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Abstract

This paper investigates the nature of dependence between stock prices and exchange rate in Nigeria for the period running from January 2000 to December 2015, which covers the boom, bust and recovery cycles that characterized the stock market. Both Granger causality test in mean and quantiles are used with the latter being more robust to non-normalities and non-linearity in the data. For the entire sample, the result shows a bi-directional dependence between stock prices and exchange rates. However, at sub-sample periods, the results show no dependence between stock prices and exchange rate during tranquil times but a one-way dependence from stock prices to exchange rate during the boom and bust as well as the recovery cycles. Overall, the evidence indicates the dominance of the portfolio balance effect with stock prices leading exchange rate. Hence, stabilizing the stock market is imperative for exchange rate management to minimize the transmission of systemic risk and contagion between both markets.

Keywords: Stock Prices; Exchange Rate; Granger Causality; Nigeria.
JEL Classification: C21; D53; F31; G1

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1 Introduction

There is no doubt that financial markets such as the stock and foreign exchange markets have become increasingly interdependent. In recent times, such dependence has been fostered by the integration and synchronization of financial markets around the globe. For instance, emerging and developing countries have adopted several financial liberalization policies including the elimination of capital controls and switching to a flexible exchange rate regime which has resulted in the emergence of new financial markets (Phylaktis and Ravazzolo, 2005). This in turn has encouraged the free movement of international capital flows both for portfolio investment and diversification. Higher capital flows exert pressure on the supply and demand of currencies, thereby increasing the volatility of the foreign exchange markets, which can lead to currency risk, amplified contagion effects and sensitivity to external shocks such as witnessed during the recent global financial crisis. As a result, the dynamic interaction between stock prices and exchange rates remains an important issue in the literature as both variables are crucial for a country's development.

Mainstream economic theory highlights two arguments for the interdependence between stock prices and exchange rates, namely, the "flow-oriented" (or international trading effect) and the "stock-oriented" (or portfolio balance effect) models of exchange rates. The "flow-oriented" model (see Dornbusch and Fischer, 1980) argues that exchange rate causes stock prices since changes in the exchange rates affect international competitiveness and influences an economy's real income and output, which in turn affect stock prices expressed as the discounted present value of a firm's future cash flows. Thus, a depreciation (appreciation) of the exchange rate enhances (reduces) the competitiveness of firms and affects positively (negatively) their earnings and stock prices. On the other hand, the "stock-oriented" model (see Frankel, 1983; Branson, 1993) posit a converse relationship in that changes in stock prices affect aggregate demand and money demand through wealth and liquidity effects. This leads to changes in interest rate which impact on capital flows, and consequently changes in the exchange rates. For example, a decrease in stock prices causes a reduction in domestic wealth which lowers both the demand for money and interest rates. Moreover, lower interest rates discourage capital flows, which causes exchange rate depreciation. Therefore, on the basis of both theoretical models, there is no consensus on the nature of dependence (i.e. direction of causality) between stock prices and exchange rates.

This lack of consensus is also observed on the empirical front as a number of studies have investigated this relationship using different methodologies and data sets for different countries with mixed and inconclusive evidence.[1] For instance, traditional techniques of vector autoregression (VAR) and cointegration, variants of conditional variance models which deals with volatility transmission, and regime switching models have been used to capture the interdependence between stock prices and exchange rates with results pointing towards the existence of a unidirectional, bi-directional, and sometimes no relationship between both variables. More so, it has been shown in the literature that the correlations between asset markets tend to be higher during periods of financial crisis than in tranquil or normal times (Hatemi-J and Roca, 2005; Lin, 2012). When asset markets are under crisis, returns will be lower and volatility higher, which implies that the relationship between stock prices and exchange rates would become strengthen during turbulent periods. Hence, in investigating the stock prices and exchange rates interactions not only does the methodology matter, but it is also expedient to consider the nexus at periods of tranquillity and turbulence as the direction of causality could differ during these times.

In this paper, the objective is to revisit the stock price and exchange rate interactions for a developing economy such as Nigeria. Although a number of studies exist on the nexus for Nigeria (see e.g. Aliyu, 2009; Oyinlola et al., 2012; Fowowe, 2015; Salisu and Oloko, 2015), the results have been mixed as in the general literature. More so, these studies have used least square (LS) models which captures only the conditional mean but not the whole distribution of the stock prices and exchange rate nexus, and variants of conditional variance models that explores only volatility transmission between both variables. In variance to these studies, this paper specifically investigates the non-linear causal relationship between stock returns and exchange rate changes in Nigeria for the period January 2000 to December 2015, which includes the 2008 Nigerian stock market crash following the global financial crisis. Causal relations between both variables is examined not only for the entire period but also sub-sample periods characterized by the boom, bust and recovery cycles of the stock market. Following Chuang et al. (2009), causality is investigated from the perspective of conditional quantiles. The Granger causality in quantiles test is estimated by means of quantile regression (QR) (see Koenker, 2005), and is used to evaluate whether the relationship is interdependent over the entire QR parameter process. The advantage of the QR model is in its robustness and coverage of the entire conditional quantile functions unlike the conditional mean OLS method that is susceptible to the so-called averaging effect, and bias given the special features of financial data such as non-normalities in the distribution and non-linearity.[2] This justifies the increasing popularity of the QR model in the financial literature for modelling the dependence between financial variables (see Chuang et al., 2009; Tsai, 2012; Ding et al., 2014; Yang et al., 2014; Boako et al., 2016).

[1] See the Literature Review section

[2] In addition, the QR model is robust in the presence of outliers and avoids the assumption that the error terms are independent and identically distributed (i.i.d).

Going forward, the balance of the paper is as follows: Section 2 provides a review of the related literature. Section 3 describes the methodology and dataset. Section 4 presents the empirical results and discussion; and lastly, Section 5 provides the conclusion.

2 Literature Review

The empirical literature on the stock prices and exchange rate dynamics is extensive. The common thread running through the literature is the existence of a mixed and inconclusive evidence which cuts across different methodologies and datasets for different countries. A number of studies have examined this relationship for the U.S. and other industrialized economies (see e.g. Aggarwal, 1981; Jorion, 1990; Bahmani-Oskooee and Sohrabian, 1992; Bodnar and Gentry, 1993; Bartov and Bodnar, 1994; Donnelly and Sheehy, 1996; Nieh and Lee, 2001). Aggarwal (1981) finds a positive correlation between the U.S. dollar and her stock market returns. Nieh and Lee (2001) find no evidence of a long-run equilibrium relationship between stock prices and exchange rates in G-7 countries except for one-day significant linkages in some countries. Kim (2003) shows that stock prices are negatively correlated in the U.S. either in the short or long run. Alagidede et al. (2011) investigates the nature of the causal linkage between stock markets and foreign exchange markets in Australia, Canada, Japan, Switzerland, and UK from January 1992 to December 2005, and finds causality from exchange rates to stock prices for Canada, Switzerland, and UK; weak causality in the reverse direction is only for Switzerland. In addition, they show possible non-linear-causality based on the Hiemstra–Jones test which indicate causality from stock prices to exchange rates in Japan and weak causality of the reverse direction in Switzerland. Caporale et al. (2014) find evidence of unidirectional Granger causality from stock returns to exchange rate changes in the US and the UK, in the opposite direction for Canada, and bidirectional causality for the Euro area and Switzerland using data on the banking crisis between 2007 and 2010.

As for emerging market economies, the 1997 Asian currency crisis provided the motivation to investigate the causal dynamics between the exchange rates and stock prices (see e.g. Abdalla and Murinde, 1997; Granger et al., 2000; Pan et al., 2007; Zhao, 2010; Lin, 2012; Andreou et al., 2013; Yang et al., 2014). Granger et al. (2000) finds evidence that exchange rates influences stock prices in Korea, in the opposite direction for Hong Kong, Malaysia, Philippines, Singapore and Taiwan, whereas no relationship was observed for Japan and Indonesia. Abdalla and Murinde (1997) examined the nexus between stock and foreign exchange markets in India, Korea, Pakistan, and Philippines and finds unidirectional causal linkage between exchange rates and stock prices for Pakistan and Korea, causality from exchange rate to stock price in India and no causal relationship in the case of Philippines. Hatemi-J and Roca (2005) investigates the link between exchange rates and stock prices in four ASEAN countries (Malaysia, Indonesia, Philippines, and Thailand), and finds significant linkages before but not at all during the crisis period. Pan et al. (2007) show evidence of a significant causal relation from exchange rates to stock prices before the 1997 Asian crisis for Hong Kong, Japan and Malaysia, and the reverse causal relation for Hong Kong, Korea and Singapore; whilst no causality was observed during the Asian crisis for all Asian countries except the causal relation from exchange rates to stock prices for Malaysia. For six Pacific Basin countries, Phylaktis and Ravazzolo (2005) finds no long-run equilibrium in these countries (except Hong Kong), whereas the inclusion of the US stock market showed more evidence in favour of cointegration while the multivariate causality tests suggest that the US stock market drives the system. Lin (2012) finds a stronger comovement between exchange rates and stock prices during crisis periods with spillover effects running from stock prices to exchange rates. Tsai (2012) finds a negative relationship between stock and foreign exchange markets which is more pronounced when exchange rates are extremely low or high. Andreou et al. (2013) investigates bi-directional linkages between the stock and foreign exchange markets of a number of emerging economies, and finds find significant bidirectional spillovers between stock and foreign exchange markets. Yang et al. (2014) finds both stock and foreign exchange markets are negatively correlated for nine Asian markets although causal relations are heterogeneous across quantiles.

Studies on the stock prices and exchange dynamics are not lacking for African countries and Nigeria in particular (see e.g. Aliyu, 2009; Oyinlola et al., 2012; Zubair, 2013; Salisu and Oloko, 2015; Fowowe, 2015; Boako et al., 2016). Aliyu (2009) finds strong evidence of long run bidirectional relationship between stock prices and exchange rate in Nigeria for the sample period starting from 1st February, 2001 to 31st December, 2008. Oyinlola et al. (2012) investigates the long-run and short-run dynamics of stock prices and exchange rate in Nigeria, and finds a unidirectional relationship from stock prices to exchange rate. Zubair (2013) finds absence of long-run relationship between stock prices and exchange in Nigeria before and during the period of the global financial crisis. Salisu and Oloko (2015) find the existence of both significant negative return and persistent volatility spillovers from the stock market to the foreign exchange market in Nigeria. Fowowe (2015) investigates the stock prices and exchange rates relationship in Nigeria and South Africa, and finds causality from exchange rate to stock prices for Nigeria but no causality in the case of South Africa. Boako et al. (2016) examines the dependence structure between stock returns and exchange rates in Ghana by means of bayesian quantile analysis with evidence supporting the international trade-oriented model than the portfolio balance theory.

3 Methodology and Data

3.1 Testing Causality in mean

Traditionally, when a variable x does not Granger cause another variable y (see Granger, 1969, 1980), it implies that

$$F_{y_t}(\eta|(\mathcal{Y},\mathcal{X})_{t-1}) = F_{y_t}(\eta|\mathcal{Y}_{t-1}), \quad \forall \eta \in \mathbb{R} \tag{1}$$

holds almost surely (a.s.), where $F_{y_t}(\cdot|\mathcal{Y}_{t-1})$ is the conditional distribution of y_t and $(\mathcal{Y},\mathcal{X}_{t-1})$ is the information set generated by y_i and x_i up to time $t-1$. That is, Granger non-causality holds when the past information of x_t does not alter the conditional distribution of y_t. However, if Eq.(1) does not hold, then x_t is said to Granger cause y_t. As defined by Eq.(1), Granger non-causality will be referred to as 'Granger non-causality in distribution'.

Since estimating and testing conditional distributions are practically cumbersome, it is more common to test a necessary condition of Eq.(1), namely,

$$\mathbb{E}(y_t|(\mathcal{Y},\mathcal{X})_{t-1}) = \mathbb{E}(y_t|\mathcal{Y}_{t-1}), \qquad a.s., \tag{2}$$

where $\mathbb{E}(y_t|\mathcal{F})$ is the mean of $F_{y_t}(\cdot|\mathcal{F})$. We say that x_t does not Granger cause y_t in mean if Eq.(2) holds; otherwise, x_t Granger causes y_t in mean. In the same vein, we define non-causality in variance (see Cheung and Ng, 1996) and non-causality in other moments.[3] Eq.(2) is usually tested by evaluating a linear model of $\mathbb{E}(y_t|(\mathcal{Y},\mathcal{X})_{t-1})$:

$$\alpha_0 + \sum_{i-1}^{p} \alpha_i y_{t-i} + \sum_{j-1}^{q} \beta_j x_{t-j}$$

which depends on the past information of $y_{t-1}, ..., y_{t-p}$ and $x_{t-1}, ..., x_{t-q}$. Eq.(2) amounts to testing the null hypothesis that $\beta_j = 0, j = 1, ..., q$, that is, whether any lagged x_t has a significant effect on the conditional mean of y_t. A rejection of this null hypothesis suggest that x_t Granger causes y_t. However, failing to reject the null is compatible with non-causality in mean but says nothing about causality in other moments or other distribution characteristics.

[3] Note that these notations of non-causality are necessary for, but not equivalent to, Granger non-causality in distribution.

3.2 Testing causality in quantiles

The limitation of the non-causality in mean (or in variance) test is such that it cannot be carried over to other distribution characteristics or different parts of the distribution. Thus, characterizing non-causality in different quantile ranges becomes expedient. Given that a distribution can be completely determined by its quantiles, Granger causality can be extended and expressed in terms of conditional quantiles. Following Chuang et al. (2009), Granger non-causality test in quantiles is equivalent to

$$Q_{y_t}(\tau|(\mathcal{Y},\mathcal{X})_{t-1}) = Q_{y_t}(\tau|\mathcal{Y}_{t-1}), \qquad \forall\tau \in (0,1),\ a.s., \tag{3}$$

where $Q_{y_t}(\tau|(\mathcal{Y},\mathcal{X})_{t-1})$ denotes the τ-th quantile of the distribution $F_y(\cdot|\mathcal{F})$ which is equivalent to Eq.(1). If Eq.(3) holds, then x_t does not Granger cause y_t in all quantiles. However, Granger causality can be defined in the quantile range $[a,b] \subset (0,1)$ as

$$Q_{y_t}(\tau|(\mathcal{Y},\mathcal{X})_{t-1}) = Q_{y_t}(\tau|\mathcal{Y}_{t-1}), \qquad \forall\tau \in [a,b],\ a.s., \tag{4}$$

To this end, causality in quantiles can be postulated with a model for $Q_{y_t}(\tau|(\mathcal{Y},\mathcal{X})_{t-1})$ and estimated by quantile regression methods (Koenker and Bassett, 1978; Koenker, 2005).[4] To show this, let $\boldsymbol{Y}_{t-1,p} = [y_{t-1},\ldots,y_{t-p}]'$, $\boldsymbol{X}_{t-1,q} = [x_{t-1},\ldots,x_{t-p}]'$ and $\boldsymbol{Z}_{t-1} = [\mathbf{1},\boldsymbol{Y}'_{t-1,p},\boldsymbol{X}'_{t-1,q}]'$, we assume that the following model is correctly specified for the τ-th conditional quantile function:

$$Q_{y_t}(\tau|\boldsymbol{Z}_{t-1}) = a(\tau) + \boldsymbol{Y}'_{t-1,p}\boldsymbol{\alpha}(\tau) + \boldsymbol{X}'_{t-1,q}\boldsymbol{\beta}(\tau) = \boldsymbol{Z}'_{t-1}\boldsymbol{\theta}(\tau)$$

where $\boldsymbol{\alpha}(\tau) = [\alpha_1(\tau),\alpha_2(\tau),\ldots,\alpha_p(\tau)]'$ and $\boldsymbol{\beta}(\tau) = [\beta_1(\tau),\beta_2(\tau),\ldots,\beta_q(\tau)]'$ are $p-$ and $q-$dimensional parameter vectors repectively, and $\boldsymbol{\theta}(\tau) = [a(\tau),\boldsymbol{\alpha}(\tau)',\boldsymbol{\beta}(\tau)']'$ is the k dimensional parameter vector with $k = 1+p+q$.[5] For a given τ, the parameter vector $\boldsymbol{\theta}(\tau)$ is estimated by minimizing asymmetrically weighted absolute deviations:

$$\hat{\boldsymbol{\theta}}(\tau) = arg\ \underset{\theta}{min} \sum_{t-1}^{T} \rho_\tau(y_t - \boldsymbol{Z}'_{t-1}\theta(\tau))$$

[4] Koenker (2005) provides a comprehensive study of quantile regression

[5] Note that the $\tau-$th conditional quantile of the error $e_{t\tau} = y_t - \boldsymbol{Z}'_{t-1}\boldsymbol{\theta}(\tau)$ is zero, a consequence of correct model specification.

where $\rho_\tau(\cdot)$ is the usual check function[6] and solved using a linear programming algorithm (see Koenker, 2005). Thus, given a linear model for conditional qauntiles, the non-causality in quantiles in Eq.(3) amounts to testing

$$H_0 : \boldsymbol{\beta}(\tau) = 0 \qquad \forall\tau \in (0,1),$$

where $\boldsymbol{\beta}(\tau) = [\beta_1(\tau), \beta_2(\tau), ..., \beta_q(\tau)]'$ and the significance of the entire quantile parameter process $\boldsymbol{\beta}(\cdot)$, computed on the basis of a Wald statistics as below:

$$\mathcal{W}_T(\tau) = T\boldsymbol{\beta}(\tau)'(\boldsymbol{R}\hat{\Omega}_{ZZ}^{-1}\boldsymbol{R'})\boldsymbol{\beta}(\tau)/[\tau(1-\tau)]$$

where R is a $q \times k$ selection matrix such that $\boldsymbol{R\theta}(\tau) = \boldsymbol{\beta}(\tau)$, and $\hat{\Omega}(\tau)$ is a consistent estimator of $\Omega(\tau) = \boldsymbol{D}(\tau)^{-1}\boldsymbol{M}_{ZZ}\boldsymbol{D}(\tau)^{-1}$, $\boldsymbol{M}_{ZZ} := lim_{T\to\infty}T^{-1}\sum_{t-1}^{T}\boldsymbol{Z}_{t-1}\boldsymbol{Z'}_{t-1}$, and $\boldsymbol{D}(\tau) := lim_{T\to\infty}T^{-1}\sum_{t-1}^{T} f_{t-1}(F_{t-1}^{-1}\boldsymbol{Z}_{t-1}\boldsymbol{Z'}_{t-1}$, with F_{t-1} and f_{t-1} being the distribution and density functions respectively of y_t conditional on $\mathbb{Z}_{t-1}$, the information set generated by $\boldsymbol{Z}_{t-1}, \boldsymbol{Z}_{t-2}, \ldots$ (see Koenker, 2005; Koenker and Xiao, 2006).

Under suitable conditions, Koenker and Machado (1999) and Chuang et al. (2009) show that the sampling distribution of the Wald test statistic follows the sum of squares of q independent Bessel processes:

$$\sup_{\tau\in\mathfrak{T}} \mathcal{W}_T(\tau) \xrightarrow{d} \sup_{\tau\in\mathfrak{T}} \left\| \frac{\boldsymbol{\beta}_q(\tau)}{\sqrt{\tau(1-\tau)}} \right\|^2 \tag{5}$$

where $\mathcal{W}_T(\tau)$ denotes the Wald statistic for the quantile $\tau \in [a,b]$ and $\boldsymbol{\beta}_q(\tau)$ is a vector of q independent Brownian bridges such that $\boldsymbol{\beta}_q(\tau) = [\tau(1-\tau)]^{1/2}\mathcal{N}(0, \boldsymbol{I}_q)$ in distribution. Empirically, the sup-Wald statistic is calculated as

$$sup\, \mathcal{W}_T = \sup_{i=1,2,\ldots,n} \mathcal{W}_T(\tau_i)$$

where $\tau_i \in [a,b]$ with $a = \tau_1, \ldots, \tau_n = b$. Over the range $[a,b]$, the sup-Wald test can be used to identify the different quantile interval for which causality exist. The rejection of the null hypothesis for some interval $[a,b]$ suggest that causality arises outside of the interval under consideration. Thus, Granger causality in quantiles provides further insights into the nonlinear dependence between x_t and y_t. The critical values of the sup-Wald test can be

[6]The check function is defined for any $\tau \in (0,1)$ as

$$\rho_\tau(\varepsilon)_{t\tau} = \begin{cases} \tau\varepsilon_{t\tau}, & \text{if } \varepsilon_{t\tau} \geq 0 \\ (\tau-1)\varepsilon_{t\tau}, & \text{if } \varepsilon_{t\tau} < 0 \end{cases}$$

simulated with the standard Brownian motion using a Gaussian random walk with 3000 i.i.d $\mathcal{N}(0,1)$ innovations, which is presented in DeLong (1981) and Andrews (1993, 2003).

3.3 Data

The data for the empirical analysis includes monthly stock price and exchange rate indices for the Nigerian economy for the sample period running from January 2000 to December 2015, which includes a total of 192 observations. The stock price index is measured using the Nigerian Stock Exchange All-Share Index (ASI) which is sourced from the Central of Nigerian (CBN) *Statistical Bulletin* online, while the exchange rate (EXR) is expressed in local currency per unit of the U.S. dollar, (i.e. Naira per US dollar rate) which is obtained from the IMF's *International Financial Statistics* database.

For purpose of dissecting the causal relationship between stock price and exchange rate, the total sample period is further divided into three sub-sample periods which are chosen arbitrarily considering the boom, bust and recovery cycles that characterized the stock market.. Thus, four sample periods are considered for the Granger causality test, namely: Period I which is the full sample period ranging from 2000:1 to 2015:12; Period II which is referred to as the 'tranquil times' ranges from 2000:1 to 2005:12; Period III which ranges from 2006:1 to 2010:12 covers the period of the global financial crisis and the Nigerian stock market crash; and Period IV which ranges from 2011:1 to 2015:12 is referred to as the 'recovery period'.

The return series of the stock price and exchange rate indices are calculated as $S_t = 100 \times [lnP_{S,t} - lnP_{S,t-1}]$ and $E_t = 100 \times [lnP_{E,t} - lnP_{E,t-1}]$ where $P_{S,t}$ and $P_{E,t}$ represent the respective price indices. Within this context, a positive exchange rate return (i.e. increasing exchange rate) signifies exchange rate depreciation and the converse of a negative exchange rate return indicates exchange rate appreciation. Similarly, a positive (negative) stock returns suggest stock market appreciation (depreciation). The rationale for using the return series instead of their levels is because financial time series exhibit non-stationarity properties which may lead to spurious inferences on the regression analysis. Although arguments exist that differencing the variables to maintain the basic assumptions of stationarity will lead to loss of information with regards to a possible linear combination of the variables in their levels (Phylaktis and Ravazzolo, 2005), Zivot and Wang (2005) maintains that nothing is lost when considering the choice of simple returns. Moreover, simple returns are interchangeable with continuously compounded returns (i.e. log returns) as there is no substantial difference between both in the empirical literature (see Tsay, 2002).

4 Empirical results

4.1 Preliminary analysis

The graphical plots for the levels and returns series of both stock prices and exchange rate is presented in Figure 1. A quick eye-balling of both variables in their levels suggest distinct patterns of relationship. Between 2000 and 2005, the stock market experienced phenomenal growth with significant expansion in market activities as indicated in the upward trend of the stock price index. This boom coincided with the depreciation of the exchange rate which suggest a positive co-movement between both variables. Most of the stock market growth starting in 2004 was induced by the banking sector recapitalization drive of the Central Bank of Nigeria which led to mergers and acquisition in the banking sector and a concomitant inflow of large portfolio investment into the stock market. This expansion was sustained into the first quarter of 2008, and within this period the exchange rate appreciated significantly.

Following the emergence of the 2007 global financial crisis in the U.S. and its subsequent spread to other parts of the world, the stock market plummeted in second quarter of 2008 with sharp decline in stock prices due to large portfolio investment outflows, and within the same year, there was a significant depreciation of the exchange rate. Regrettably, the global financial crisis and the outflows of portfolio investment exposed the weak risk management and corporate governance malpractices that was inherent in the Nigerian financial sector during the bank recapitalization exercise, as banks raised additional capital through huge borrowing and margin finance which fuelled speculative lending to the stock market and its subsequent asset bubble (Oyinlola et al., 2012). Although, the stock market has made significant recovery since 2011 to restore investor confidence, the exchange rate remained relatively stable before experiencing a sharp depreciation in 2015. This may be linked to the declining foreign reserves following the dip in crude oil prices in the international market which was also triggered by the global financial crisis, and in addition to the excess demand for foreign currencies in the Nigerian economy.

In sum, the graphical plot show that there is no definite relationship between both variables as the nexus could be symmetric or asymmetric at different time profiles. Moreover, the plots for both variables in levels and returns series show patterns of volatility. This is more evident with the returns series plot which exhibit mean reversion properties and volatility clustering. Thus, a simple eye-balling of the plot cannot show any conclusive evidence as to the nature of dependence between stock prices and exchange rate in the Nigerian economy context. Hence, a robust approach would be to subject the data to

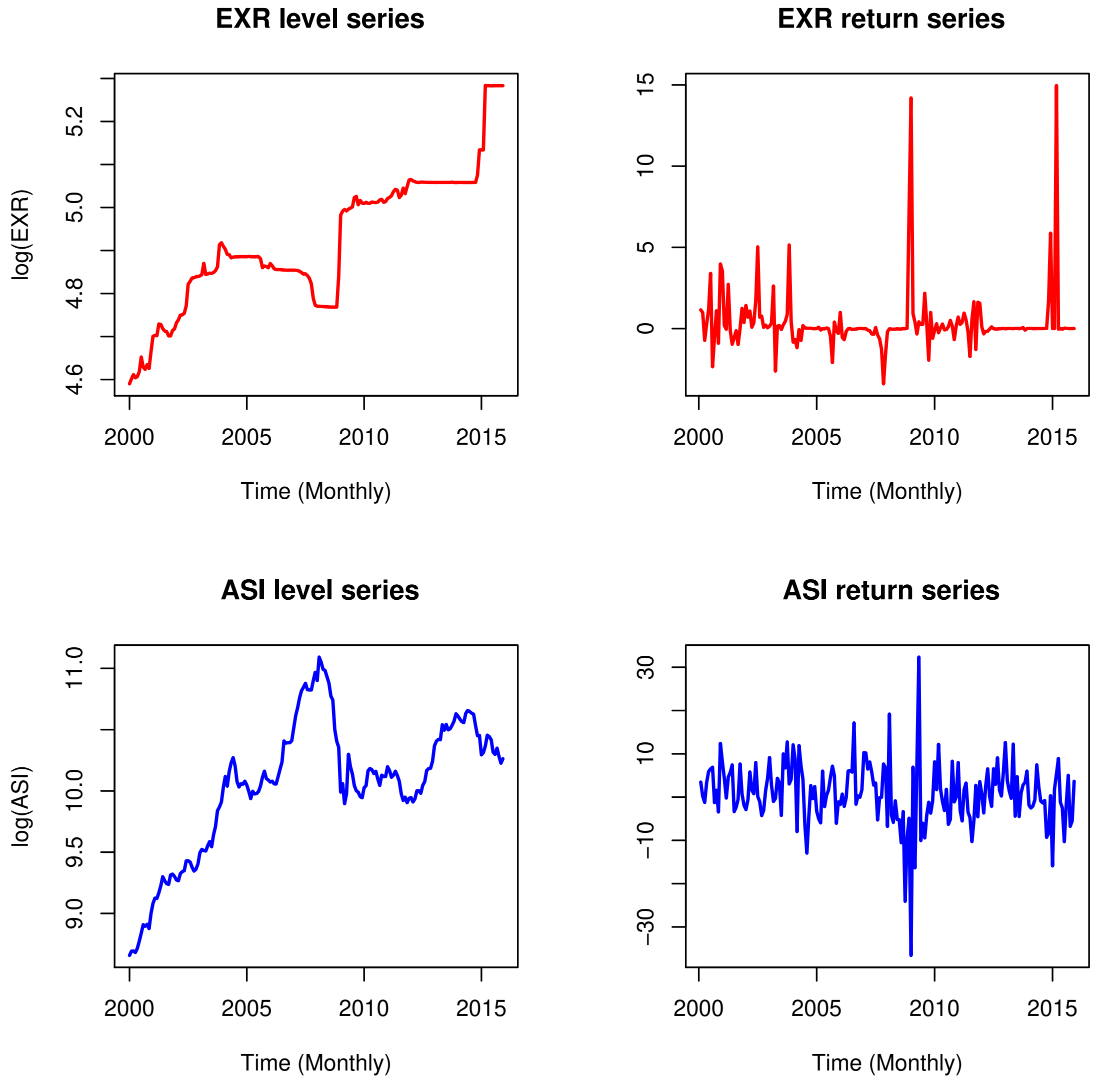

Figure 1: Time plots of stock prices and exchange rate both in levels and returns series.

empirical validation using techniques that can uncover such dependence or independence of the relationship.

In addition to the time series plot, Table 1 presents the descriptive statistics of the variables in levels and returns series. Concentrating on the return series, it can be seen that their means and medians are close to zero, and approximately zero for the median of the exchange rate returns.[7] In terms of the standard deviation, the stock price returns exhibit larger variation in its distribution (i.e. higher volatility) than the returns on exchange rate. Overall, both variables exhibit mean-reversion and volatility clustering which is typical of financial time series data. The kurtosis statistic indicates that the stock price returns is platykurtic (i.e. thin tailed), while the exchange rate returns is leptokurtic (i.e. fat tailed).

[7]This mean reversion property is clearly shown in Figure 1. For Table 1, the returns series (i.e. log first difference of the levels series) has been pre-multiplied by 100.

Table 1: Summary statistics

	ASI	EXR	S_t	E_t
Mean	10.042	4.920	0.840	0.363
Median	10.106	4.886	0.384	0.000
Standard deviation	0.548	0.158	7.096	1.893
Minimum	8.657	4.590	−36.588	−3.405
Maximum	11.092	5.284	32.352	14.964
Kurtosis	2.952	2.775	8.521	35.872
Skewness	−0.609	0.162	−0.486	4.996
Jarque-Bera	11.899^a	1.251	250.2^a	9394.2^a

Note: ^{a} indicates 1% significance level.

For skewness, stock price and exchange rate returns are negatively and positively skewed respectively, which implies that both variables are asymmetric. Moreover, the Jarque-Bera statistic which combines both properties of kurtosis and skewness indicates a rejection of the normality assumption for both variables.

Table 2: Unit roots test

Variables	Specification	ADF	DFGLS	ZA
ASI	Constant	−2.681	0.134	−3.952 [2008:8]
	Constant & trend	−1.690	−0.824	−4.473 [2008:8]
EXR	Constant	−0.543	1.389	−3.062 [2005:8]
	Constant & trend	−1.715	−1.928	−3.026 [2008:8]
S_t	Constant	−11.774^a	−6.861^a	−12.505^a[2008:3]
	Constant & trend	−11.969^a	−7.688^a	−12.548^a [2008:3]
E_t	Constant	−11.226^a	−7.713^a	−11.549^a [2008:12]
	Constant & trend	−11.200^a	−8.306^a	−11.538^a[2008:12]

Note: ADF is the Augmented Dickey-Fuller test; DFGLS is the Dickey-Fuller Generalized Least Squares test; and ZA is the Zivot-Andrews test with structural break. ^{a}, ^{b}, ^{c} indicates 1%, 5% and 10% significance level.

Furthermore, the stationarity properties of the variables in levels and returns series is verified using three unit roots tests. This include: the standard Augmented Dickey-Fuller (ADF) test of Dickey and Fuller (1979); the Dickey-Fuller generalized least squares (DFGLS) test of Elliot et al. (1996) which is more powerful than the ADF test because it applies the well-known Dickey–Fuller τ-test to locally demeaned or demeaned and detrended series; and the Zivot and Andrews (1992) (ZA) test which caters for structural breaks. The summary of the unit roots test is presented in Table 2. At their levels, all three unit roots tests fail to reject the null hypothesis of non-stationary for both stock price and exchange rate variables as they both exhibit random walk. However, both variables in their returns (or differenced) series are stationary which is consisted with their mean reverting properties as shown in

Figure 1. This stationarity property is consistent irrespective of the model specification, that is, with only constant or constant and trend as well as in the presence of structural breaks in the data.

4.2 Causality analysis

To investigate the nature of dependence for the relationship between stock prices and exchange rates changes, the following models is estimated:

$$S_t = a_0(\tau) + \sum_{i=1}^{p} \alpha_i(\tau) S_{t-i} + \sum_{j=1}^{q} \beta_i(\tau) E_{t-j} + \varepsilon_{S,t} \tag{6}$$

$$E_t = b_0(\tau) + \sum_{i=1}^{p} \psi_i(\tau) S_{t-i} + \sum_{j=1}^{q} \varphi_i(\tau) E_{t-j} + \varepsilon_{E,t} \tag{7}$$

where S_t and E_t are as defined above. Granger causality in quantile based on the sup-Wald statistics is applied to Eq. (6) and (7) respectively over the interval of [0.05, 0.95]. If the null hypothesis $H_0 : \beta_1(\tau) = \beta_2(\tau) = \cdots = \beta_q(\tau) = 0$ for τ in [0.05, 0.95] is not rejected, then E_t does not Granger cause S_t. Similarly, if the null hypothesis $H_0 : \psi_1(\tau) = \psi_2(\tau) = \cdots = \psi_p(\tau) = 0$ for τ in [0.05, 0.95] is not rejected, then S_t does not Granger cause E_t. Analogous to the Granger causality in quantile specification in Eq. (6) and (7), the counterpart linear Granger causality test between both variables is estimated for comparison using a bivariate autoregressive models as follows:

$$S_t = a_0 + \sum_{i=1}^{p} \alpha_i S_{t-i} + \sum_{j=1}^{q} \beta_i E_{t-j} + \varepsilon_{S,t} \tag{8}$$

$$E_t = b_0 + \sum_{i=1}^{p} \psi_i S_{t-i} + \sum_{j=1}^{q} \varphi_i E_{t-j} + \varepsilon_{E,t} \tag{9}$$

where $\varepsilon_{S,t}$ and $\varepsilon_{E,t}$ are i.i.d random disturbances. The Granger causality in mean between S_t and E_t is computed by the F-statistics of the least square (LS) method.[8] The Granger causality tests both in mean and quantiles for the relationship between stock prices and exchange rate is presented in Table 3.

For the full sample period (Period I), the sup-Wald test statistics of the Granger causality in quantiles reject the null of non-causality as both stock price and exchange rate show significant feedback interactions (i.e. two-way dependence). In other words, there is a

[8] Based on the Akaike Information Criterion (AIC), the optimum lag selection is two for both markets.

Table 3: Granger causality test

Period	$H_0: E_t$ does not Granger cause S_t sup-W_T(QR)	F(LS)	$H_0: S_t$ does not Granger cause E_t sup-W_T(QR)	F(LS)
I	9.265^c	0.441	17.942^a	13.47^a
II	7.869	1.263	5.238	1.225
III	8.081	1.093	10.391^b	10.037^a
IV	8.082	1.046	10.390^b	15.607^a

Note: Critical values for sup-W_T statistics on [0.05, 0.95] are 13.01, 9.84, and 8.19 at 1%, 5% and 10% significance level respectively. Period I is the full sample period (2000:1–2015:12), Period II is tranquil times (2000:1–2005:12), Period III is boom and bust period (2006:1–2010:12), and Period IV is the recovery period (2011:1–2015:12). ^{a}, ^{b}, ^{c} indicates 1%, 5% and 10% significance level.

significant bi-directional causal relationship between returns on stock price and exchange rate changes: exchange rate Granger cause stock returns at 10% significance level, and at the same time, stock returns Granger cause exchange rate at 1% significance level. This evidence suggest the existence and interplay of both the international trading and the portfolio balance effect models over the entire sample period. Moreover, this bi-directional causal relationship is consistent with the findings of Aliyu (2009), and that of Fowowe (2015) only in the case where exchange rate changes causes stock returns. Meanwhile, the linear causality show evidence of a one-way dependence from stock price return to exchange rate changes, again supporting the portfolio balance effect between stock price and exchange rates, and thus confirms the findings of Oyinlola et al. (2012) with the same methodology.

For the tranquil times (Period II), both Granger causality in mean and quantiles do not reject the possibility of a causal relationship between stock returns and exchange rate changes in both directions respectively. This means that both the stock and foreign exchange markets show little interactions during this period. In other words, it could either be that both markets were less integrated or that an efficient transmission of information existed between them. One plausible explanation for this outcome is that the boom in stock market activities rallied up at the turn of the 21st century with the automation of the Nigerian stock exchange market.[9] Moreover, the economic reforms of government during this period, particularly the 2004 banking sector reforms which emphasized the consolidation and recapitalization of banks fuelled the boom in the equity market as banks sort to raise additional capital with equities quadrupling in value than in previous years. Thus, the stock market experienced a beehive of trading activities as equities became an haven for wealth maximization.

Period III is characterized by the bubble and bust cycles in the stock market. As shown in Figure 1, during this period the Nigeria stock market reached its highest historical peak

[9] The Nigerian Stock Exchange (NSE) was automated on April 27, 1999.

in terms of the All-Share Index and plummeted massively following the spillover effects of the global financial crises of 2007-2009, and the exchange rate appreciated and depreciated respectively in both scenarios. As shown in Table 3, the Granger causality in mean and quantiles suggest that stock returns leads to exchange rate changes, whereas these tests reject possible causality from exchange rate changes to stock returns. This evidence indicate the existence of the portfolio balance effect due to the volatile nature of the stock market during this period. Furthermore, the evidence confirms the fact in the literature in which stock and foreign exchange markets interaction deepens during periods of bubbles and financial crises as considerable quantities of foreign portfolio capital enters or leaves the stock market causing the exchange rate to appreciate or depreciate. Thus, during financial downturn, the spillover effects of high volatility in stock market activities causes instabilities in other financial markets such the foreign exchange market. This outcome is consistent with the findings of Salisu and Oloko (2015) for Nigeria, and other studies that have shown that the stock market led the foreign exchange market during the Asian financial crisis as well as the banking crisis of 2007-2010 in advanced economies (see Granger et al., 2000; Caporale et al., 2014; Yang et al., 2014). Furthermore, for the recovery period (Period IV), the evidence based on both Granger causality tests supports the dependence between stock prices and exchange rates as stock price returns leads the changes in exchange rates. This implies that relationship between stock prices and exchange rates is being driven by international capital flows, and not trade flows. This can be attributed to the measures undertaken to restore investor confidence which has returned stability to market activities, and also encouraged capital inflows.

All in all, the evidence indicate a bi-directional effect between stock prices and exchange rates over the entire period. Thus, exchange rate changes can influence stock prices of listed firms through the international trading effect, whereas stock market changes through the capital account balance effect can influence the volatility of the exchange rate as foreign capital flows into and out of the Nigerian stock market. On the other hand, with exception of Period II in which there is no dependence between stock prices and exchange rates, both linear and non-linear dependence is observed for Periods III and IV. Here, the channel of dependence runs from stock prices to exchanges rates. Moreover, the strength of the dependence is stronger during periods of bubbles and financial downturn of the stock market than in tranquil times. Thus, for the Nigerian economy, the results show the dominance of the portfolio balance effect as volatilities in the stock market is likely to spillover into the foreign exchange market causing volatilities in the exchange rate. As such, stabilizing the stock market becomes paramount for the country's exchange rate management in order to reduce the transmission of systemic risk and contagion between both markets.

5 Conclusion

This paper investigates the interdependence between stock prices and exchange rate in Nigeria for the period running from January 2000 to December 2015 which is characterized by the boom, bust and recovery cycles of the stock market. Granger causality test in mean and quantiles were used to gauge possible dependence between returns on stock prices and exchange rate. Granger causality test in quantiles which is estimated by means of quantile regression (QR) is more robust to the non-normalities and non-linearity features of financial data than its counterpart mean causality test. Hence, it is able to exploit the possible non-linear dependence between both variables over the entire QR parameter process.

The results are summarized as follows. First, there is a bi-directional dependence between stock prices and exchange rates over the entire sample period. Second, this dependence between both variables does not exist during tranquil or normal times. Third, during the periods of market bubbles and bust, the dependence becomes strengthen with the channel of effect running from stock prices to exchange rates. Similarly, the dependence from stock prices to exchange rates is observed during the recovery period in the aftermath of the stock market crash. Overall, the evidence suggest the dominance of the portfolio balance effect for the stock prices and exchange rate nexus in Nigeria. This means that stock market volatilities can be transmitted to the foreign exchange market thereby causing volatilities in the exchange rate. Hence, it is imperative for policy makers to take into account the stock market changes and dynamics in designing policies for the exchange rate management in the country. In this context, stabilizing the stock market can minimize the transmission of systemic risk and contagion between both markets.

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