using the modified Hinich and Brooks model developed in this study, this study will check if the common failure of the GARCH formulation encountered in the American, European, and Asian stock markets will also be features of the present study, as well as whether the common failure of the GARCH formulation encountered in the more developed and stable economies is also a characteristic of the Nigerian and Botswana economies.

II. SPECIFICATION OF GARCH MODELS

Bollerslev (1986), represented the GARCH model as following:

Let $\{y(t)\}$ be the time series of an exchange rate return, then

$$y(t)=\sigma_t\varepsilon_t$$

$$\sigma_t^2=\alpha_0+\sum_{i=1}^{p}\alpha_i y_{t-1}^2+\sum_{j=1}^{q}\beta_j\sigma_{t-j}^2$$

The fact that volatility changes over time is captured by the GARCH model formulation. We established the GARCH model's non-suitability, which was evident in the literature, particularly for developed countries; however, the literature did not demonstrate the incorporation of windowed tests for linear and non-linear foreign exchange data in GARCH modeling. This method could help the GARCH model model foreign exchange in both rich and emerging economies.

III. DERIVATION OF GARCH MODEL WINDOW TEST

Many tests have been proposed over the years, including Brock (1996), Brooks and Hinich (2001), and Cagdas, H. A., et al. (2009) for the examination of serial dependence in both linear and non-linear series found in both economic and financial time series data. These tests were based on basic bicorrelation and cross bicorrelation functions. The portmanteau H-test (Hinich, 1996) and C-test (Brooks, 1996) were used to analyze exchange rate modeling and economic and financial timeseries modeling.In-depth checking and extensive evaluation of serial dependence in GARCH modeling of foreign currency could be employed to properly exploit the overview of these statistics.

Let $\{z(t_k)\}$ stand for the adapted sampled data process specified as, $z(t_k)=\dfrac{y(t_k)-\mu_y}{\sigma_y}$, where μ_y is the expected variance value of the process and σ_y^2 is its variance.

$y_t=\sigma_t\varepsilon_t$ and

$\sigma_y^2=\alpha_0+\sum_{i=1}^{p}\alpha_i\alpha_{t-i}^2+\sum_{j=1}^{q}\beta_j\sigma_{t-j}^2$, y_t follows a $GARCH(pq)$

Hinich test (H) and Chris test (C) employed the use of non-overlapped data window, such that if n is the window length, then the $k-th$ window is $Z(t_k)$ are the standardized observations, obtained

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by subtracting the sample mean of the window and divide same by its standard deviation.

The non-overlapped window is $\{z(t_{k+1}), z(t_{k+1}+1), ..., z(t_{k+1}+n-1)\}$, where $t_{k+1} = t_{k+n}$.

The H_0 for each window is that $y_{(tk)}$ are actualizations of a stationary pure noise process that has zero bi-correlation. The H_A is that the process established within the window is random with some non-zero bi-correlation. $C_{zzz}(r,s) = E[z(t)z(t+r)z(t+s)]$ in the set $0 < r < s < L$, L= n^b (where L is lags number that define the window) and b is a parameter determined by the analyst usually taking as $0 < b < 0.5$. The H and C statistics are advanced so as to entrap both the non-linear and linear serial dependence within a window and they are defined as follows:

$$H = \sum_{s=2}^{L}\sum_{r=1}^{s-1}\left[G^2(r,s)/(T-s)\right] \sim \chi^2((L-1)L/2) \quad (1)$$

$$\text{and } C = \sum_{r=1}^{L}\left[C^2(r)/(T-r-1)\right] \sim \chi^2 L \quad (2)$$

Where

$$G(r,s) = (n-s)^{\frac{1}{2}} Czzz(r,s) \quad \text{and}$$

$$C(r) = \sum_{k=1}^{T-S} Z(t_k)Z(t_{k+r})$$

Mcleod and Li (1983) suggested a data-driven test for measuring serial dependence of linearity vs unspecified serial dependency in non-linear scenarios in foreign exchange forecasting that was reliable in measuring both linear and non-linear situations. The test statistic as defined is

$$ML(p) = n(n+2)\sum_{j=1}^{p}(n-j)^{-1}\hat{p}_2^2(j) \rightarrow \chi^2_{p-r} \quad p > r \quad (3)$$

Where $\hat{p}_2(j)$ are the autocorrelation coefficients of the squared residuals calculated by

$$\hat{p}_2(j) = \frac{\sum_{t=j+1}^{n}\left(\hat{\varepsilon}_t^2 - \hat{\sigma}^2\right)\left(\hat{\varepsilon}_{t-k} - \hat{\sigma}^2\right)}{\sum_{t=1}^{n}\left(\hat{\varepsilon}_t^2 - \hat{\sigma}^2\right)} \quad j = 1, 2, ..., p$$

Where $\hat{\sigma}^2 = \sum \hat{\varepsilon}_t^2 / n$

The test statistic defined in (3) was proposed to deliver a more exact way of examining specific GARCH model for overlapped data window, which was not the case in H-test and C-test, thus according Hong and Lee (2003). This study proposed equation (4) to compare the simple ratio of linear to non-linear series as given here under.

$$F_{H*C^{-1}} = \frac{\sum_{s=2}^{L}\sum_{r=1}^{s-1}\left[G^2(r,s)/(T-s)\right]}{\sum_{r=1}^{L}C^2(r)/(T-r-1)} \sim F(L\text{-}1)L/2, L \quad (4)$$

Equation (4) is used to compare serial non-linearity dependency to an unexplained linearity dependency for an overlapped linear window that was not described by the H and C tests separately. We developed a ratio of H and C tests to provide a more robust means of checking the GARCH model for both linear and non-linear serial dependence in a single sweep without sacrificing generality (4). For the investigation, a threshold of 0.01 was employed. As a result, the probability of rejecting the null hypothesis is one in every one hundred (100) windows. With this low threshold level, the likelihood of obtaining false rejections of the null hypothesis establishing the presence of dependencies where they may not exist are seriously diminished, excluded, or reduced. To establish whether the bi-correlation test is suitable for data characterization using the GARCH formulation. This is achieved by converting the exchange rate returns into binary data, where

$$\{y(t)\} : y(t) = 1 \text{ if } Z(t) \geq 0$$

$$y(t) = -1 \text{ if } Z(t) < 0 \quad (5)$$

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Assume $Z(t)$ are functions of GARCH process whose innovations ε_t are symmetric about zero mean then the binary set $y(t)$ will be a stationary pure noise series. The basic idea behind binary transformation is to convert GARCH into pure noise. A GARCH process with symmetric innovations, in other words, allows for independently distributed binary output. When a data is converted using binary process the moments computed are well-behaved relative to asymptotic theory, consequent upon this, if the null hypothesis of pure noise is not accepted by the H or C Statistics, it implies that there present some statistical structures feasible in the series that cannot be explained by GARCH models. The non-acceptance of the null hypothesis could be linked to serial dependence in the innovations, but this contradicts the GARCH model assumptions.

If the data were input into and ran through the set of programs created for the tests, the results may demonstrate that a large number of the windows are not unimportant when compared to the 1% threshold level, or they could show that they are. As a result, the data could not have come from a stationary GARCH model. If this occurs, the results indicate that the use of GARCH models for the Nigerian and Batswana exchange rate series is flawed. If the situation is reversed, it suggests that the GARCH type of model is appropriate for the Nigerian and Batswana exchange rate series. A hybrid model will suffice if the test has more non-linear findings.

IV. DATA AND DATA ANALYSIS

The study's data is based on monthly exchange rate data from the Federal Republic of Nigeria, the United Kingdom, Botswana, and Japan, with the United States of America Dollar serving as a reference point. The British Pound, Japanese Yen, Nigerian Naira, and Batswana Pula are the currencies of the countries under investigation. The data used in the study covered a thirty-seven-year span (from January, 1981, to December, 2018). The study made use of the SPSS (statistical package for social sciences), Melvin J. Hinich's T23 programs, and a set of programs designed by the authors.

Table 1 provides summary statistics of all the exchange rates data used for the study

TABLE 1

STATISTICS	NAIRA	POUND	PULA	YEN
Mean	39.71946	11.144981	13.244710	134.4616
Median	11.88610	2.689200	3.469250	86.3400
Maximum	155.7600	2.418000	7.968100	305.6700
Minimum	0.346900	0.483300	0.742225	76.21000
Std. Dev.	28.14566	0.615260	2.152726	33.34406
Skewness	0.673046	0.466798	0.484286	0.909426
Kurtosis	1.636425	1.627428	1.812347	2.457050
Jarque-Bera	37.91909	20.97777	23.45002	46.65587
Probability	0.000000	0.000000	0.000000	0.000000
Sum	22075.44	508.3714	1440.651	69024.97
Sum Sq. Dev.	1497747.	167.6956	2052.963	1777524.
Observations	444	444	444	444

Figure 1 shows that the standard deviation is large (for the Nigerian Naira and the Japanese Yen), signaling significant degree variations in the exchange rates data for Japan and Nigeria, while it is low (for the United Kingdom and Batswana), indicating that their currencies are relatively stable. The data used were not symmetric, as evidenced by the large right tail of the skewness. The data are leptokurtic or fat tailed, as evidenced by the significant kurtosis value. The Jarque-Bera test revealed that the data is non-normal, and hence the normality hypothesis is rejected.

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TABLE 2: C AND H STATISTICS FOR THE WHOLE SAMPLE OF BINARY TRANSFORMED DATA

	NAIRA	POUND	PULA	YEN
NUMBER OF OBSERVATION	444	444	444	444
NUMBER OF LAGS	19	19	19	19
$P-value$	0.0000	0.0000	0.0000	0.0000
C and H Statistic	0.0000	0.0000	0.0000	0.0000

Table 2 above presents the results obtained for C and H Statistic tests for the binary transformed data set y_t. The results for the four countries under study show that the null hypothesis of pure noise is not accepted by both C and H Statistics for the four countries under study, this violates the assumption of covariance stationary of GARCH models. The implication of this is that GARCH models cannot guarantee an adequacy of all the series used for the study.

TABLE 3: WINDOWED TEST RESULTS FOR BINARY TRANSFORMED DATA

SERIES	TOTAL NUMBER OF WINDOWS	SIGNIFICANT C WINDOWS	SIGNIFICANT H WINDOWS	TOTAL NUMBER OF SIGNIFICANT C AND H WINDOWS
NAIRA	101	38**(37.25%)**	61**(60.40%)**	62 **(61.39%)**
POUND	101	24 **(23.76%)**	51 **(50.5%)**	54 **(53.47%)**
PULA	101	39**(38.61%)**	57**(56.44%)**	59 **(58.84%)**
YEN	101	40**(39.6%)**	59**(58.42%)**	61 **(60.40%)**

The results of a windowed test utilizing the T23 computer software and a collection of programs built by the authors are presented in the table above. The number of windows where the null of pure noise is not accepted by the c in column 3 of the above table The percentage of such rejection is revealed by the parentheses beneath the statistic. The rejection of the null hypothesis is related with significant C or H or both, just as the fourth column presents the significant H windows with their proportion as their parenthesis in the significant windows produced. The data for total significant windows of H and C are shown in the last column. As a result of the threshold value of 1%, the results show that the majority of significant windows for the countries under study are very large, and the expectation is that pure noise is due to probability (one percent).

V. IMPLICATIONS OF RESULTS AND CONCLUSION

The performance of the H part is revealed in column three, whereas the performance of the C part is revealed in column four. That is, when data processing is done on an individual basis (H handles the non-linear aspect of the series and C handles the linear components of the series). When H and C are utilized together, however, there is a significant improvement when compared to column three (H) and column four (C). H and C were run together, resulting in Column five (H and C combined), which performed significantly better than either H or C.

In conclusion, processing the data using H and C concurrently gave more dependable and superior outcomes than processing the data separately. The episodic reliance behavior found in the study series' exchange rates could be a major roadblock for would-be investors, policy analysts, and other stakeholders who want to mimic the study series.

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