UDK: 336.748.12(667)
DOI: 10.2478/jcbtp-2020-0008

Journal of Central Banking Theory and Practice, 2020, 1, pp. 135-167
Received: 21 February 2019; accepted: 27 June 2019

Nana Kwame Akosah [*], Paul Alagidede [**], Eric Schaling [***]

[*] Wits Business School, University of the Witwatersrand, South Africa and Bank of Ghana, Ghana

Email: akosahk@gmail.com, 1770303@students.wits.ac.za

[**] Wits Business School, University of the Witwatersrand, South Africa

Email: paul.alagidede@wits.ac.za

[***] Wits Business School, University of the Witwatersrand, South Africa

Email: eric.schaling@wits.ac.za

Interest Rate and Exchange Rate Volatility Spillovers: Multiscale Perspective of Monetary Policy Transmission in Ghana

Abstract: Ghana`s economy is characterised by acute exchange rate volatility alongside persistent and high consumer inflation. This places the economy among the sub-Saharan African countries with the highest inflation over the years. Therefore, we explore in-sample and out-of-sample macro-volatility spillovers to determine the effectiveness of monetary policy and also ascertain the relevance of the exchange rate in Ghana's interest rate setting at both time and multiscale domains. The study reveals scale-dependent interconnectedness among the macro-variables as their causal linkages broadly intensify at the longer time-scale. We find the real policy rate and the exchange rate to be net transmitters of shocks, while inflation and output gaps are net receivers of shocks from the system. Output gap, however, is the largest net receiver of shocks from the system. The empirical findings generally buttress the prerequisite to uphold exchange rate stability in order to inure general macroeconomic stability in Ghana. In addition, the extent of spillover dynamics from policy interest rate to and from the targeted macro-variables (particularly output gap and inflation) appears to be moderate even in the long run, surmising less effective monetary policy transmission in Ghana.

Key Words: Volatility Spillover, Nonlinear Causality, Variance Decomposition, Multi-scale.

JEL: C32, E42, E43, E47, E52, E58, F31, F41

1. Introduction

One major concern for economic policy makers, especially in emerging/developing inflation targeting (IT) economies is the movement of exchange rate. The conundrum of whether exchange rate should be allowed to independently/freely float in such IT economies largely hinges on the relatively higher pass-through from the latter to prices as well as large proportion of foreign currency denominated liabilities (both private and public) in these economies. For instance, Hausmann et al (1999, 2001) show that Emerging and Developing Economies (EDEs) with a *de-jure* floating exchange rate behave differently from their developed counterparts. They argue that EDEs show greater inclination to interfere in the foreign exchange market to influence the value and volatility of their currencies either using reserves or interest rate policy. Consequently, the EDEs do not permit the same degree of flexibility for exchange rate to adjust to shocks due to its dire economic ramifications for these economies.

Indeed, the extant literature remains open-ended on whether or not it is prudent for EDEs to permit full exchange rate flexibility alongside IT framework. A strand of the literature emphasises a flexible market-determined exchange rate as a precondition for successful adoption of IT (see, Mishkin and Schmidt-Hebbel, 2002; and McCallum, 2007). Another realm of the literature (see, Airaudo et al., 2016) however emphasises that a tight management of exchange rate (via direct official sterilized purchases/sales of foreign exchange) is pivotal for successful IT implementation and outcomes in EDEs with sufficiently high degree of substitutability between domestic and foreign currencies. This policy dilemma largely reflects the formidable role exchange rate plays in the macroeconomic dynamics of small-open EDEs.

With Ghana as the second longest practicing IT economy in Africa (after South Africa)[1] and the exchange rate system is best classified as a managed rather than independently float[2] (see IMF, 2016), it is of interest to consider how exchange rate influence the interest rate setting and the overall monetary transmission mechanism in Ghana. Indeed, the influence of exchange rate in Ghana cannot be overlook due to the peculiar macroeconomic characteristics of the latter, particularly overreliance of imports for domestic economic activities and a sizeable pro-

[1] Ghana started IT framework in November 2002, although the official announcement for the adoption was in May 2007 (see Bawumia, 2010).

[2] The central bank, however, maintained a presence in the market to provide foreign exchange to meet part of the demand. The Bank is obliged to do this because a sizable portion of the proceeds from traditional exports was surrendered to it.

portion of imports in the consumer inflation (CPI) baskets. As clearly exhibited in Appendix 1A, the domestic currency (Ghana Cedi) has undoubtedly remained very volatile over the years alongside unstable economic growth momentum and persistent and high inflation. Notably, the persistent and high inflation in recent years places Ghana among the sub-Saharan African (SSA) economies with highest consumer inflation (see Akosah and Dasah, 2015), while the recent pick-up in economic growth also ranks Ghana among the fastest growing economies in SSA. Monetary policy response has broadly tracked macro-dynamics in order to uphold the price stability objective. This is conspicuous from the chart in Appendix 1A as the tightening (or easing) policy stance has generally followed rapid depreciation (or appreciation/stability) of the domestic currency with onward implications on inflation and economic growth in Ghana.

Against this background, the current paper has two main focuses. First, it ascertains the effectiveness of monetary policy transmission in Ghana by exploring the extent of interest rate spillovers to the real sector (output gap) and consumer inflation. Second, it determines the extent of exchange rate influence in domestic interest rate setting and the overall monetary transmission mechanism by ascertaining exchange rate volatility spillovers to key policy targeted macro-variables (especially inflation and output gap).

Although the core objectives of the current study are not new in the Ghanaian literature on monetary policy transmission, the preceding studies (including, Akosah, 2015; Akosah and Dasah, 2015; Kovanen, 2011; etc) focused predominantly on static time-domain analysis which encompasses only two time-scales (short and long run). However, such empirical analyses provided virtually no information about the frequency dimension of macroeconomic interactions despite the well-articulated policy relevance of frequency domain analysis in the extant literature. Notably, Aguiar-Conraria, et al. (2008, 2012) assert that monetary authority may simultaneously operate at more than two time-scales, while Gallegati et al (2015) and Lynch and Zumbach (2003) also argued that economic and financial processes can be the results of decisions of heterogeneous agents with different time horizons. Besides, macroeconomic data are time-varying and subject to structural change. Therefore, time-domain analysis does not provide the complete picture of interactions between policy and macroeconomic variables.

The dearth of studies that methodically analyse and quantify spillovers from policy instruments (interest rate) and exchange rate to the key targeted macroeconomic variables (inflation and output gap) at frequency domain motivates the use of wavelet transforms and linear/nonlinear granger causality techniques in this current study. Thus, the current study differs as it explores policy effectiveness at both time- and multi-scale domains, and hence offers all-encompassing analysis than the existing literature on effectiveness of monetary policy transmission in Ghana.

Our study thus offers a number of cogent contributions to the macroeconomic literature on frontier and developing economies. First, the use of a more novel technique like Maximal Overlap Discrete Wavelet Transform (MODWT)[3] with Debauches least asymmetric filter of length (LA8) to obtain wavelet time-scale coefficients for the analysis of macro interdependence at multiple time-scales is a contribution worth mentioning. Second, the parallel application of Diks and Panchenko (2006) nonlinear Granger non-causality test and, Diebold-Yilmaz (2012) and Barunik and Krehlik (2017) methodologies to empirically evaluate the relevance of exchange rate in macro-dynamics for small open frontier economy at multi-scale domain within a single study is equally a notable contribution. The uniqueness of this study hinges on the fact that empirical studies have widely employed either linear/nonlinear Granger non-causality test (e.g. Diks and Panchenko [DP], 2006 approach) or Diebold and Yilmaz (DY, 2012) and Barunik and Krehlik (BK, 2015) methodologies but not both approaches to measure macroeconomic volatility spillovers in a single study. More so, these approaches have been predominantly focused on interconnectedness between financial markets (including Cryptocurrencies) or commodity markets (i.e. Karanaso et al., 2018; Corbet et al., 2018; Das et al., 2018; etc). So far, few number of papers have analysed directional and intensity of spillovers across macroeconomic variables, although the focus is quite different from the current paper. For instance, Barunik et al (2017) and Greenwood-Nimmo et al (2016) examined volatility spillovers between forex market and federal fund rate, while Curcuru et al (2018) explored monetary policy spillover between US and German bond yields. To the best of our knowledge, the extant literature offers no empirical evidence on the co-movements and (non)linear spillovers among key monetary policy instruments and targeted macro-variable in a multi-scale domain. In addition, such empirical perspective coupled with a complementary application of DP2006, DY2012 and BK2015 techniques remains non-existent in the extant literature on frontier economies. This is where we seek to bridge the knowledge gap. Besides, our study offers complementary approaches, and hence, proffers more comprehensive analysis on connectedness and shock transmission.

The empirical findings generally buttress the prerequisite to uphold exchange rate stability in order to inure general macroeconomic stability in Ghana. In addition, the extent of spillover dynamics from policy interest rate to and from the targeted macro-variables (particularly output gap and inflation) appears to be

[3] See Section 3.4 for the overriding advantages of MODWT over DWT.

moderate even at the long run, surmising less effective monetary policy transmission in Ghana.

Section 2 provides the empirical methodology and data used for the analysis; Section 3 presents the empirical results and inference, while Section 4 concludes and offers policy suggestions.

2. Empirical methodology

This section introduces the methodologies used to explore the dynamic co-movements and spillovers of the selected macro-variables in this study. The theoretical outline of methods employed in this study is presented as below:

2.1 Wavelet pairwise and multiple correlation

Since the time-domain analysis overlooks salient frequency at which macro-interaction take place, we sort to present more encompassing and robust macro-interdependence. As a result, we employ wavelet analysis which is one of the most preferred forms of wavelet-based analysis for measuring co-movements in two different macro-data in a time-frequency domain (see Das et al, 2018; Boako and Alagidede, 2017, etc.). A wavelet is simply a small wave, which can be stretched over time to obtain frequency constituents from complex signals. The wavelet function, i.e. the mother wavelet, can be expressed mathematically as

$$\beth_{\varsigma_p,\Phi_s}(t) = \frac{1}{\sqrt{\Phi_s}} \beth\left(\frac{t-\varsigma_p}{\Phi_s}\right) \tag{1}$$

Where $\frac{1}{\sqrt{\Phi_s}}$ connotes the normalization factor which ensure that wavelets are compatible across scales and time series; Φ_s is the dilation (scale) factor that controls the width of the wavelet. On one hand, it stretches the macro-data into a long wavelet function to measure the low frequency movements (long-run cycles). On the other hand, it compresses the data series into a short wavelet function to measure the high frequency movements. ς_p is the translation factor that determines the time location of the wavelet.

We first explore wavelet coherence analysis (WCA) which is one of the most preferred forms of wavelet-based analysis for measuring co-movements in two different macro-data in a time-frequency domain (see Das et al, 2018; Boako and Alagidede, 2017, etc.). We measure the correlation of a pair of our macro-data in time-frequency domain using the wavelet squared coherence (WSC) with continuous transforms $W_n^x(\varsigma_p, \Phi_s)$ and $W_n^y(\varsigma_p, \Phi_s)$. The WSC may be defined as[4]

$$R_t^2(\varsigma_p, \Phi_s) = \frac{\left|\vartheta\left(\vartheta^{-1} W_n^{xy}(\varsigma_p, \Phi_s)\right)\right|^2}{\vartheta\left(\vartheta^{-1}\left|W_n^x(\varsigma_p, \Phi_s)\right|^2\right) . \vartheta\left(\vartheta^{-1}\left|W_n^y(\varsigma_p, \Phi_s)\right|^2\right)}; \quad R_t^2(.) \in [0,1] \quad (2)$$

where $\vartheta(.)$ represents a smoothing parameter; and $R_t^2(\varsigma_p, \Phi_s)$ denotes the localized coherency coefficient over time-frequency domain. The coefficient of WSC ranges from 0 to 1, which denotes weaker to higher co-movements. The mapping of wavelet coherence contours, which signifies statistical significant region, offers deeper insights regarding co-movements of the macro-pairs.

A wavelet coherence phase angel is applied to determine lead/lag linkages between two macro-datasets. In the graphical plot, the phase vectors are shown by arrows. For instance, the left-tailed (→) /right-tailed (←) arrows show the two macro series under consideration are in-phase/anti-phase respectively. The in-phase and anti-phase phenomenon depicts positive and negative co-movement respectively. The upward (↑), right-upward (↗) and downward (↙) arrows show that the first macro series leads the second one. Likewise, the downward (↓), left upward (↖) and downward (↘) arrows represent that the second macro series leads the first one (see, Das et al., 2018). A cone of influence for the wavelet coherence is constructed which indicates where edge effects occur in the coherence data. Due to the edge effects, less credence is given to areas of apparent high coherence that are outside or overlap the cone of influence.

In order to overcome the limitations associated with the use of pairwise wavelet correlation analysis within a multivariate set of economic variables (Fernández-Macho, 2012[5]), we further explore wavelet multiple correlation (WMC) method. Suppose that $Y = (Y_1, Y_2, \dots, Y_q)$ are the realization of multivariate stochastic process Y_t where $t = 1, 2, \dots, Q$. We then compute wavelet multiple correlation (WMC) as:

$$\tilde{\Upsilon}_y(\psi_j) = \sqrt{1 - \frac{1}{\max \;\; diag\ Q_j^{-1}}} \quad (3)$$

[4] For instance, refer to Das et al (2018); Boako and Alagidede (2017).

[5] The WMC measures the overall statistical relationships that may occur among a set of observations at different time-scales. It offers protection against the standard type 1 error (see Cohen et al, 2003) that may prevail in carrying out all possible pairwise comparisons in a multi-scale context.

Here, the correlation matrix of $\tilde{Z}_{ij}$ is given by Q_j. Alternatively, WMC could be expressed as:

$$\tilde{\Upsilon}_y(\psi_j) = \frac{Cov\,(\tilde{\zeta}_{ijt}, \tilde{\zeta}_{ijt})}{\sqrt{Var(\tilde{\zeta}_{ijt})Var(\hat{\tilde{\zeta}}_{ijt})}} \tag{4}$$

Where ζ_{ij} is chosen in order to maximize $\tilde{\Upsilon}_y(\psi_j)$, and $\hat{\tilde{\zeta}}_{ij}$ are the fitted values in the regression of $\tilde{\zeta}_{ij}$ on the rest of wavelet coefficients at scale ψ_j. The scale j for each of the univariate time series $(y_{i1}, y_{i2}, \dots, y_{iq})$, for $i = 1, 2, \dots, q$ are determine using wavelet transforms (which is explained in section 2.3).

2.2 Measuring macroeconomic spillovers

Besides the wavelet analysis, we thoroughly assess the extent of macro interdependence or spillovers by further exploring other robust in-sample and out-of-sample frameworks. For the in-sample analysis, we specifically utilized the conventional parametric (or linear) Granger non-causality tests alongside the Diks and Panchenko (hereafter DP) nonparametric Granger non-causality test to uncover nonlinear transmission among the macro-variables. For the latter method, we stick to the specified conventions and bandwidth of Diks and Panchenko (2006) (henceforth DP2006). For robustness, the macro-spillovers are further examined using out-of-sample techniques such as the generalised forecast error variance decomposition (GFEVD) approaches by Diebold-Yilmaz (2012) and Barunik and Krehlik (2015). The application of both techniques in this study is principally to resolve the potential deficiencies associated with each approach so as to ensure robust estimates.

2.2.1 Linear and nonlinear causality framework

We utilize the classical Granger causality technique (of Granger, 1969) in a VAR framework to discover interdependence between macro-pairs. Given any two stationary data pair, say Z_t and W_t, variable W_t linearly Granger-causes W_t provided that lags of W_t offer useful information for explaining current values of W_t, and vice versa. The bivariate Granger causality is specified in a VAR system as follows:

$$Z_t = \beta_1 + \sum_{s=1}^{m} \alpha_{1s} Z_{t-s} + \sum_{v=1}^{m} \sigma_{1v} W_{t-v} + \varepsilon_{1t} \tag{6}$$

$$W_t = \beta_2 + \sum_{s=1}^{m} \alpha_{2s} Z_{t-s} + \sum_{v=1}^{m} \sigma_{2v} W_{t-v} + \varepsilon_{2t} \quad (7)$$

where, β_1 and β_2 are the constant terms of the system of equation; α and σ denote estimated coefficients; m is the optimal lag length based on the Schwarz Information Criterion (BIC)[6]; ε_{1t} and ε_{2t} represent errors terms from the VAR model.

Owing to the low power limitation that characterises most linear models when detecting nonlinear causal linkages between variables, models which show higher nonlinear predictive power are often proposed. We however employ the nonparametric approach of DP (2005, 2006) to investigate possible nonlinear linkages among the macro-data due to its relative flexibility and robustness over other nonlinear methods proposed in the extant literature[7]. We specify the processes of the bivariate DP test as follows. Assuming any two pair of stationary and dependent variables, say Z_t and W_t, we denote the information sets of lags for Z_t and W_t respectively as $G_{Z,t}$ and $G_{W,t}$, before time $t-1$; and let '~' symbolizes the equivalent distribution. In this case, variable Z_t is upheld to Granger-cause W_t provided that,

$$\left(W_{t+1},\ldots,W_{t+m}\right)\Big|\left(G_{Z,t},G_{W,t}\right)\sim\left(W_{t+1},\ldots,\ W_{t+m}\right)\Big|G_{Z,t} \quad (8)$$

where, m is an integer $(m \geq 1)$ which represents the forecasting horizon. For the lag vectors $Z_t^{l_z} = \left(Z_{t-l_z+1},\ldots,Z_t\right)$ and $W_t^{l_w} = \left(W_{t-l_w+1},\ldots,W_t\right)$, given $\left(l_z, l_w \geq 1\right)$, we test for conditional independence using determinate number of lags, l_z and l_w based on a null hypothesis of:

$$H_0 : W_{t+1}\Big|\left(Z_t^{l_z};W_t^{l_w}\right)\sim W_{t+1}\Big|W_t^{l_w} \quad (9)$$

Considering that the null hypothesis of Granger non-causality is a claim about the invariant distribution of $\left(l_z + l_w + 1\right)$ - dimensional vector $\Psi_t = \left(Z_t^{l_z}, W_t^{l_w}, X_t\right)$, where for the lead vector $X_t = W_{t+1}$, the time index is dropped and simply written

6 In determining the optimal lag length, we set the lag number to 20.

7 The DP test is a modified version of the widely used HJ test of Hiemstra and Jones (1994), while the latter is also an improved version of the maiden nonparametric test by Baek and Brock (1992). Essentially, the DP approach alleviates the severe over-rejection rates that epitomise the HJ test under the null hypothesis of Granger non-causality between variables. Furthermore, Diks and Wolski (2016) extend the bivariate DP test to a multivariate case, and endorsed that the DP approach of detecting Granger non-causality is much consistent and robust against several range of alternatives. Consequently, its adoption in this study is duly justified.

as $\Psi = \left(Z, W, X\right)$. For notational flexibility, we set $l_z + l_w = 1$, and $m = 1$, and assume that Ψ vector follows a continuous random variable. The null hypothesis of non-causality in (9) may be expressed in a joint probability density function $g_{Z,W,X}(z,w,x)$ with its marginal satisfying the condition:

$$\frac{g_{Z,W,X}(z,w,x)}{g_W(w)} = \frac{g_{Z,W}(z,w)}{g_W(w)} * \frac{g_{W,X}(w,x)}{f_W(w)} \tag{10}$$

where, for every determinate value of w, the continuous random variables Z and X are conditionally independent on $W = w$. Therefore, under the revised null hypothesis H_0, DP (2006) espoused that:

$$\psi \equiv E\left[g_{Z,W,X}(Z,W,X)g_W(W) - g_{Z,W}(Z,W)g_{W,X}(W,X)\right] = 0 \tag{11}$$

using a chosen weight function given as $\Omega(z,w,x) = g_W^2(w)$. DP deduced an estimator of ψ in an expression given by:

$$T_p(\xi_p) = \frac{(2\xi_p)^{-\Gamma_Z - 2\Gamma_W - \Gamma_X}}{p(p-1)(p-2)} * \sum_i \left[\sum_{m,m\neq s}\sum_{v,v\neq s}(I_{sm}^{ZWX} I_{sv}^{W} - I_{sm}^{ZW} I_{sv}^{WX})\right] \tag{12}$$

Here, $I_{sv}^{\Psi} = I\left(\left\|\Psi_s - \Psi_v\right\| < \xi_p\right)$; and ξ_p denote the bandwidth parameter. By representing the local density estimators of a Γ_Ψ - variate random vector Ψ and Ψ_s as:

$$\hat{g}_\Psi(\Psi_i) = \frac{(2\xi_p)^{-\Gamma_\Psi}}{p-1} * \sum_{v,v\neq s} I_{sv}^{\Psi} \tag{13}$$

the $T_p(\xi_p)$ statistic of the DP test reduces to:

$$T_p(\xi_p) = \frac{(p-1)}{p(p-2)} * \sum_i \left(\hat{g}_{Z,W,X}(Z_s,W_s,X_s)\hat{g}_W(W_s) - \hat{g}_{Z,W}(Z_s,W_s)\hat{g}_{W,X}(W_s,X_s)\right) \tag{14}$$

Given that $\Gamma_Z = \Gamma_W = \Gamma_X = 1$, when $\xi_p = Bp^{-\varpi}$, for $(B > 0, \varpi \in (0.25, 0.67))$, $T_p(\xi_p)$ converges in distribution to the standard normal:

$$\sqrt{p} * \frac{\left(T_p(\varepsilon_p) - \psi\right)}{\Phi_p} \xrightarrow{d} N(0,1) \tag{15}$$

where the asymptotic variance of $T_p(\bullet)$ is given by Φ_p.

2.2.2 Generalised forecast error variance decomposition (GFEVD)

To complement the causality analysis, we also employ the DY2012's generalised forecast error variance decomposition (GFEVD) methodology to measure macroeconomic spillovers. In line with Diebold and Yilmaz (2012), Koop, Pesaran and Potter (1996), and Pesaran and Shin (1998), we estimate a covariant stationary N-variable VAR(p) model which takes a general form

$$Z_t = \sum_{i=1}^{p} \alpha_i Z_{t-i} + v_t, \tag{16}$$

where Z_t is $N \ x \ 1$ vector of endogenous variables, α_i are $N \ x \ N$ autoregressive coefficients matrices and v_t are the vector of error terms assumed to be independently and identically distributed (serially uncorrelated). In this study, the VAR contains 4 variables (N = 4), namely real policy interest rate, inflation, output gap and exchange rate. The moving average representation of equation (16) is $Z_t = \sum_{i=1}^{\infty} A_i v_{t-i}$, where A_i is a $N \ x \ N$ coefficient matrices that obey the recursion $A_i = \omega_1 A_{i-1} + \omega_2 A_{i-2} + \ldots + \omega_p A_{i-p}$ with A_0 being a $N \ x \ N$ identity matrix and $A_0 = 0$ for $j < 0$.

The total, directional and net volatility spillovers are produced using GFEVD of the moving average representation of the VAR model in equation (16). The merit of GFEVD is that it jettisons the dependence on the ordering of the variables in the VAR. The variance decomposition permits us to separate the forecast variance of each variable into (i) own shock (own variance share) as the fraction of H-step error variance in forecasting Z_i that is due to shock to Z_i and (ii) cross variance share or spillovers as the fraction of H-step error variance in forecasting Z_i that is due to shock to Z_j for $j = 1,2,3,4$. According to Pesaran and Shin (1998), the H-step-ahead GFEVD is defined as

$$\psi_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^{'} A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} A_h \sum A_h^{'} e_i\right)}, \tag{17}$$

Where $\sum$ denotes a variance matric of error vector v_t, σ_{jj} is the standard deviation of the error term for the j^{th} equation and e_i is a selection vector with one as the i^{th} element and zeros otherwise. This results in an $N \ x \ N$ matrix $\psi(H) = [\psi_{ij}(H)]_{i,j=1,2}$ where each entry provides the contribution of variables j to the forecast error variance of variable i. However, since the own and cross variance shares do not sum up to unity under the GFEVD, we normalised each entry of the GFEVD matrix by row sum as

$$\tilde{\psi}_{ij}(H) = \frac{\psi_{ij}(H)}{\sum_{j=1}^{N} \psi_{ij}(H)}, \tag{18}$$

where $\sum_{j=1}^{N} \tilde{\psi}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\psi}_{ij}(H) = N$ by construction. Using the normalised volatility contribution from GFEVD, we compute total volatility spillover index, $T^{s}(H)$, as

$$T^{s}(H) = 100 * \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\psi}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\psi}_{ij}(H)} = 100 * \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\psi}_{ij}(H)}{N}, \tag{19}$$

Equation (19) gives the average contribution of spillovers from innovations in all (other) variables to the total forecast error variance. We then measure the directional spillovers received by variable i from all other variables j as:

$$D_{i\to j}^{s}(H) = 100 * \frac{\sum_{j=1,i\neq j}^{N} \tilde{\psi}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\psi} \quad (H)} = 100 * \frac{\sum_{j=1,i\neq j}^{N} \tilde{\psi}_{ij}(H)}{N}, \tag{20}$$

On the other hand, the directional spillovers from variable i to all other variables j are also computed as:

$$D_{i\leftarrow j}^{s}(H) = 100 * \frac{\sum_{j=1,i\neq j}^{N} \tilde{\psi}_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\psi}_{ji}(H)} = 100 * \frac{\sum_{j=1,i\neq j}^{N} \tilde{\psi}_{ji}(H)}{N}, \tag{21}$$

In order to identify which of the variables in the system is a transmitter or receiver of spillovers in the net terms, we compute a net spillover, N_i^s (H), for variable i by subtracting equation (20) from (21) as follows:

$$N_i^{s}(H) = D_{i\to j}^{s}(H) - D_{i\leftarrow j}^{s}(H), \tag{22}$$

While the preceding DY2012 methodology presents useful analysis on average connectedness at time domain, the recent extant literature has however articulated frequency domain interconnectedness of financial and macroeconomic variables (see, Barunik and Krehlik, 2015; Barunik et al., 2017; Corbet et al., 2018; Das et al., 2018; etc). This is motivated by the fact that innovations to economic activity usually affect variables at various frequencies with different strengths (see, Barunik and Krehlik, 2015). For robustness, we therefore apply the Barunik and Krehlik (2015) methodology which are spectral representations of variance decomposition to assess volatility spillovers among the interested macroeconomic variables at frequency domain[8].

[8] For the purpose of brevity, kindly refer to Barunik and Krehlik (2015) and Barunik et al (2017) for detailed exposition on interconnectedness at frequency domain.

2.3 Dataset

Quarterly dataset spanning the period 2001Q1-2017Q4[9] was used for the analysis of monetary policy reaction function (MPRF) for Ghana. The choice of the variables is purely based on the literature on MPRF. The variables are the real and nominal monetary policy interest rate, (R)MPR; Consumer Price Index, CPI; real GDP or output, nominal and real bilateral exchange rate. The real MPR is mathematically defined as $RMPR_t = (1 + MPR_t)/(1 + INF_{t+1}) - 1$. With the exception of MPR and neutral MPR, all the remaining variables are seasonally adjusted and are in logarithmic terms.

We compute annual CPI inflation, nominal and real bilateral exchange rate depreciation (or appreciation) as $r_{i,t} = 100 * ln(X_{i,t}/X_{i,t-4})$, for $i = 1,2,3;\ t = 1,\dots,68$; where $X_{i,t}$ and $X_{i,t-4}$ denote the value of i^{th} macro-data (CPI inflation, nominal and real bilateral exchange rate) at the current quarter (t) and a year ago (t-4) respectively. As prerequisite in this study, we further compute gaps as deviations from the interested variables (mainly CPI inflation, exchange rate and output) from a certain policy desired levels following the literature. Notably, inflation gap is defined as a deviation of CPI inflation from official inflation target of 8%. However, for the period where the target was not explicit (especially for the 2001-2007), the target was computed as a linear trend of the actual CPI inflation using the Hodrick-Prescott (HP) filter. Regarding the real GDP, the gap is computed as the difference between the actual real GDP and its trend (or potential) level, with the latter generated using band pass (BP) filter based on fixed length (Baxter-King) symmetric filter with low and upper durations of 6 and 32 quarters respectively.

For time-frequency analysis, we apply Maximal Overlap Discrete Wavelet Transform (MODWT)[10] to determine j length-Q vectors of coefficients for each of the univariate time series $(y_{i1}, y_{i2}, \dots, y_{iq})$, for $i = 1, 2, \dots, q$ The j length-Q vectors of MODWT coefficients are attained as:

$$\tilde{Z}_j = \{(\tilde{\zeta}_{1j0}, \dots, \tilde{\zeta}_{qj0}), \dots, (\tilde{\zeta}_{1j,Q/2^j-1}, \dots, \tilde{\zeta}_{qj,Q/2^j-1})\}, \quad for\ j = 1, 2, \dots, J \qquad (5)$$

[9] The choice of the sample size is to cover both the transition (IT lite) and the full inflation targeting (IT) regimes from 2002 as well as easily availability of quarterly data. However, the inclusion of one-year (2001Q1-Q4) preceding the adoption of IT lite is just to ensure that the introduction of lagged variables (especially with respective to the instruments) still maintains a sizeable data sample for the estimation. Nevertheless, our empirical results show that the inclusion or otherwise of one-year dataset preceding the IT adoption does not affect the results.

[10] For detailed readings on MODWT, see Percival and Walden (2000).

Our preference for MODWT over the classical DWT[11] is based on the fact that the former can handle any sample size T and its variance estimator is asymptotically more efficient than the classical DWT and hence more suitable when calculating wavelet correlations[12]. Besides, the MODWT is not affected by the arrival of new information. In addition, the MODWT is invariant to circularly shifting time series and has the multi-resolution detail and smooth coefficients that are linked with zero phase filter, two properties that do not hold for DWT (see, Dar et al., 2014). We thus decompose each macro-data into wavelet coefficients at different time scales utilizing the MODWT with Daubechies least asymmetric (LA) wavelet filter of length L= 8 (commonly denoted as LA8). The highest decomposition level, j is given by $\log_2(N)$, which in our case translate into $j = \log_2(68) = 6$, thus 6 maximum levels of data points. Knowing the ideal band-pass filters' nature of MODWT, with band-pass from the periodicity interval $[2^{-(j+1)}, 2^{-j})$ for $j = 1, \ldots, J$, and through inverting the periodicity range, it is deduced that the associated time periods should be taken as $(2^{j}, 2^{j+1}]$ time units (Whitcher et al, 2000). Therefore, the following respective periods are deemed to be associated with the desired wavelet coefficients of scale $\psi_j = 1, \ldots, 6$: 2~4 quarters (6months – 1year), 4~8 quarters (1-2 year scale), 8~16 quarters (2-4 year scale), 16~32 quarters (4-8 year scale), 32~64 quarters (32-64 year scale), 64~128 quarters (64-128 year scale), etc. Due to small sample dataset, we chose to examine macro-dependence and volatility spillovers at the first three time-scales to proxy for short-, medium-, and long run dynamics of macroeconomic shocks in Ghana.

3. Empirical results and inferences

This section presents empirical results and inferences on domain-specific in-sample and out-of-sample correlation and causal (lead/lag) relationships among the selected macroeconomic variables to ascertain the effectiveness of monetary policy as well as the role of exchange rate in Ghana's interest rate setting and particularly, the policy objective.

---

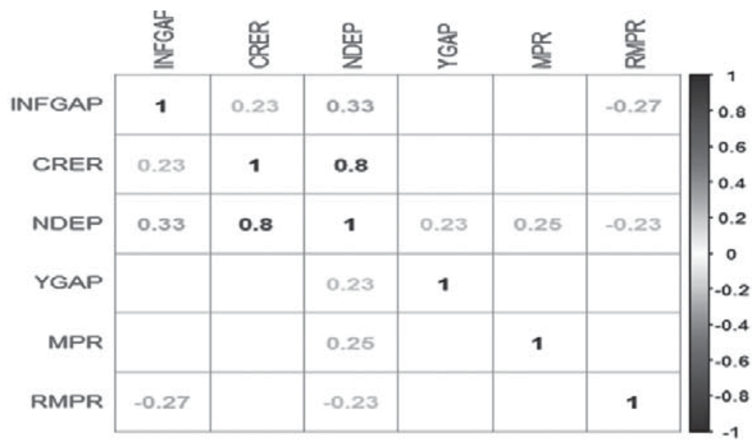
[11] Discrete Wavelet Transforms (DWT) is a time series analysis technique that can handle non-stationary by working in the combined time-and-scale-domain (see, Percival and Walden, 2000; Gencay et al., 2002).

[12] See Percival and Walden (2000) and Daubechies (1992) for detailed readings on MODWT and its competitive advantages over the conventional DWT as well as wavelet filters.

3.1 Domain specific in-sample macro-spillovers

The in-sample spillover analysis begins with pairwise correlation outcomes at time-domain and this is exhibited in Figure 1. A closer glance at the scalogram in Figure 1 unveils general low-to-moderate interactions among the macro-variables in Ghana, with the exception of nominal and real exchange rate link. The figure further uncovers significant negative linkages for the RMPR-INFGAP and RMPR-NDEP pairs, but shows positive significant correlations for the MPR-NDEP, NDEP-INFGAP, NDEP-YGAP and CRER-INFGAP pairs.

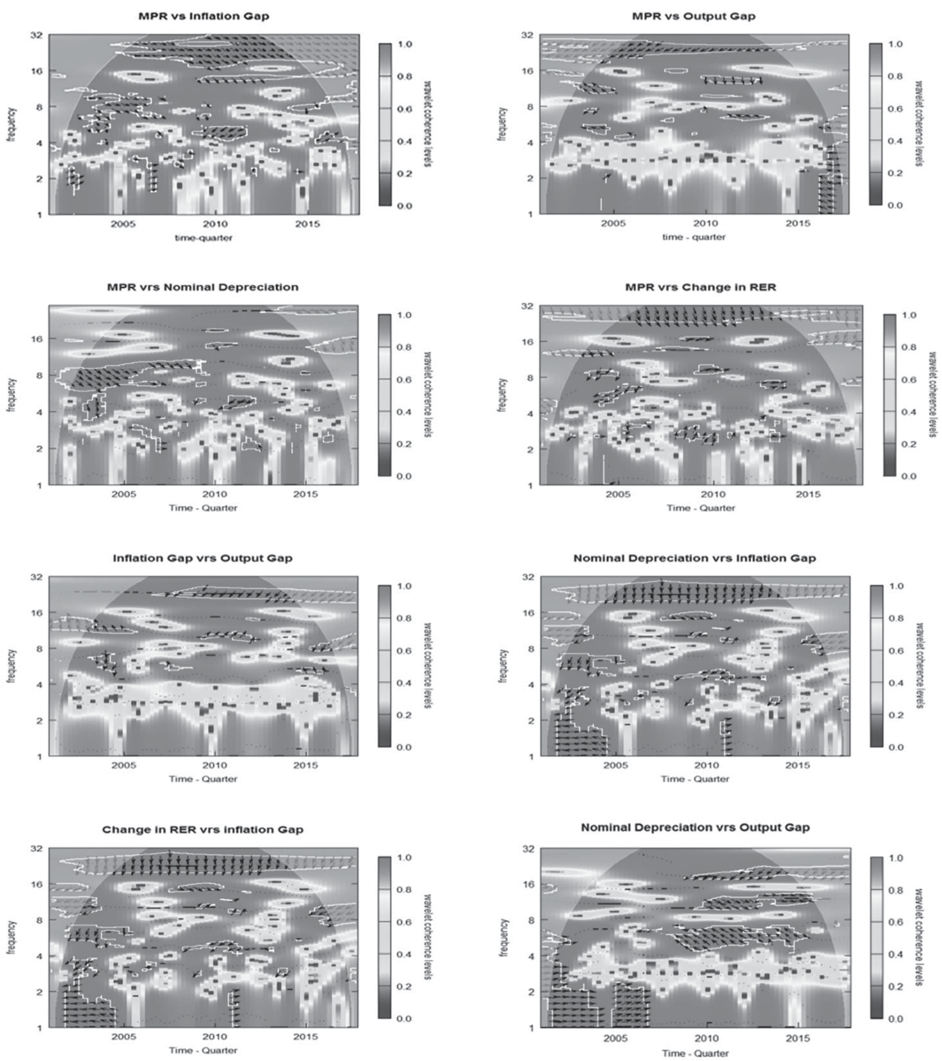
Figure 1: Linear correlation matrix for the macro-variables at time-domain



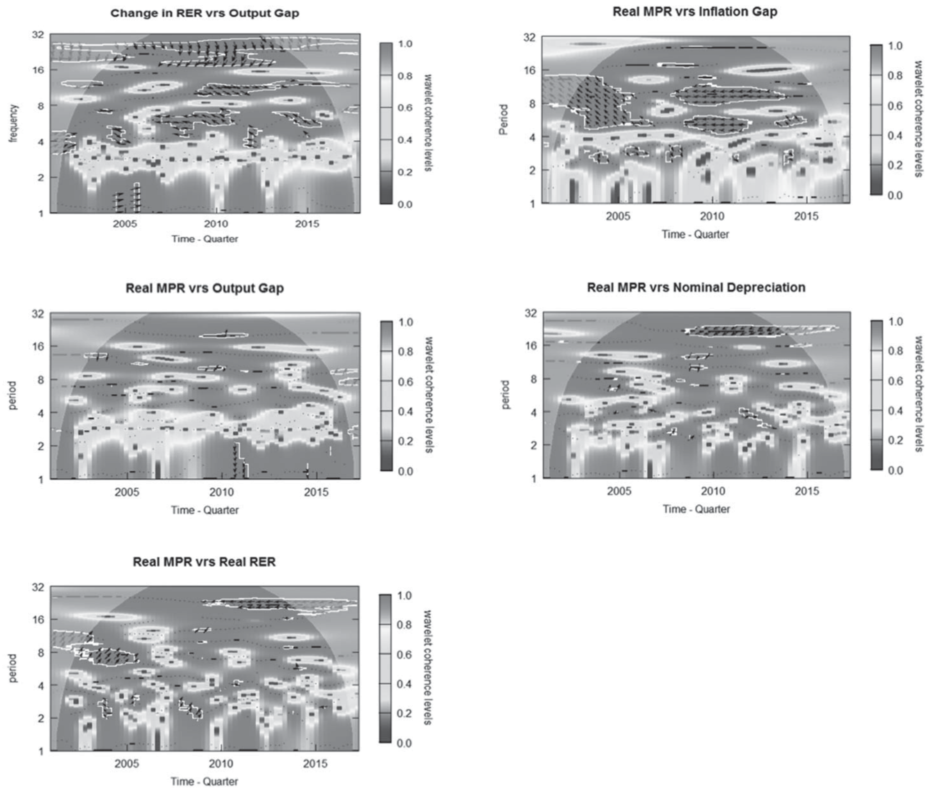
Note: The heat-map gives the static correlation levels over the aggregate time period which get stronger (or shows exact positive or inverse correlation) as the colour becomes warmer. A blank spot (or portion) with no digits denote insignificant correlation, while coloured digits shows statistical significant at 5%. However, the links for NDEP-RMPR, NDEP-YGAP and CRER-INFGAP are only statistically significant at 10% level. MPR and RMPR denote nominal and real monetary policy interest rate respectively; INFGAP is inflation gap; YGAP is output gap, NDEP and CRER represent nominal and real bilateral exchange rate respectively.

Although the correlation outcome at the time-domain is intuitive, it does not connote causation and there is also the penchant for the latter to conceal potential macro-linkages at the frequency domain. To overcome these problems, wavelet techniques are employed as they enable inferences at the time-frequency domain and also proffer lead/lag relationships between macro-pairs. Figure 2 displays pairwise wavelet coherence plots for selected key macro-variable at three time-scales, while Figure 3 presents wavelet multiple correlation (WMC) results for the linear combination of macro-variables. In particular, the application of WMC technique is to eschew possible spurious detection of correlation often associated with the simple pairwise wavelet scales (see, Das et al., 2018; Andries et al., 2016; Tiwari et al., 2013; Fernández-Macho, 2012[13], etc.). The WMC essentially helps to decipher simultaneous macro-interconnectedness at the time-frequency domain.

Figure 2: Pairwise Wavelet Coherency (PWC) Plots for Macro-Interdependence

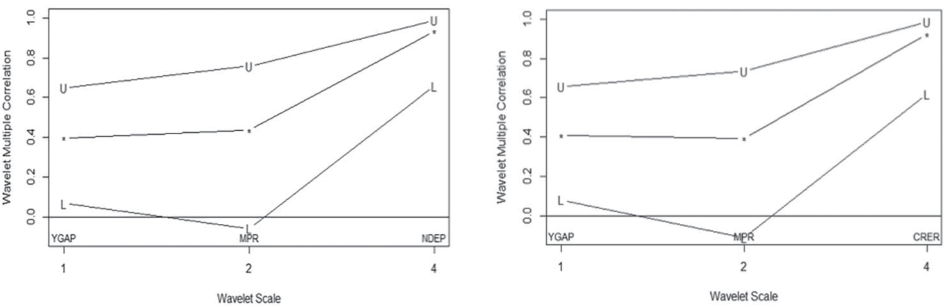


[13] The WMC measures the overall statistical relationships that may occur among a set of observations at different time-scales. It offers protection against the standard type 1 error (see Cohen et al, 2003) that may prevail in carrying out all possible pairwise comparisons in a multi-scale context.



Note: the wavelet coherency heat-map gives the multi-scale correlation. The 5% significance level estimated from Monte Carlo Simulations is designated by white contour. The red (blue) colours signify region with high (low) coherency. The coherence power colour bar shows the power of coherence coefficient. MPR denotes nominal monetary policy interest rate; RER is real exchange rate

Figure 3: Wavelet multiple correlations (WMC) for the macro-variables



A. Scale Correlation for MPR, INFGAP, YGAP & NDEP

B. Scale Correlation for MPR, INFGAP, YGAP & CRER

Note: The blue lines correspond to the upper and lower bounds of the 95% confidence interval. MPR denotes nominal monetary policy interest rate; INFGAP is inflation gap; YGAP is output gap; NDEP and CRER represent nominal and real bilateral exchange rate respectively.

In general, the both figures unveil correlation range of 0.4 - 1.0, indicating a moderate-to-high macro-interdependence. It is however scale-dependent as correlations among the variables broadly intensify with scales. Particularly, the PWC analysis reveals somewhat stronger linkages at the medium-to-longer time-scale while the scalogram for WMC conspicuously points to robust correlations among the macro-variables at the longer time scale (8-16 quarters and beyond). By implication, monetary policy is rather more effective in the medium-to-longer run which is broadly in line with the medium-to-long run objective of price stability in Ghana. However, the lead/lag relationships from the pairwise scalograms (in Figure 3) are somewhat uncertain. In contrast, the WMC plots (in Figure 3) uncovers output gap and MPR as the potential leaders at the shorter scale (1-4 quarters) and medium scale (4-8 quarters) respectively, while exchange rate becomes a potential leader at the longer time horizon (8-16 quarters and beyond). The initial maximization of the correlation by output gap against the linear combination of other macro-variables and the subsequent potential dominance of MPR intuitively reinforce the general notion that monetary authority aptly reacts to looming aggregate demand pressures in order to rein in inflation. We are however of the view that in spite of warding off pairwise spurious outcomes, the WMC results tend to omit salient bivariate macro-interactions that may be critical for effective monetary policy implementation. As a result, we further consider Granger non-causality tests so as to sufficiently pinpoint the extent and direction of interdependence among the key macro-variables. After undertaking the appropriate treatment to ensure stationary of all the variables as required (see Appendix A2 for the unit root test results), Table 1 accordingly presents the empirical results of in-sample linear/parametric Granger non-causality tests for the macro-variables both at time- and multi-scale domains.

Table 1: In-sample linear causality test for macro interconnectedness

Linkage	Panel A	Panel B: Stationary Granger Causality		
	Full Sample	D1	D2	D3
MPR≠>INFGAP	0.21(0.64)	1.34(0.24)	4.63(0.00)^{A}	9.39(0.00)^{A}
INFGAP≠>MPR	2.80(0.09)^{C}	5.74(0.00)^{A}	2.15(0.07)^{C}	3.76(0.00)^{A}
MPR≠>YGAP	17.2(0.00)^{A}	0.72(0.73)	2.57(0.04)^{B}	9.12(0.00)^{A}
YGAP≠>MPR	8.70(0.19)	2.02(0.03)^{B}	0.86(0.48)	3.11(0.01)^{B}
MPR≠>NDEP	3.00(0.22)	1.07(0.38)	1.28(0.28)	1.36(0.25)
NDEP≠>MPR	1.1 (0.58)	1.13(0.34)	0.42(0.79)	0.97(0.42)
MPR≠>CRER	5.7 (0.05)^{C}	5.59(0.00)^{A}	2.70(0.03)^{B}	2.39(0.05)^{C}
CRER≠>MPR	0.98 (0.61)	2.21(0.07)^{C}	0.41(0.79)	1.57(0.18)
RMPR≠>INFGAP	65.0(0.00)^{A}	8.67(0.00)^{A}	8.53(0.00)^{A}	9.17(0.00)^{A}
INFGAP≠>RMPR	43.3(0.00)^{A}	14.29(0.00)^{A}	4.43(0.00)^{A}	3.07(0.01)^{B}
RMPR≠>YGAP	16.2(0.01)^{B}	11.09(0.00)^{A}	1.38(0.24)	10.09(0.00)^{A}
YGAP≠>RMPR	60.8(0.00)^{A}	1.94(0.14)	0.53(0.71)	2.19(0.07)^{C}
RMPR≠>NDEP	17.5(0.09)^{C}	2.91(0.02)^{B}	1.02(0.39)	1.23(0.30)
NDEP≠>RMPR	31.1(0.00)^{A}	0.72(0.57)	0.50(0.73)	2.05(0.09)^{C}
RMPR≠>CRER	5.8(0.67)	9.54(0.00)^{A}	5.79(0.00)^{A}	3.89(0.00)^{A}
CRER≠>RMPR	12.7(0.12)	1.828(0.12)	0.58(0.67)	2.21(0.07)^{C}
INFG≠>YGAP	17.5 (0.00)^{A}	1.19(0.31)	0.57(0.68)	2.87(0.02)^{B}
YGAP≠>INFG	33.2 (0.00)^{A}	3.79(0.00)^{A}	1.28(0.28)	3.48(0.01)^{B}
INFG≠>NDEP	4.60 (0.60)	0.37(0.82)	0.29(0.88)	0.43(0.78)
NDEP≠>INFG	1.50 (0.96)	2.97(0.02)^{B}	1.13(0.34)	4.14(0.00)^{A}
INFG≠>CRER	7.80 (0.00)^{A}	1.28(0.27)	0.70(0.59)	2.22(0.07)^{C}
CRER≠>INFG	5.40 (0.02)^{B}	2.91(0.02)^{B}	2.05(0.09)^{C}	3.23(0.01)^{B}
YGAP≠>NDEP	23.9 (0.00)^{A}	2.31(0.06)^{C}	1.18(0.32)	0.23(0.91)
NDEP≠>YGAP	10.6 (0.10)	7.34(0.000)^{A}	0.72(0.58)	4.78(0.00)^{A}
YGAP≠>CRER	11.8 (0.06)^{C}	5.25(0.00)^{A}	2.99(0.02)^{B}	1.38(0.24)
CRER≠>YGAP	2.90 (0.82)	1.27(0.28)	0.81(0.51)	1.61(0.17)

Note: Numbers in brackets are p-values; the superscripts A, B & C represent 1%, 5% & 10% significant levels respectively. D1, D2 & D3 denote scale 1 (2-4 quarters), scale 2 (4-8 quarters) and scale 3 (8-16 quarters and beyond); RMPR is real Monetary Policy Rate computed as (1+MPR)/(1+inflation)-1. NDEP and CRER are bilateral nominal depreciation and real exchange rate respectively for units of domestic currency per one US dollar. YGAP and INFG represent output gap and inflation gap respectively

At a glance, the table broadly unveils significant linear contemporaneous and lagged spillovers among the selected macro-variables. The full sample results (in Panel A) reveal either a dual or single linear transmission links, with the exception of the NDEP-MPR and RMPR-INFGAP pairs. On a whole, the full-sample linear causal linkages can be categorised into two dynamic transmission conduits as follows: (i) YGAP↔INFGAP→MPR→YGAP and (ii) YGAP↔INFGAP↔RMPR↔YGAP→NDEP (CRER). These observed channels of linear causalities at time-domain reinforces that policy responds to aggregate demand pressures. In other words, monetary policy exerts some notable influence on output growth and this is consistent with the findings of Awdeh (2018) for Lebanon.

For completeness, we further explore subsample analyses to capture macro interlinkages at multiple time-scales. Panel B of Table 1 shows quiet fascinating lead/lag dynamics from the multi-scale linear Granger non-causality tests as the strength of macro- interconnectedness broadly varies across the time-scales. The multi-scale outcomes are broadly consistent with the full sample results, and hence, re-emphasising that monetary authority acts in response to aggregate demand and supply shocks in order to uphold price stability. Notably, the evidence of bi-directional linear macro spillovers becomes more apparent at the longest scale where majority of the pairs show strong significant interconnectedness. Specifically, the multi-scale analysis uncovers that output gap leads inflation gap and both variables lead nominal MPR in their interdependence structure. In addition, it is equally discernible that exchange rate (particularly nominal) leads inflation and output gap in the shock transmission dynamics in Ghana. This is largely unsurprising due to the overreliance of imports for domestic economic activities and a sizeable proportion of imported (final and intermediate) goods in the consumer inflation basket in the economy. However, nominal/real exchange rate and real MPR have dual interlinkages with the latter as a leading variable while a significant feedback effect is visible at the longer time-scale. This observation, together with significant spillovers from exchange rate to inflation and output gap, buttresses the prerequisite to uphold exchange rate stability in order to inure general macroeconomic stability in Ghana.

Other interesting observations from Panel B are worth highlighting. A unidirectional linear causal effect is observed from output gap to real exchange rate across multi-scales. This is economically intuitive as increasing economic growth momentum enhances investor confidence which in turn attracts foreign inflows and invariable strengthens the domestic currency in real terms. Moreover, the lack of significant feedback from real exchange rate to output gap across multi-scale is conceivably attributable to the predominant exports of primary commodities (such as gold, cocoa and crude oil) which tend to weakly affected by real exchange rate dynamics as Ghana is a price-taker at the international market.

Table 2: DBS Test Results for Full and Multiscale dataset

		Dimensions				
	Data Type	2	3	4	5	6
AR(1): MPR	Full Sample	2.659[0.00]^A	2.858[0.00]^A	3.913[0.00]^A	4.660[0.00]^A	5.142[0.00]^A
	D1	4.530[0.00]^A	4.885[0.00]^A	5.638[0.00]^A	6.198[0.00]^A	6.320[0.00]^A
	D2	3.122[0.00]^A	3.557[0.00]^A	3.906[0.00]^A	4.621[0.00]^A	5.032[0.00]^A
	D3	3.725[0.00]^A	3.584[0.00]^A	3.412[0.00]^A	4.260[0.00]^A	4.611[0.00]^A
AR(1): RMPR	Full Sample	3.795[0.00]^A	5.377[0.00]^A	6.418[0.00]^A	6.865[0.00]^A	7.188[0.00]^A
	D1	3.718[0.00]^A	5.243[0.00]^A	6.076[0.00]^A	7.158[0.00]^A	8.014[0.00]^A
	D2	5.411[0.00]^A	6.602[0.00]$_A$	7.598[0.00]^A	8.626[0.00]^A	9.475[0.00]^A
	D3	2.866[0.00]^A	3.631[0.00]^A	3.924[0.00]^A	4.937[0.00]^A	5.566[0.00]^A
AR(1): INFGAP	Full Sample	3.365[0.00]^A	4.527[0.00]^A	5.354[0.00]^A	5.880[0.00]^A	6.170[0.00]^A
	D1	3.088[0.00]^A	4.401[0.00]^A	4.777[0.00]^A	4.917[0.00]^A	5.513[0.00]^A
	D2	2.524[0.01]^B	4.459[0.00]^A	4.701[0.00]^A	4.728[0.00]^A	4.523[0.00]^A
	D3	3.315[0.00]^A	4.282[0.00]^A	4.234[0.00]^A	4.729[0.00]^A	5.163[0.00]^A
AR(1): YGAP	Full Sample	8.886[0.00]^A	8.415[0.00]^A	8.610[0.00]^A	8.751[0.00]^A	9.436[0.00]^A
	D1	7.247[0.00]^A	8.589[0.00]^A	10.591[0.00]^A	12.120[0.00]^A	13.566[0.00]^A
	D2	2.592[0.00]^A	5.024[0.00]^A	7.240[0.00]^A	8.576[0.00]^A	9.456[0.00]^A
	D3	5.063[0.00]^A	5.735[0.00]^A	6.292[0.00]^A	7.006[0.00]^A	7.168[0.00]^A
AR(1): NDEP	Full Sample	6.053[0.00]^A	5.622[0.00]^A	5.810[0.00]^A	6.080[0.00]^A	6.156[0.00]^A
	D1	5.448[0.00]^A	5.707[0.00]^A	5.575[0.00]^A	5.990[0.00]^A	7.403[0.00]^A
	D2	2.469[0.01]^B	4.094[0.00]^A	5.248[0.00]^A	5.913[0.00]^A	6.670[0.00]^A
	D3	3.375[0.00]^A	2.519[0.01]^B	2.049[0.04]^B	3.537[0.00]^A	4.621[0.00]^A
AR(1): CRER	Full Sample	1.194[0.23]	1.530[0.12]	2.052[0.04]^B	3.054[0.00]^A	3.910[0.00]^A
	D1	1.928[0.05]^C	3.133[0.00]^A	2.829[0.00]^A	3.630[0.00]^A	5.448[0.00]^A
	D2	5.916[0.00]^A	6.344[0.00]^A	8.003[0.00]^A	9.138[0.00]^A	9.959[0.00]^A
	D3	3.173[0.00]^A	2.361[0.02]^B	1.906[0.06]^C	2.833[0.00]^A	4.414[0.00]^A

Note: the z-statistic is reported at various embedded dimensions. The p-values are reported in square brackets. The superscript A, B & C denotes 1%, 5% & 10% significant levels respectively. D1, D2 & D3 denote scale 1 (2-4 quarters), scale 2 (4-8 quarters) and scale 3 (8-16 quarters and beyond); MPR_t, $INFGAP_t$, $YGAP_t$, $NDEP_t$ and $CRER_t$ denote monetary policy rate, deviation of inflation from target, output gap, nominal and real exchange rate respectively, while $RMPR_t$ is real policy rate.

Nonetheless, the literature (for instance, Andries et al, 2016) asserts that the interpretation of linear correlation/causality results should be done with utmost caution as such estimates may fail to adequately capture possible nonlinear linkages. As a consequent, we further explore possible nonlinear linkages in order to authenticate and hence, steer clear of potential biasedness in the preceding empirical results. In line with the past studies (see Das et al., 2018), we first carried out DBS test[14] with a null hypothesis of linearity on the residuals of AR(1) process for the respective macro-variables. Table 2 presents the results for the DBS test. It is generally discernible from the table that the null hypothesis of independent and identical distribution (*i.i.d*) could not be accepted for the residuals of all the macro-variables across the dimensions for the full sample as well as the multi-scaled data. This favourable evidence of nonlinearity in the macro data engenders the risk of undependability of the preceding linear causality results. In view of this, the intent of performing nonlinear causality test to validate or complement the linear results is accordingly justified.

Table 3: Nonparametric Granger Causality Test for the macro-data

Direction	Full Sample	D1	D2	D3
MPR≠>INFGAP	0.39(0.34)	1.61(0.05)^{C}	1.68(0.04)^{B}	0.28(0.39)
INFGAP≠>MPR	0.93(0.17)	-1.15(0.87)	-0.44(0.67)	0.13(0.44)
MPR≠>YGAP	1.86(0.96)	1.61(0.05)^{C}	0.45(0.32)	-0.00(0.50)
YGAP≠>MPR	1.05(0.85)	-0.07(0.52)	0.79(0.21)	0.55(0.29)
MPR≠>NDEP	0.03(0.48)	0.88(0.19)	-0.96(0.83)	-0.37(0.64)
NDEP≠>MPR	-0.54(0.71)	-0.43(0.66)	0.87(0.19)	0.16(0.44)
MPR≠>CRER	-1.12(0.86)	-0.29(0.61)	-1.14(0.87)	0.28(0.39)
CRER≠>MPR	-1.38(0.91)	0.68(0.25)	0.94(0.17)	0.39(0.35)
RMPR≠>INFGAP	1.44(0.07)^{C}	1.51(0.06)^{C}	1.84(0.03)^{B}	2.07(0.02)B
INFGAP≠>RMPR	0.41(0.34)	0.69(0.24)	0.36(0.36)	0.54(0.29)
RMPR≠>YGAP	0.81(0.21)	-0.83(0.79)	0.87(0.19)	-0.51(0.69)
YGAP≠>RMPR	-0.12(0.54)	0.06(0.47)	-0.12(0.55)	-0.23(0.59)
RMPR≠>NDEP	1.43(0.07)^{C}	-0.79(0.78)	-0.45(0.67)	0.26(0.39)
NDEP≠>RMPR	0.88(0.19)	-1.01(0.84)	-0.85(0.80)	0.56(0.29)
RMPR≠>CRER	1.06(0.14)	-0.42(0.66)	0.46(0.32)	0.66(0.25)
CRER≠>RMPR	0.97(0.17)	0.85(0.19)	-0.96(0.83)	0.66(0.25)
INFG≠>YGAP	0.70(0.24)	-0.44(0.67)	-1.21(0.88)	0.05(0.45)
YGAP≠>INFG	1.23(0.11)	1.24(0.11)	-0.58(0.72)	-0.22(0.59)
INFG≠>NDEP	0.62(0.27)	1.06(0.14)	-0.28(0.61)	1.04(0.15)

[14] For details on DBS test, refers to Brock et al., (1996)

NDEP≠>INFG	-0.99(0.84)	-0.27(0.61)	0.58(0.28)	-0.83(0.79)
INFG≠>CRER	1.17(0.12)	0.08(0.46)	0.46(0.32)	0.28(0.39)
CRER≠>INFG	0.46(0.32)	-0.13(0.55)	0.11(0.46)	-0.58(0.72)
YGAP≠>NDEP	0.14(0.44)	-0.32(0.62)	0.20(0.41)	-1.02(0.85)
NDEP≠>YGAP	0.09(0.46)	-0.44(0.66)	-0.87(0.81)	-1.10(0.86)
YGAP≠>CRER	0.32(0.37)	0.45(0.32)	0.67(0.25)	-0.37(0.64)
CRER≠>YGAP	0.44(0.33)	0.05(0.48)	-0.17(0.56)	0.79(0.21)

Note: The p-values are reported in brackets. The superscript B & C denotes 5% & 10% significant levels respectively. D1, D2 & D3 denote scale 1 (2-4 quarters), scale 2 (4-8 quarters) and scale 3 (8-16 quarters and beyond); MPR_t, $INFGAP_t$, $YGAP_t$, $NDEP_t$ and $CRER_t$ denote monetary policy rate, deviation of inflation from target, output gap, nominal and real exchange rate respectively, while $RMPR_t$ is real policy rate.

Considering the outcome of the DBS test, we proceed to perform an in-sample nonparametric (nonlinear) Granger causality test based on DP (2006) methodology. In doing so, we followed the protocols of DP2006 to set the lag length to 2, i.e. $l_z = l_w = 2$, and a bandwidth of 0.5 for all pairs. Table 3 presents the results for DP2006 test. At first glance, the table clearly unveils a general insubstantial evidence of nonlinear transmissions among the macro-data across time- and multi-scale domains. This surmises that the detected in-sample linear causal linkages at both time-spectrum and wavelet time-frequency domain (in Table 1) are broadly adequate for economic inferences in the context of Ghana.

Nonetheless, some isolated cases of significant nonlinear linkages are noticeable from the table. Particularly, the full sample analysis reveals significant unidirectional nonlinear interlinkages for macro-pairs RMPR-INFGAP and RMPR-NDEP (at 10% level) with RMPR as a transmitter. Thus, positive real policy rate has nonlinear dampening effect on inflation and also strengthens the domestic currency in nominal terms which is intuitively plausible. The nonlinear analysis unveils that policy rate has significant nonlinear influence of both inflation and output gap at time-frequency domain. This observation is not surprising as the monetary policy transmission mechanism (MPTM) clearly demonstrates that policy interest rate affect both inflation and output via several conduits. By implication, such scale-dependent nonlinear policy influence on key macro targeted variables may not be discernible from standard empirical analysis that is based purely on time-domain.

3.2 Out-of-sample macro volatility spillovers at analytical domains

We assert that the preceding in-sample analysis does not explicitly quantify the magnitude of spillovers and fails to reveals out-of-sample predictability of the linkages among the macro-variables. In view of these limitations, this section explores the generalised forecast error variance decomposition (GFEVD) techniques to determine the relative contributions to forecast uncertainties by the selected macro-variables. Our preference for these approaches is mainly based on the fact that variance decomposition (VD) from a vector Autoregression (VAR) model proffers crucial information about how much of the future uncertainty of variable A is due to innovations to variable B. Therefore, VD is utilized to adequately capture system or macro interdependence/connectedness (Diebold and Yilmaz, 2012, 2009). By summing up information in VD[15], one can quantify how the system is interconnected. For robustness, we apply both the Diebold and Yilmaz (2012) and Barunik and Krehlik (2015) methodologies which focus on time-domain and frequency-domain respectively.

Table 4 presents the magnitudes of directional, pairwise and total interconnectedness (spillovers) among real interest rate, inflation gap, output gap and real exchange rate based on the GFEVD methodology of Diebold-Yilmaz (2012) at different forecast horizons (H=10, 50 and 100 quarters). It is clearly evident from the table that average total connectedness among the macro-variable is about 50% for forecast horizon up to 10 quarters (H=10) and increases to about 68% with H=50 quarters ahead.

Table 4: Time-domain spillovers table for macro-data

H = 10 Quarters ahead						
	Real Policy Rate	Inflation Gap	Output Gap	Real Exchange Rate	Contribution from Others (CFO)	CFO Ranking
Real Policy Rate	47.64	19.11	12.72	20.53	13.09	2
Inflation Gap	25.57	50.29	1.85	22.28	12.43	3
Output Gap	59.06	3.01	33.45	4.47	16.64	1
Real Exchange Rate	26.98	1.28	2.81	68.93	7.77	4
Contribution to Others (CTO)	27.9	5.85	4.35	11.82		

[15] VD is closely related to recent network theory and the lately acclaimed measures of systemic risks, such as expected shortfall and CoVar.

CTO Ranking	1	3	4	2		
Contribution including own	75.54	56.14	37.8	80.75	Overall Spillover	
Net Spillover (NS)	14.81	-6.57	-12.29	4.05	49.92	
NS Ranking	1	3	4	2		
			H = 50-Quarters ahead			
Real Policy Rate	28.68	11.86	9.22	50.25	17.83	2
Inflation Gap	27.71	32.32	9.12	30.85	16.92	3
Output Gap	44.78	9.29	9.54	36.40	22.62	1
Real Exchange Rate	27.12	8.4	7.81	56.67	10.83	4
Contribution to Others (CTO)	24.9	7.39	6.54	29.37		
CTO Ranking	2	3	4	1		
Contribution including own	53.58	39.71	16.08	86.04	Overall Spillover	
Net Spillover (NS)	7.07	-9.53	-16.08	18.54	68.2	
NS Ranking	2	3	4	1		
			H = 100 Quarters ahead			
Real Policy Rate	35.12	11.21	8.31	45.37	16.22	2
Inflation Gap	31.63	21.18	7.49	39.69	19.7	3
Output Gap	46.64	9.98	8.21	35.16	22.95	1
Real Exchange Rate	27.21	7.66	6.73	58.40	10.4	4
Contribution to Others (CTO)	26.37	7.21	5.63	30.06		
CTO Ranking	2	3	4	1		
Contribution including own	61.49	28.39	13.84	88.46	Overall Spillover	
Net Spillover (NS)	10.15	-12.49	-17.31	19.65	69.27	
NS Ranking	2	3	4	1		

Note: the table shows the estimated spillovers from (along column) and to (along row) of various combinations of macroeconomic variables, estimated using the Diebold and Yilmaz (2012) methodology. The rankings 1 to 4 indicates highest to lowest spillovers to (or from) variable i within the estimated system.

Table 5: Frequency-domain spillovers table for macro-data

	Real Policy Rate	Inflation Gap	Output Gap	Real Exchange Rate	From ABS	From Within
			Short Scale			
Real Policy Rate	1.93	0.84	0.05	0.39	0.32	5.37
Inflation Gap	5.64	7.53	0.13	1.49	1.81	30.50
Output Gap	0.74	0.04	0.24	0.85	0.41	6.85
Real Exchange Rate	0.45	0.27	0.24	2.98	0.24	3.99
To ABS	1.71	0.29	0.10	0.68	2.78	
Ranking	1	3	4	2		Overall Connectedness
To WTH	28.68	4.82	1.74	11.48		**46.71**
Ranking	1	3	4	2		
Net Spillovers (NS)	1.39	-1.53	-0.30	0.45		
NS Ranking	1	4	3	2		
			Medium Scale			
Real Policy Rate	29.21	5.64	3.49	11.92	5.26	9.88
Inflation Gap	21.15	6.20	3.21	10.60	8.74	16.40
Output Gap	41.50	7.08	6.32	21.41	17.50	32.85
Real Exchange Rate	21.61	2.91	1.92	18.90	6.61	12.41
To ABS	21.06	3.91	2.15	10.98	38.11	
Ranking	1	3	4	2		Overall Connectedness
To WTH	39.55	7.33	4.04	20.62		**71.54**
Ranking	1	3	4	2		
Net Spillovers (NS)	15.80	-4.83	-15.34	4.37		
NS Ranking	1	3	4	2		
			Long Scale			
Real Policy Rate	3.97	4.73	4.77	33.05	10.64	26.08
Inflation Gap	4.85	7.45	4.16	27.60	9.15	22.44
Output Gap	4.40	2.87	1.66	12.90	5.04	12.36
Real Exchange Rate	5.15	4.49	4.57	36.52	3.55	8.71
To ABS	3.60	3.02	3.38	18.39	28.39	
Ranking	2	4	3	1		Overall Connectedness
To WTH	8.83	7.41	8.28	45.09		**69.60**
Ranking	2	4	3	1		
Net Spillovers (NS)	-7.04	-6.13	-1.67	14.84		
NS Ranking	4	3	2	1		

Note: the table shows the estimated spillovers from (along column) and to (along row) of various combinations of macroeconomic variables, estimated using the Barunik and Krehlik (2015) methodology. To ABS and To WTH refer to absolute and within connectedness of the estimated system. Long scale refer to forecast horizon of greater than 10 quarters, medium scales for forecast horizon between 4 and 10 quarters, while short scale captures forecast period up to 4 quarters.

A close examination of both tables conspicuously unveils that real policy rate and exchange rate as net transmitters of shock to the systems, while inflation and output gaps are net receivers of shocks from the system across analytical domains. The empirical estimates from the both analytical domains reveal that policy rate is the dominant transmitter of shock to the system in the short-to-medium run at time domain (and at the short run for frequency domain), while real exchange rate subsequently emerges as the largest propagator of shocks to the entire system (including own shocks) for longer forecast horizon for time domain (but at medium-to-longer forecast horizons for frequency domain). We also observe a strong dual linkage between real policy rate and exchange rate (at time domain) at least in the short run. The subsequent dominance of exchange rate shock in the system implies that exchange rate is a crucial transmission channel of monetary policy than interest rate in case of Ghana, particularly in the longer time horizon. This is consistent with Krušković (2018) who identified exchange rate as a very significant transmission channel than the interest rate both in emerging markets and Serbia.

Output gap is the largest receiver of shocks from the system, followed by inflation gap and this is consistent across forecast horizons. Notably, the effect of monetary policy shock on output outstrips that on inflation across forecast horizons, particularly at analytical time domain (see Table 4). This is intuitively plausible as policy decisions (or changes in policy instruments, either via interest rate or exchange rate) are initially targeted at the business cycle (aggregate demand pressures) and the onward effect on general prices (inflation), in line with the literature on monetary policy transmission mechanism. However, impact of exchange rate spillovers on inflation seems to be relatively stronger than that on output across forecast horizons in both time and frequency domains. Conceivably, adjustments in policy interest rate impact investment and consumption decisions of households with onward repercussions on aggregate demand (output). This observation is broadly consistent with the findings of Praščević and Ješić (2019) that in normal conditions, whereby there is no zero-lower bound, monetary policy (via the Taylor rule) is in charge of the stabilization of the macroeconomy. Likewise, the observed relatively stronger exchange rate spillovers to inflation is intuitively plausible as changes in the former variable impact firm's marginal cost of production with a consequential influence on prices.

Nevertheless, the directional spillovers results also demonstrate that inflation shocks provide relatively higher explanation to variation in real policy rate than that emanating from output gap across the forecast horizon. Thus, monetary authority appears to put more weight on upholding low and stable prices. The empirical results thus articulate a continuous relevance of upholding exchange rate stability, which undoubtedly is the anchor for the attainment of overall macroeconomic stability in Ghana. It is however very conspicuous that interest rate shocks are relatively important for output, while exchange rate shocks wield predominant effects on inflation in the case of Ghana. Nonetheless, table 4 reveals that the extent of spillover dynamics from policy rate to and from the targeted macro-variables (particularly output gap and inflation) appears to be moderate even in the long run, surmising less effective monetary policy transmission at frequency domain in the long run.

4. Conclusion and policy suggestions

We explore the extent of co-movements and interconnectedness of key macroeconomic policy variables (including inflation, output gap, exchange rate and policy interest rate) at both time- and multi-scale domains in order to (1) determine the effectiveness of monetary policy in Ghana and (2) ascertain the relevance of exchange rate in interest rate setting in Ghana. Adopting a more systematic approach, we explore several in-sample and out-of-sample estimation techniques to ensure robust estimates and valid economic inferences.

In general, the study unveils scale-dependent interconnectedness among the selected macro-variables, as observed single- and bi-directional causal interlinkages broadly strengthen at the longer time scale. We identified that both output gap and inflation gap lead nominal MPR in their interdependent dynamics, consistent with the general notion that monetary authority acts in response to aggregate demand and supply shocks. There are also significant spillovers from exchange rate to MPR, inflation and output gap. This is conspicuous from both the in-sample and out-of-sample analyses, and robustly accentuates the important influence of real exchange rate in domestic macroeconomic dynamics.

By implication, the empirical findings intuitively buttress the prerequisite to uphold exchange rate stability in order to inure general macroeconomic stability in Ghana. Yet, the extent of spillover dynamics from policy interest rate to and from the targeted macro-variables (particularly output gap and inflation) appears to be moderate at the long run, surmising less effective monetary policy transmission in Ghana. This empirical observation accordingly warrants deliberate policy efforts to address inherent structural weaknesses, particularly related to the financial (banking) system, to hasten and intensify onward policy response by the financial (banking) sector and the entire real sector economy.

5. References

1. Aguiar-Conraria, L., Azevedo, N., & Soares, N, J., (2008). Using wavelets to decompose the time–frequency effects of monetary policy. *Physica A,* 387(12): 2863-2878. https://doi.org/10.1016/j.physa.2008.01.063
2. Aguiar-Conraria, L., Martins, M., & Soares, N, J., (2012). The yield curve and the macro-economy across time and frequencies. *Journal of Economic Dynamics and Control*, Vol. 36, Issue 12, pp. 1950-1970. https://doi.org/10.1016/j.jedc.2012.05.008
3. Airaudo, M., Buffie, E. F., & Zanna, L-F., (2016). Inflation targeting and exchange rate management in least developed countries. IMF Working Paper, WP/16/55, pp. 1-65.
4. Akosah, N. K., (2015). Is the monetary policy rate effective? Recent evidence from Ghana. Graduate Institute of International and Development Studies Working Paper No. 14/2015.
5. Akosah, N. K., & Dasah, J.B., (2015). Is monetary policy effective in dampening fiscally-induced exchange market pressures? Evidence from Ghana. *Macroeconomics and Finance in Emerging Market Economies,* 9(2), 148-166. http://dx.doi.org/10.1080/17520843.2015.1077874
6. Andries, A.M., Ihnatov, I., & Tiwari, A.K., (2016). Comovement of exchange rate. A wavelet analysis. *Emerging Market Finance and Trade*, 52, 574-588. https://dx.doi.org/10.1018/1540496X.2014.998563
7. Awdeh A., (2018). Monetary policy and economic growth in Lebanon. *Journal of Central Banking Theory and Practice,* 2, 147-171. http://dx.doi.org/10.2478/jcbtp-2019-0018
8. Baek, E., & Brock, W., (1992). A general test for nonlinear Granger causality: Bivariate model. Working paper, Iowa State University and University of Wisconsin, Madison.
9. Barunik, J., & Krehlik, T., (2015). Measuring the frequency dynamics of financial and macroeconomic connectedness. Available at: arXiv.org > stat > arXiv:1507.01729.
10. Barunik, J., Kocenda, E., & Vacha, L., (2017). Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance* 77, 39-56. http://dx.doi.org/10.1016/j.jimonfin.2017.06.003
11. Bawumia, M., (2010). Monetary policy and financial sector reform in Africa: Ghana's experience. Oxford University Press, ISBN: 978-1-453854501
12. Boako, G., & Alagidede, P., (2017). Co-movement of African's equity markets: Regional and global analysis in the frequency-time domain. *Physica A*, 468, 359-380. http://dx.doi.org/10.1016/j.physa.2016.10.088

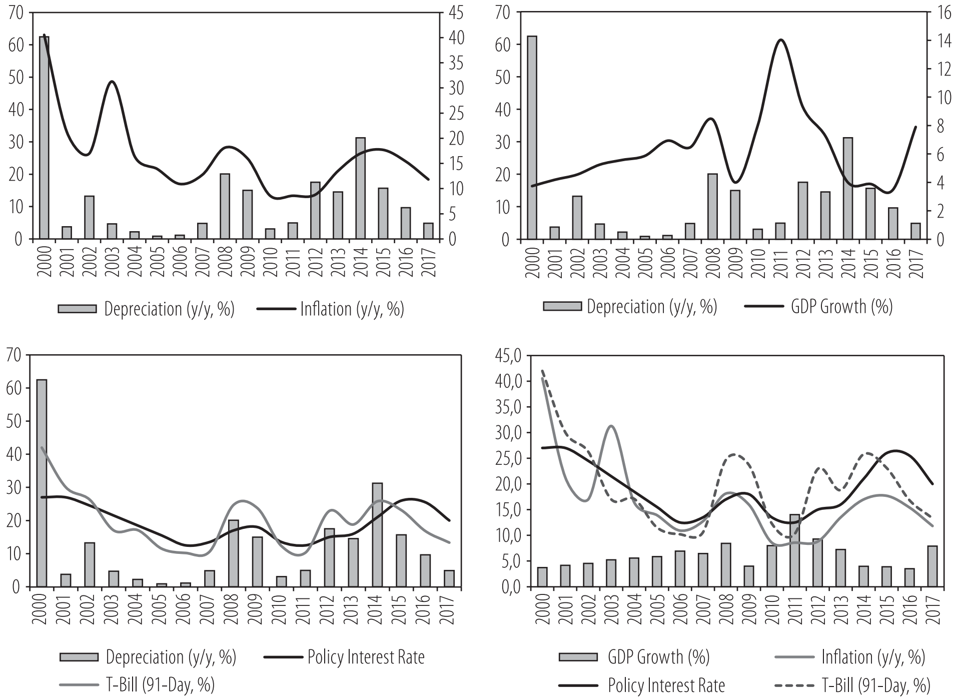
13. Cohen. J., Cohen. P., West. S., & Aitken, L., (2003). Applied Multiple Regression and Correlation Analysis. Third edition, 1, *Lawrence Erlbaum Associates, Inc., New Jersey.*
14. Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L., (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, 28-34. https://doi.org/10.1016/j.econlet.2018.01.004.
15. Curcuru, S. E., De Pooter, M., & Eckerd, G., (2018). Measuring monetary policy spillovers between U.S. and German bond yields. International Finance Discussion papers 1226. https://doi.org/10.17016/IFDP.2018.1226
16. Dar, A.B., Samantaraya, A., & Shah, F.A., (2014). The predictive power of yield spread: evidence from wavelet analysis. *Empirical Economics*, 46(3) 887-901. https://doi.org/10.1007/s00181-013-0705-6
17. Das, D., Kannadhasan, M., & Al-Yahyaee, K., (2018). A wavelet analysis of co-movement in Asian gold markets. *Physica A,* 492, 192-206. https://doi.org/10.1016/j.physa.2017.09.061
18. Daubechies, I., (1992). Ten lectures on wavelets. SIAM, Philadelphia.
19. Diebold, F.X., & Yilmaz, K., (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal* 119, 158-171. https://doi.org/10.1111/j.1468-0297.2008.02208.x
20. Diebold, F.X., & Yilmaz, K., (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1): 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006
21. Diks, C., & Panchenko, V., (2005). A note on the Hiemstra-Jones test for Granger non-causality. *Studies in Nonlinear Dynamics & Econometrics, 9(2):* 1558-3708. https://doi.org/10.2202/1558-3708.1234.
22. Diks, C., & Panchenko, V., (2006). A new statistic and practical guidelines for nonparametric granger causality testing. *Journal of Economic Dynamics & Control,* 30, 1647-1669. https://doi.org/10.1016/j.jedc.2005.08.008
23. Diks, C., & Wolski, M., (2016). Nonlinear Granger causality: Guidelines for multivariate analysis. *Journal of Applied Econometrics,* 31, 1333-1351. https://doi.org/10.1002/Jae.2495
24. Brock, W., Dechert, D., Sheinkman, J., & LeBaron, B., (1996). A test for independence based on the correlation dimension. *Econometric Reviews,* 15(3), 197–235.
25. Fernández-Macho, J., (2012). Wavelet multiple correlation and cross-correlation: A multiscale analysis of Eurozone stock markets. *Physica A*, 391, 1097-1104. https://doi.org/10.1016/j.physa.2011.11.002
26. Gallegati, M., Gallegati, M., Ramsey, J. B., & Semmler, W., (2011). The US wage Philips curve across frequencies and over time. *Oxford Bulletin of Economics and Statistics*, 74(4), 489-508.

27. Gencay, R., Selcuk, F., & Witcher, A., (2002). an introduction of wavelets and other filtering methods in finance and economics. Academic Press.
28. Granger, C. W. J., (1969). Investigating causal relations by econometric models and cross- sectional methods. *Econometrica*, 37(3), 424-438. https://doi.org/10.2307/1912791
29. Greenwood-Nimmo, W., Nguyen, V.H., & Rafferty, B., (2016). Risk and return spillovers among the G10 currencies. *Journal of Financial Markets* 31, 43-62. https://doi.org/10.1016/j.finmar.2016.05.001
30. Hiemstra, C., & Jones, J. D., (1994). Testing for linear and nonlinear Granger causality in the stock price-volume relation. *Journal of Finance,* 49(5), 1639-1664. https://doi.org/10.2307/2329266
31. Hausmann, R., Pinizza, U., & Stein, E., (2001a). Why do countries float the way they float? *Journal of Development Economics*, 66(2), 387-414. https://doi.org/10.1016/S0304-3878(01)00168-7
32. Hausmann, R., Pinizza, U., & Stein, E., (2001b). Original sin, passthrough and fear of floating. https://www.researchgate.net/publication/228692710
33. International Monetary Fund, (2014). Annual report on exchange rate arrangements and exchange restrictions. IMF, Washington, D.C (October 2014). ISSN (Online) 2304-0831. http://www.imf.org/external/pub/nft/2014/areaers/ar2014.pdf
34. Karanaso, M., Ali, F.M., Margaronis, Z., & Nath, R., (2018). Modelling time varying volatility spillovers and conditional correlations across commodity metal futures. *International Review of Financial Analysis,* 57, 246-256. https://doi.org/10.1016/j.irfa.2017.11.003
35. Koop, G., Pesaran, M. H., & Potter, S. M., (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics,* 74(1): 119-147.
36. Kovanen, A., (2011). Monetary policy transmission in Ghana: Does the interest rate channel work? *IMF Working Paper*, No. 11/275, pp. 1-33.
37. Krušković, B. D., (2018). Exchange rate and interest rate in the monetary policy reaction function. *Journal of Central Banking Theory and Practice,* 1, 55-86. http://dx.doi.org/10.1515/jcbtp-2017-0004
38. Lynch, P. E., & Zumbach, G. O., (2003). Market heterogeneities and the causal structure of volatility. *Journal of Quantitative Finance* 3(4): 320-331. https://doi.org/10.1088/1469-7688/3/4/308
39. McCallum, B.T., (2007). Monetary policy in East Asia: The case of Singapore. Monetary and Economic Studies, Institute for Monetary and Economic Studies, Bank of Japan, 25(1), 13-28, Available: RePEc:ime:imemes:v:25:y:2007:i:s1:p:13-28

40. Mishkin, S.M., & Schmidt-Hebbel, K., (2002). One decade of inflation targeting in the world: what do we know and what do we need to know. In: Norman Loayza and Raimundo Soto, eds., Inflation Targeting: Design, Performance, Challenges (Central Bank of Chile: Santiago 2002): 171-219.
41. Percival, D. B., & Walden, A., (2000). Wavelet methods for time series analysis. Cambridge University Press.
42. Pesaran, H. H., & Shin, Y. B., (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1): 17-29. https://doi.org/10.1016/S0165-1765(97)00214-0
43. Praščević, A & Ješić, M., (2019). Modelling macroeconomic policymakers' interactions under zero lower bound environment: The new Keynesian theoretical approach. *Journal of Central Banking Theory and Practice,* 1, 5-38. http://dx.doi.org/10.2478/jcbtp-2017-0001
44. Tiwari A. K., Dar, A. B., Bhanja, N., & Shar, A., (2013). Stock market integration in Asian countries: evidence from wavelet multiple correlations. *Journal of Economic Integration*, 28: 441-456.
45. Whitcher, B., Guttorp, P., & Percival, D. B., (2000). Wavelet analysis of covariance with application to atmosphere time series. *Journal of Geophysical Research*: *Atmospheres,* 105(D11): 14941-14962

Appendix A

1. Macro-Dynamics in Ghana



Source: Authors' construction based on data from Bank of Ghana, Ghana Statistical Services and Ministry of Finance and Economic Planning

2. Unit Root Test

	Augmented Dickey-Fuller (ADF) Test				Philips-Perron (PP) Test				Kwiatkowski-Philips-Schmidt-Shin (KPSS) Test		
	Ho: Series is non-stationary				Ho: Series is non-stationary				Ho: Series is stationary		
	None	Constant	Constant & Trend	First Difference	None	Constant	Constant & Trend	First Difference	Constant	Constant & Trend	First Difference
MPRt	[0.30]	[0.24]	[0.58]	[0.00]*	[0.30]	[0.33]	[0.73]	[0.00]*	{0.23}	{0.22}*	{0.24}
RMPRt	[0.04]**	[0.01]**	[0.03]**	[0.00]*	[0.01]**	[0.00]*	[0.01]**	[0.00]*	{0.67}	{0.09)	{0.07}
INFGAPt	[0.00]*	[0.01]**	[0.00]*	[0.00]*	[0.00]*	[0.00]*	[0.00]*	[0.00]*	{0.45}	{0.06}	{0.02}
YGAPt	--	{7.964}*^	{2.22}*^	{6.91}*^	[0.00]*	[0.00]*	[0.00]*	[0.00]*	{0.08}	{0.06}	{0.64}**
NDEPt	[0.06]***	[0.09]***	[0.14]	[0.00]*	[0.00]*	[0.00]*	[0.00]*	[0.00]*	{0.21}	{0.08}	{0.13}
CRERt	[0.02]**	[0.20]	[0.16]	[0.00]*	[0.01]**	[0.109]	[0.15]	[0.00]*	{0.49}**	{0.08}	{0.03}

Note: ^ is the MSB test statistic based on Ng-Perron modified unit root tests; {} and [] denote test statistics and p-values respectively; *,**&*** denote 1%, 5% & 10% alpha levels respectively. MPRt, INFGAPt, YGAPt, NDEPt and CRERt denote monetary policy rate, deviation of inflation from target, output gap, nominal and real exchange rate respectively, while RMPRt is real policy rate.