Centre for Econometric And Allied Research

CEAR

WORKING PAPER SERIES: WPS/0031

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Cite as:

Salisu A. A and Umar B. Ndako (2017) A new look at the stock price – exchange rate nexus - *Centre for Econometric and Allied Research, University of Ibadan Working Papers Series, CWPS 0031*

A new look at the stock price – exchange rate nexus

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Abstract

The extant literature on exchange rate forecasting on the basis of the Dornbusch-Frankel, Frenkel-Bilson and Hooper-Morton models prominently reveals the dominance of the autoregressive models over the theory-based models. Some studies have however attempted to upturn the results by including the lagged dependent variable in the theory-based models which somewhat implies comparing a modified random walk with a traditional random walk. We follow a different approach both in terms of theory and methodology. We offer an innovative exposition of the Portfolio Balance theory to stock price – exchange rate nexus. Consequently, a predictive model for exchange rate where stock price is a predictor is formulated. The formulated model is expressed in both linear and nonlinear form in order to account for the role of asymmetric changes in stock prices in exchange rate forecasting. Thereafter, we employ the Lewellen (2004) and Westerlund and Narayan (2014) methods which account for any inherent statistical properties of the predictors. Our results validate the Portfolio Balance theory where we show that the sector-level stock prices consistently turn up as good predictors of the exchange rates. The predictive model proposed in this work does not require the inclusion of a lagged dependent variable to beat the autoregressive models which is the practice in the existing literature. We further demonstrate that asymmetry matters to a large extent in the nexus both for the in-sample and out-of-sample predictability.

JEL Classification: C53; F31; G11

Key Words: portfolio balance theory; US sectoral stock prices; exchange rates; asymmetry

A new look at the stock price – exchange rate nexus

1. Introduction

In recent years, the emergence of new markets, financial globalization and implementation of flexible exchange rates regimes across countries have brought about dramatic changes in many economies (Ali, et al. 2015), one of which is the bridge in gap between domestic and foreign financial markets. The financial markets integration has implications for understanding the dynamism of exchange rate movements to changes in fundamentals in the domestic economy (Stillwagon, 2016). Financing and investment decisions are affected by fluctuations in exchange rates; and these fluxes create uncertainty which makes decision making and profit anticipation difficult (Khan and Abbas 2015). This has brought to fore the need to understand the role of risks associated with exchange rate movements in investment decisions, international investors hedging and portfolio diversification process (Aydemir and Demirhan, 2009; Kutty, 2010). Consequently, research interests have been motivated to unveil any probable interconnection between financial and foreign exchange markets. In other words, the search for evidence in favour of the linkages between exchange rate shocks and real and financial variables of the economy is a clear motivation for assessing the nexus between exchange rate and stock market prices.

The modelling of stock prices has been conducted on the basis of different classes of asset pricing models; the Arbitrage Pricing Theory of Ross, (1976) and a plethora of Capital Asset Pricing Models (CAPM) (for example Sharpe, 1964; Lintner, 1965; Merton, 1973, 1990; Breeden, 1979; Jagannathan and Wang, 1996; Fama and French, 1993, 1995, 1996, 2015, 2017). These models suggest that returns of financial assets such as stocks are influenced by economic and financial risks (see also Fama and French, 2004; Salisu, et al., 2017; Swaray and Salisu, 2017). In line with the foregoing theories, a good number of the empirical literature has examined the forecasting accuracy of different economic variables in the predictive model of stock market.

Most of the studies appear to focus more prominently on the role of oil price shocks in the stock price model.[1] A host of other studies examine the influence of exchange rate risks in stock markets models (see for example; Aydemir and Demirham, 2009; Kutty, 2010; Litsios, 2013; Dellas and Tavlas, 2013; Zubair, 2013; Al-Shboul and Anwar, 2014; Raza et al., 2016; Zivkov et al., 2016).

Intuitively however, the present study departs markedly from these preceding ones both in terms of theory and methodology. The focus of the present study is to examine the predictive role of stock prices in exchange rate modelling rather than the reverse predictability evident in the literature.[2] The observed trend in the literature is quite understandable for a number of reasons. First, in the valuation of stocks, it is important to account for both market (systematic) risks and exchange rate risk is a major consideration in this regard particularly for large stock markets with evidence of large inflows of foreign portfolio investments. Second, asset pricing theories such as the International CAPM (see Stulz, 1981a, 1981b, 1995) and the Arbitrage Pricing Theory (APT) (see Ross, 1976) have continued to offer very strong motivation for the inclusion of exchange rate in the stock price model.

Our clear departure from the empirical literature is underscored by the increased financial globalization and integration particularly for a large open economy like the US where the movements of financial assets may impact on exchange rate behaviour (see also Khan and Abbas, 2015). The underlying theoretical motivation for such direction of relationship is provided by the Portfolio Balance theory (with contributions from Black, 1973; Dornbusch, 1975; Boyer, 1977; Branson, et al. 1977; Kouri and de Macedo, 1978; Allen and Kenen, 1980; Branson, 1983; and Frankel, 1983). The theory underscores the influence of financial assets (including demand

[1]A review of some of these papers is available in El-Sharif et *al.* (2005); Narayan and Gupta (2014); Narayan and Sharma (2014); Salisu and Isah(2017b) and Swaray and Salisu (2017).

[2] We do acknowledge papers dealing with exchange rate forecasting (see Moosa and Burns, 2014a,b&c; for a review); however, all these papers do not account for the role of stock price and therefore their models and consequently their analyses are not viewed from the perspective of the Portfolio Balance theory. See also section 2.0 of this paper for a review of relevant papers on exchange rate forecasting.

and supply of money) in exchange rate adjustments. This influence is rooted in the behaviour of risk averse investors who seek to diversify their investment portfolio from countries with lower stock returns to countries with higher stock returns, leading to high demand (currency appreciation) for the currencies of the countries with higher stock return at the expense of the countries with lower stock returns (see Ulku and Demirci, 2012; Salisu and Oloko, 2015 for more details).

In addition, the theory also opines that portfolio adjustments (i.e. movements in the foreign capital inflows and outflows) occur whenever there is a change in the stock prices (see Kutty, 2010; Zivkov, et al 2016 for more detailed discussion of the theory). For instance, increase in demand for domestic stocks will cause higher needs for domestic currency, which eventually leads to its appreciation. Conversely, decline in the stock prices will result in diminished corporate wealth leading to the reduction in the country's wealth. This may lead to a fall in the demand for money; monetary authorities therefore reduce the interest rates to alleviate this situation. When interest rates are lower, capital may flow out of the country to take advantage of higher interest rates in other part of the world resulting in currency depreciation.

The foregoing has put reliance on the portfolio balance theory and induced interest in assessing the role of stock price in exchange rate dynamics. Empirically and adopting the portfolio balance model, Friedman (1988) and Boyle (1990) have suggested that modelling of the equilibrium exchange rate must be extended to include stock markets in addition to bond and equity markets. Subsequently, a number of studies (for example Smith, 1992; Tsai 2012; Kutty, 2010; Khan and Abbas 2015; Zivkov, et al 2016) find evidence in support of the nexus between stock price and exchange rate in causal or impact analyses. The point of departure of the present study therefore is to conduct a predictability analysis that considers stock price as a predictor of exchange rate in a forecasting model.

Our methodology follows the approach of Lewellen [LW hereafter] (2004) and Westerlund and Narayan [WN hereafter] (2012, 2014) to analyse the predictive model for the stock price – exchange rate nexus. This approach simultaneously captures any potential endogeneity and persistence effects in the predictive model and in addition, the WN (2014) method also accounts for conditional heteroscedasticity effect which is a prominent feature of high frequency series. Ignoring such effects when they exist may bias the forecast results (see WN, 2014). This approach has also been used to analyse the predictive model for stock returns nexus both at the aggregate and firm levels (see Narayan and Gupta, 2014; Narayan and Sharma, 2014; Bannigidadmath and Narayan, 2015; Narayan and Bannigidadmath, 2015; Devpura et al., 2017; Salisu et al., 2017a), inflation (see Salisu and Isah, 2017a; and Salisu et al., 2017b) and expenditure (see Makin et al., 2014).

In addition, we also account for the role of asymmetry in the stock price – exchange rate nexus. This consideration is particularly motivated by the studies of Kilian (2009), Kilian and Vigfusson (2011) and Atems et al. (2015) which suggest that exchange rate responds asymmetrically to oil price shocks. A number of other studies (for example Koutmos and Martin, 2007; Hsu *et al.*, 2009; Naifar and Al Dohaiman, 2013; Dieci and Westerhoff, 2013; Ali, et al. 2015; Bahmani-Oskooee and Saha, 2016) have affirmed asymmetry in the nexus between exchange rate and stock market prices although the asymmetries run from exchange rate to stock prices. The theoretical basis for considering asymmetry in the stock market and exchange rate nexus is rooted in the financial market model of Dieci and Westerhoff (2013). In the model, the stock markets are linked via and with the foreign exchange market given that international transactions of stock market traders go through the foreign exchange market. The model shows that the stock and foreign exchange markets are, by construction, nonlinearly interwoven and that interactions between them may give rise to endogenous dynamics. Thus, accounting for stock price asymmetries in the predictive model for exchange rate will constitute valuable information in the design of investment and hedging strategies for portfolios diversification.

For a more robust analysis, we utilize both the aggregate and industry level stock prices. The idea is to ascertain whether the portfolio balance theory-based predictive model for exchange rate is not sensitive to the choice of stock prices. In addition, three prominently traded US currency pairs are analysed. These currency pairs majorly reflect the G7 countries involving Germany and France (represented with Euro/USD), Canada (CAD/USD) and United Kingdom (GBP/USD).[3] The behaviour of these exchange rates is hypothesized to be representative of other US exchange rates. All These considerations offer robust insights in relation to the nexus between exchange rate and stock price.

Following this section, we structure the rest of the paper as follows. The next section provides a review of the literature on exchange rate forecasting. Thereafter, the discussion of the predictive model and the underlying estimation and forecasting procedures is rendered in Section 3. In Section 4, we offer some preliminary analyses while Section 5 presents and discusses the results. Section 6 concludes the paper.

2.0 A review of the literature on exchange rate forecasting

Exchange rate forecasting and predictability has a long history in international finance. Researchers are relentlessly searching for appropriate models to provide accurate and reliable forecasts for exchange rates to aid investors and monetary authorities. One of the theories that have guided researchers in exchange rate modelling is the uncovered interest rate parity theory which situates cross-country interest rate differential as a key explanatory variable for modelling exchange rate (see Chen, et al, 2016; Lansing and Ma, 2017 for empirical findings). Others are purchasing power parity theory, asset pricing models (for example Lintner, 1965; Sharpe, 1964 and the three-factor model of Fama and French, 1993) and the flow models.

Further, the forecasting of exchange rate has been largely conducted on the basis of the structural "models of the 1970s;" Frenkel-Bilson (Frenkel, 1976; Bilson, 1978), Dornbusch-Frankel (Dornbusch, 1976; Frankel, 1979) and Hooper-Morton (Hooper

[33] USD is the US dollar, CAD is the Canadian dollar and GBP is the Great Britain Pound Sterling.

and Morton, 1982) asset models (see Meese and Rogoff, 1983 for more expositions of the models). These theoretical models capture the predictive power of such variables as relative money supplies, relative incomes, short-term interest rate differentials and relative prices among others for exchange rate forecasting (see Moosa and Burns, 2014a; Moosa and Burns, 2014b; Moosa and Burns, 2014c; Burns and Moosa, 2015; Ahmed, et al. 2016 for empirical literatures).

However, Meese and Rogoff (1983) cast a dark shadow on the efficacy of these economic models for forecasting exchange rates. Meese and Rogoff (1983) put these economic models of exchange rate to test and show that none of them yield any forecasting improvement in root mean square error or mean absolute error over the random walk model. The major message in Meese and Rogoff (1983) is that economic fundamentals such as money supply, real income, trade balance, inflation rate and interest rates could not forecast future exchange rates better than a simple random walk forecast. This implies that exchange rate is well approximated by a driftless random walk (see Wright, 2008; Lansing and Ma, 2017 for empirics).

In support of the Meese and Rogoff (1983) submission, Cheung, et al. (2005) examines the out-of-sample performance of the interest rate parity, monetary, productivity-based and behavioural exchange rate models and concludes that none of the models consistently outperforms the random walk at any horizon. Also, Ahmed, et al. (2016) examines the predictability of bilateral exchange rates from asset pricing models and find that all versions of the factor models largely fail to outperform the benchmark random walk model for the out-of-sample forecasting of exchange rate. Further, Ince, et al. (2016) also find weaker evidence of predictability for the traditional interest rate differential, purchasing power parity, and monetary models against the random walk model.

The failure of traditional fundamental variables to improve forecasts of future exchange rates has been dubbed the exchange rate disconnect puzzle and this Conundrum has been seen as the major weakness of international macroeconomics (see Bacchetta and van Wincoop, 2006; Lansing, and Ma, 2017). Consequently, the exchange rate disconnect puzzle spurred economists to look for new directions of research. One such attempts to solve the puzzle is by introducing the lagged dependent variable (i.e. a random walk component) to make the model dynamic. However, studies have raised doubts on this proposition that exchange rate models can outperform the random walk in out-of-sample forecasting if the models are specified in a dynamic form, arguing it that amounts to trying to beat a random walk with another random walk model (see Moosa and Burns, 2014b; Moosa and Burns, 2014c; Burns and Moosa, 2015 for more). Thus, on the basis of the foregoing arguments, we refrain from modelling exchange rate with such autoregressive models.

Another attempt by economists to solve the Meese-Rogoff puzzle led them to consider incorporating the Taylor's rule. A twist in the literature promotes the view that Taylor's rules are helpful in predicting exchange rates (see more in Engel and West, 2006; Molodtsova and Papell, 2009; Byrne, et al. 2016). The Taylor's rule (Taylor, 1993) specifies that the central bank adjusts the short run nominal interest rate in response to changes in inflation and the output gap (see Engel and West, 2005, Engel, et al. 2008, Mark, 2009; Molodtsova and Papell, 2009 for more) and these have implications on exchange rates determination in that the home country also targets the real exchange rate (Engel and West, 2005). This paradigm shift to Taylor rule fundamentals model was motivated by the shift in policy evaluation from money supply to interest rate as the instrument of monetary policy (Ince, et al. 2016).

In this vein, following Engel and West (2006), there have been attempts to incorporate Taylor's rule fundamentals into the exchange rate model due to suggestion that it could help outperform random walk model for exchange rate forecasting. Consequently, a number of studies have shown that the Taylor rule model has better performance in the expectation of exchange rate determination than random walk model (see for example Engel, et al. 2007; Molodtsova and Papell, 2009; Wilde, 2012; Ince, et al. 2016; Wang, et al. 2016; Byrne, et al. 2016; Ince, et al.

2016). Commenting on the recent studies, Wang and Wu (2012) in a study of OECD countries show that the Taylor rule model is significantly better in the expectation of exchange rate dynamics than the random walk model. Ince, et al. (2016) evaluates the short-run out-of-sample predictability for the exchange rates of eight different currencies against the US dollar and find strong evidence in favour of the Taylor rule model compared to the random walk model. Wang, et al. (2016) and Byrne, et al. (2016) also show that the Taylor rule-based exchange rate model outperforms the random walk model.

We depart from these previous studies that adopt the aforementioned models of exchange rate even though augmented with the Taylor's rule. We situate our exchange rate modelling around the portfolio balance theory. This allows us to take advantage of the predictive content of stock prices for forecasting exchange rates. The nexus between stock prices and exchange rate to support the consideration of stock price in the predictive model of exchange rates has been carefully outlined in the previous section from arguments presented by the portfolio balance theory and such empirical studies as Friedman, 1988; Boyle 1990; Smith, 1992; Tsai 2012; Kutty, 2010; Khan and Abbas 2015; Zivkov, et al 2016. Interestingly, our results challenge the status quo not only in accentuating the predictive power of stock prices with the portfolio balance theory in forecasting exchange rates, it also provides direction in the light of Meese-Rogoff puzzle to show that random walk model could be outperformed in exchange rate forecasting.

Some other studies have also argued that economic models of exchange rates can outperform the random walk in out-of-sample forecasting if for example, forecasting power is not measured by mean square error but by direction accuracy and profitability (see Moosa, 2013; Moosa, and Burns, 2014a; Moosa and Burns, 2014c). The argument is that the RMSE of the economic models rise faster than that of the random walk and as such lead to failure to outperform the random walk. Thus, in addition to the inclusion of peculiarities like persistence, endogeneity, asymmetry and conditional heteroscedasticity in the exchange rate forecast model, we also complement the mean square error measure with the Campbell-Thompson and Diebold-Mariano forecast evaluation criteria.

3.0 The Model and Forecast Evaluation

3.1 The Model

Following the Portfolio Balance theory and the estimation procedure of Lewellen (LW hereafter) (2004) and WN (2014), we specify a predictive model for US exchange rates as follows:

$$e_t = \mu + \delta s_{t-1} + \eta\left(s_t - \rho s_{t-1}\right) + \xi_t \tag{1}$$

where e_t is the log of exchange rate and s_t is the log of stock price. The null hypothesis of no predictability is $H_0: \delta = 0$. A positive relationship implies appreciation in US dollar relative to reference currency [say CAD, EUR or GBP] while a negative relationship implies depreciation.[4]The first term $\left(\delta s_{t-1}\right)$ captures the traditional representation of a predictive model [in which case, the model is in bi-variate form as $e_t = \phi + \delta s_{t-1} + \varepsilon_t$]. However, LW (2004) provides justification for the inclusion of the second term $\left(s_t - \rho s_{t-1}\right)$ in order to capture any inherent persistence effect in a predictive model. This is particularly valid for high frequency predictors like stock price that seem to exhibit a high persistence effect or random walk [where $\rho = 1$] (Engle, 1982).[5]The presence of a statistically significant persistence effect may introduce endogeneity bias due to possible correlations between the predictor and the regression error.[6]Thus, it becomes necessary to pre-test the series for persistence

[4]This is because of the way the US exchange rates are measured where all the currency pairs are expressed against US dollar. In other words, a positive relationship between CAD/USD and stock price will conversely imply depreciation of Canadian dollar relative to US dollar while a negative relationship signifies appreciation of CAD/USD. The same applies to EUR/USD and GBP/USD.

[5] The persistence equation follows the WN (2014) approach which assumes $s_t = \varphi\left(1-\rho\right) + \rho s_{t-1} + \upsilon_t$ where $\upsilon_t \sim N\left(0, \sigma_\upsilon^2\right)$.

[6]This is tested using the equation $\varepsilon_t = \eta \upsilon_t + \xi_t$ where ε_t is from the traditional predictive model and υ_t is from the equation that captures persistence in s_t as in footnote 3. There is endogeneity effect if the parameter - η is found to be statistically significant. Re-arranging the endogeneity equation after

and incorporating same if found to be evident.[7]The estimation of equation (1) by the ordinary least squares (OLS) method gives a bias-adjusted OLS estimator for δ and is given as (see LW, 2004):

$$\hat{\delta}_{adj} = \hat{\delta} - \eta(\rho - 1) \tag{2}$$

Also, previous studies using high frequency predictors find that they tend to exhibit conditional heteroscedasticity effect which has to be dealt with in the estimation process (see Narayan and Gupta, 2014; Narayan and Sharma, 2014; Bannigidadmath and Narayan, 2015; Narayan and Bannigidadmath, 2015; Devpura et al., 2017; Salisu and Isah, 2017a; Salisu et al., 2017a,b). Nonetheless, we also subject our predictors to conditional heteroscedasticity test. To account for this feature, WN (2014) propose a Feasible Quasi Generalized Least Squares (FQGLS) estimator as alternative estimator to the bias-adjusted OLS estimator of LW (2004). The FQGLS estimator exploits the information contained in the conditional heteroscedastic variance of the regression residuals in order to generate more precise estimates. Their estimator assumes the regression error, that is ξ_t, follows an autoregressive conditional heteroskedastic (ARCH) structure - $\hat{\sigma}^2_{\xi,t} = \alpha + \sum_{i=1}^{q} \psi_i \hat{\xi}^2_{t-i}$, and the resulting $\hat{\sigma}^2_{\xi,t}$ can be used as a weight in the predictive model (see also Narayan and Gupta, 2014; Bannigidadmath and Narayan, 2015; Narayan and Bannigidadmath, 2015; Devpura et al., 2017). The estimation of the weighted predictive model by OLS is described as the FQGLS estimator. Thus, the estimator can be described as a GLS-based t-statistic for testing $\delta = 0$ is given as:

$$t_{FQGLS} = \frac{\sum_{t=q_m+2}^{T} \tau_t^2 s_{t-1}^d e_t^d}{\sqrt{\sum_{t=q_m+2}^{T} \tau_t^2 \left(s_{t-1}^d\right)^2}} \tag{3}$$

where $\tau_t = 1/\sigma_{\xi,t}$ is used in weighting all the data in the predictive model and $s_t^d = s_t - \sum_{s=2}^{T} s_t / T$. As previously mentioned, the asymmetric version of equation (1)

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substituting $\upsilon_t = s_t - \varphi(1-\rho) - \rho s_{t-1}$ and $\varepsilon_t = e_t - \phi - \delta s_{t-1}$ gives a predictive model expressed in equation (1) where $\mu = \phi + \eta\varphi(1-\delta)$.

[7]However, in the absence of these effects, equation (1) reduces to the traditional predictive model where $e_t = \phi + \delta s_{t-1} + \varepsilon_t$.

is partitioned into two for positive and negative changes in stock price as given below:

$$e_t = \mu^+ + \delta^+ s_{t-1}^+ + \gamma^+ \left(s_{t-1}^+ - \rho^+ s_{t-1}^+ \right) + \xi_t^+ \tag{4a}$$

$$e_t = \mu^- + \delta^- s_{t-1}^- + \gamma^- \left(s_{t-1}^- - \rho^- s_{t-1}^- \right) + \xi_t^- \tag{4b}$$

where s_t^+ and s_t^- denote the positive and negative stock prices respectively. In essence, equation (1) is the predictive model of exchange rate with a symmetric stock price while equations (4a) and (4b) represent the asymmetric variants. The computation of s_t^+ and s_t^- follows the Shin et al. (2014) approach as given below:[8]

$$s_t^+ = \sum_{k=1}^{t} \Delta s_{ik}^+ = \sum_{k=1}^{t} \max(\Delta s_{ik}, 0) \tag{5a}$$

$$s_t^- = \sum_{k=1}^{t} \Delta s_{ik}^- = \sum_{k=1}^{t} \min(\Delta s_{ik}, 0) \tag{5b}$$

where equations (5a) and (5b) positive and negative partial sum decompositions of stock price changes respectively.

There is evidence of asymmetry, if the coefficients of s_t^+ and s_t^- are statistically different from each other; otherwise their effect on exchange rate is considered identical.

3.2 Forecast Evaluation

The forecast evaluation is carried out for both the in-sample and out-of-sample periods. We use the 50 percent observations of the full-sample for the forecast evaluation and the rolling window approach[9] which accounts for the time-varying behavior in the stock price-exchange rate nexus is employed to produce the forecast results. We start with the in-sample evaluation which involves testing for the predictability of stock price in the exchange rate model for both the symmetric and

[8]This approach has continued to gain recognition in the literature. Examples of studies that have employed this approach to exchange rate modelling include, but not limited to, Apergis (2015), Bahmani-Oskooee et al. (2016, 2017), Bahmani-Oskooee and Aftab (2016, 2017), Bahmani-Oskooee and Kanitpong (2017), and Bahmani-Oskooee and Saha (2017).

[9]This approach has also been used by Narayan and Gupta (2014), Bannigidadmath and Narayan (2016) and Salisu et al. (2017a,b).

asymmetric variants using the GLS-based t-statistic as well as the Root Mean Square Error (RMSE). As customary when dealing with exchange rate forecasting (see Moosa and Burns, 2014a,b,c for a review), we also estimate first order $(e_t = \alpha + \rho e_{t-1} + \upsilon_t)$ and second order $(e_t = \alpha + \rho_1 e_{t-1} + \rho_2 e_{t-2} + \upsilon_t)$ autoregressive models and thereafter we compare their forecast results with those obtained from the symmetric predictive model using the Campbell-Thompson (C-T hereafter) test[10] and Diebold-Mariano (D-M) test[11]. The C-T test is described as $R^2(OOS\_R)$ statistic where $OOS\_R = 1 - \left(\widehat{MSE}_1 / \widehat{MSE}_0\right)$. The $\widehat{MSE}_1$ and $\widehat{MSE}_0$ are the mean square error (*MSE*) of the prediction from the unrestricted and restricted models, respectively. The restricted model in this case is the autoregressive model while the unrestricted version is the symmetric model. A positive value of the statistic i.e. $OOS\_R > 0$ suggests that the unrestricted model outperforms the restricted model; otherwise, it does not.

Also, the D-M testis used to test for the equality of forecast accuracy of two forecasts (in this case between the autoregressive model and the symmetric model). The test is given as:

$$\text{D-M stat} = \frac{\bar{d}}{\sqrt{\frac{1}{T}V(d)}} \sim N(0,1) \tag{6}$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T}\left[g(\xi_{it}) - g(\xi_{jt})\right]$ is the sample mean loss differential and $V(d)$ is the unconditional variance of d. The $\{\xi_{it}\}_{t=1}^{T}$ and $\{\xi_{jt}\}_{t=1}^{T}$ are the forecast errors associated with the two forecasts say $\{\hat{y}_{it}\}_{t=1}^{T}$ and $\{\hat{y}_{jt}\}_{t=1}^{T}$ respectively. The $g(\xi_{it})$ and $g(\xi_{jt})$ are the loss functions associated with these two forecasts while $d_t \equiv g(\xi_{it}) - g(\xi_{jt})$ is the loss differential. The null hypothesis of equal forecast

[10]See Campbell and Thompson (2008).
[11]See Diebold and Mariano (1995).

accuracy for two forecasts is that $E\left[d_t\right]=0$. Thus, the forecast accuracy of the symmetric and autoregressive models is considered relatively equal if the null hypothesis of the D-M test is not rejected; otherwise, it is not.

Also, the D-M test is extended to the asymmetric variants both for the in-sample and out-of-sample forecasts in order to test whether the forecast accuracy of positive and negative changes in stock prices is equal. In the literature, the forecast combination approach has also been found to improve forecast results (see Timmermann, 2013 for a review). Thus, we also consider this approach to test whether combining the forecasts of positive and negative changes in stock price will enhance individual forecasts. We consider a simple average of the forecast results of both the positive and negative changes with the individual. The Combined forecast $f\left(\hat{f}_1, \hat{f}_2\right)$ is assumed to dominate individual forecasts $\hat{f}_1$ and $\hat{f}_2$ if $E\left[L\left(\hat{f}_i, y_{T+h}\right)\right] > \min E\left[L\left(f\left(\hat{f}_1, \hat{f}_2\right), y_{T+h}\right)\right]$, for $i=1,2$. (Timmermann, 2013).

4.0 Data source and description

We utilize data covering three US exchange rates involving the British pound (GBP/USD), Euro (EUR/USD) and Canadian Dollar (CAD/USD) and US stock prices covering both the aggregate and individual sectors. All the datasets were obtained from the Bloomberg terminal and the data scope showing the start and end dates is presented in Table 1. The data are of different observation numbers albeit adjusted accordingly before estimations. Except for EUR/USD with 513 observations and a range from January 1975 to September 2017, other exchange rates have 561 observations ranging from January 1971 to September 2017. Similarly, apart from real estate sector, other sectors' stock prices have 337 observations ranging from September 1989 to September 2017; aggregate stock price spans December 1927 to September 2017 making 1078 observations.

Table 1: Frequency Table

Variables	Start Date	End Date	Obs.
Exchange Rates			
GBP/USD	29/01/1971	06/09/2017	561
EUR/USD	31/01/1975	06/09/2017	513
CAD/USD	29/01/1971	06/09/2017	561
Stock prices			
Aggregate	30/12/1927	05/09/2017	1078
Financial Sector	29/09/1989	05/09/2017	337
Info Tech Sector	29/09/1989	05/09/2017	337
Industry Sector	29/09/1989	05/09/2017	337
Energy Sector	29/09/1989	05/09/2017	337
Real Estate Sector	31/10/2001	05/09/2017	192
Telecom Sector	29/09/1989	05/09/2017	337
Material Sector	29/09/1989	05/09/2017	337
Consumer Staples	29/09/1989	05/09/2017	337
Health Sector	29/09/1989	05/09/2017	337
Consumer Disc Sector	29/09/1989	05/09/2017	337
Utilities Sector	29/09/1989	05/09/2017	337

Source: Compiled from Bloomberg terminal

Conventionally, exploring historical information derivable from series by graphical illustrations permits some insights into their possible co-movements and detection of likely responses to structural adjustments. Figure 1 plots aggregate stock price for all sectors against each exchange rate, some positive co-movements are discernible from the graphs. The three exchange rates gained strength from the technology bust given the spikes noticeable between 1999 and 2002.These gains were transient as a general value decline followed. Meanwhile, the Canadian Dollar (CAD/USD) seems less volatile when compared with Euro (EUR/USD). Generally, all the exchange rates exhibit some largely traceable positive co-movement with aggregate stock price.

Fig. 1: Aggregate Stock Price and Exchange Rate

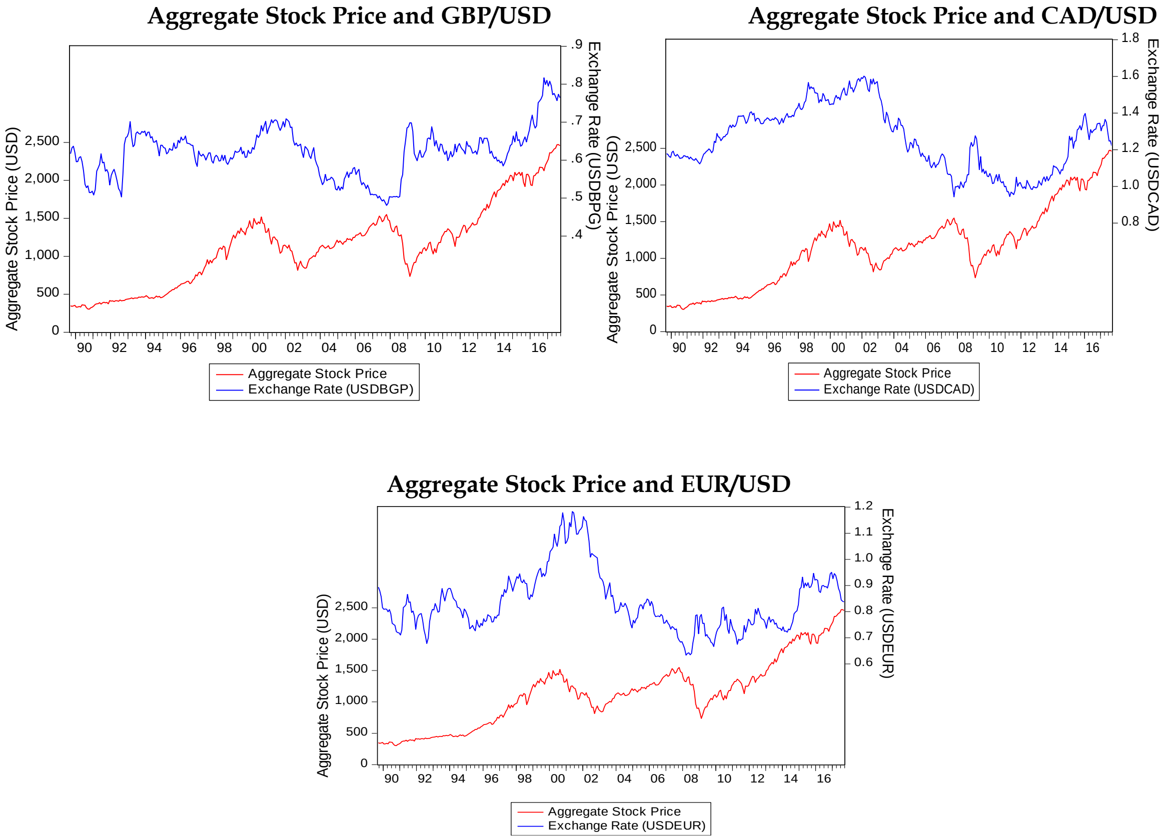
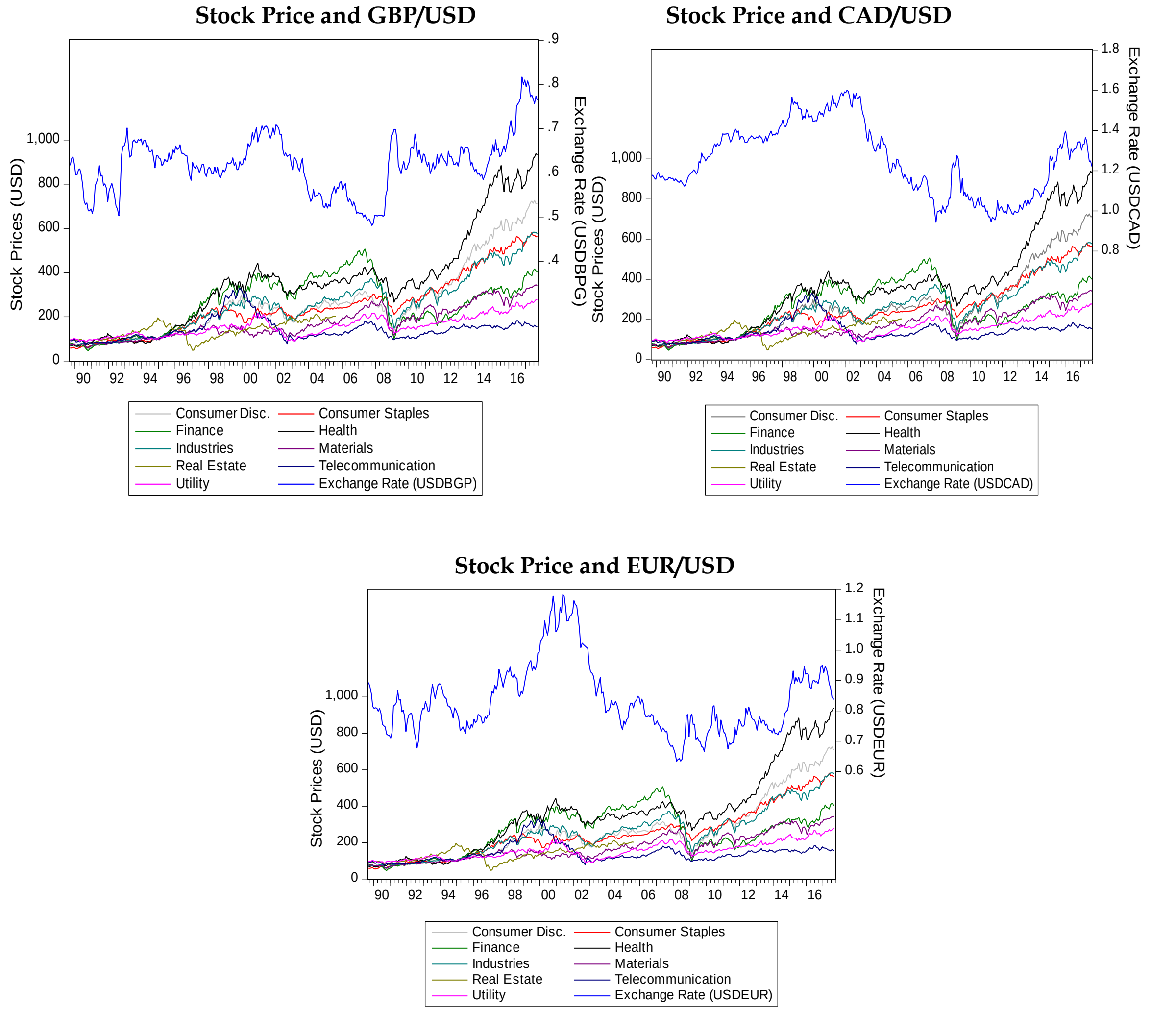


Figure 2 serves to better portray the relationships between each sector stock price and the three exchange rates. The trend exhibited by the sectors does not appear to differ markedly from that of the aggregate and a uniform response is obvious. In addition however, it can be clearly observed that adjustments in exchange rates preceded adjustments in stock prices. All series responded to the 2008 global slump, only that exchange rate responded earlier. Meanwhile, we distinctly graph the stock prices of energy and information sectors as their values tend to supress the trend behaviour of other sectors (see Figures 3 and 4).

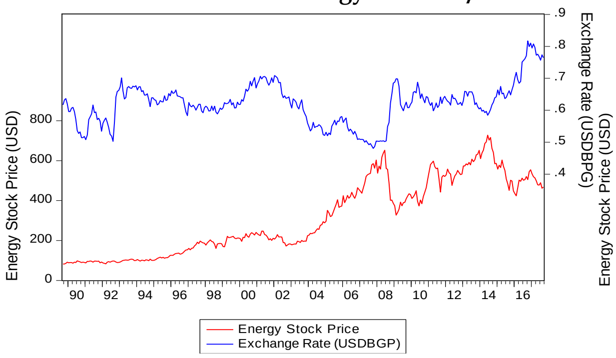
Fig. 2: Industry-Level Stock Prices and Exchange Rate



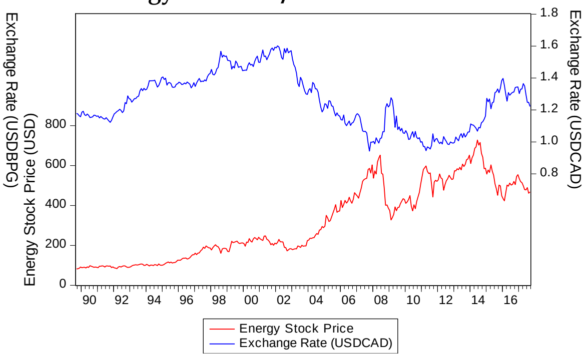
The spike observed in the information sector as in Figure 4 seems to coincide with the period when the US information technology sector boomed and busted which led to an expected declivity in technological stock prices around 2000's. Differently, the spike in energy stock price is a response to global meltdown, induced by the financial industry troubled time as evidenced around 2008.

Fig. 3: Energy Stock Price and Exchange Rate

Energy and GBP/USD



Energy and CAD/USD



Energy and EUR/USD

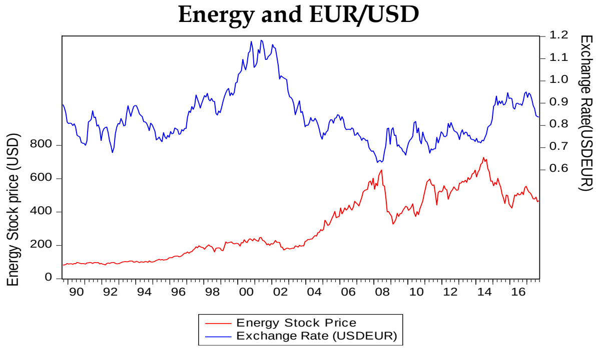
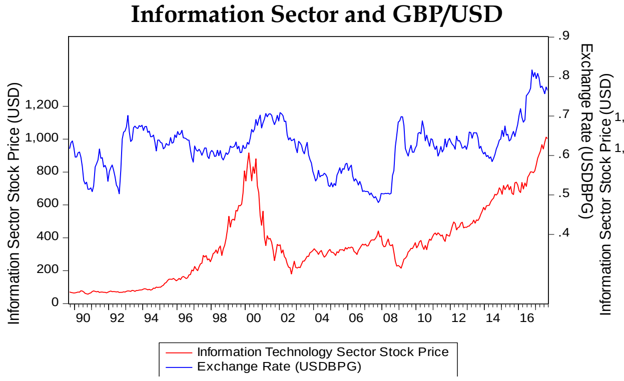
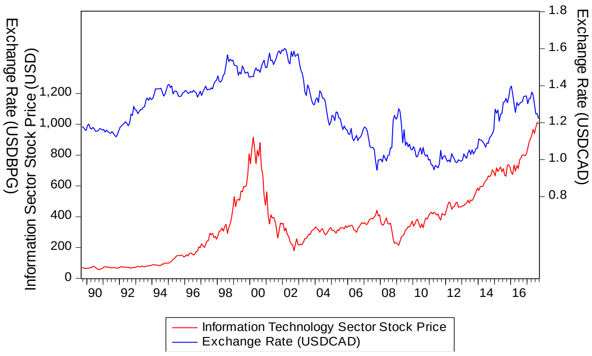


Fig. 4: Information Sector Stock Price and Exchange Rate

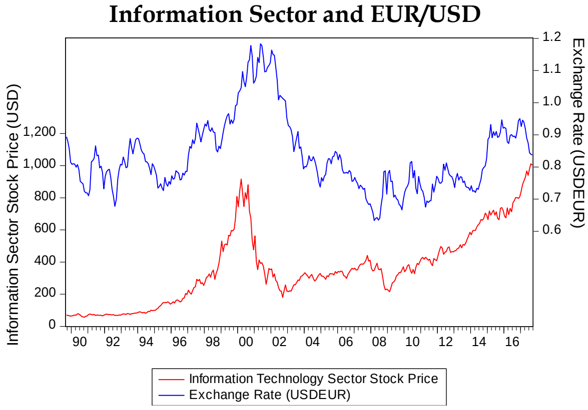
Information Sector and GBP/USD



Information Sector and USDC



Information Sector and EUR/USD



Descriptions of nature and distribution of the series are carried out as a boon to guide in data handling and estimator selection. These include mean, standard deviation, skewness and kurtosis. As in Table 2, average exchange rates per USD are 0.62, 0.84 and 1.25 for British Pound, Euro and Canadian Dollar respectively. Standard deviation estimates suggest British Pound is least in deviations. The skewness values are positive and quite close to the threshold of zero with the exception of EUR/USD. Also, the CAD/USD seems platykurtic, the other exchange rates are leptokurtic while all of them are non-normal.

Meanwhile, aggregate stock returns average 45%, an explicit assessment reveals less than half of all the sectors hovering around this figure while more than half strictly deviate from the aggregate average. The financial, energy, real estate and material sector stock returns of 45%, 52%, 41% and 44% respectively reflect the obtainable condition in the aggregate market, compared to information, industry, telecommunication, consumer staples, consumer discretionary and health sector stock returns of 79%, 61%, 15%, 67%, 67% and 78% stock returns respectively. All sectors have negative skewness in stock returns, an indication that returns are more usually negative than positive. Nonetheless, they are also non-normal like the exchange rates.

Table 2: Descriptive Statistics

Variables	Mean	Standard Deviation	Skewness	Kurtosis	Jarque Bera
Exchange Rates					
GBP/USD	0.62001	0.06419	0.23394	3.48007	6.3101(0.0426)
EUR/USD	0.83518	0.11536	1.03292	3.76947	68.238(0.0000)
CAD/USD	1.25802	0.17482	0.08903	1.96062	15.614(0.0000)
Stock Returns					
Aggregate	0.45829	5.41390	-0.61123	10.47122	2571.94 (0.000)
Financial Sector	0.46980	6.27587	-0.94239	6.87337	259.775(0.000)
Info Tech Sector	0.78979	7.10733	-0.63379	4.99957	78.4707(0.000)
Industry Sector	0.60560	4.91208	-0.71013	5.31706	103.402(0.000)
Energy Sector	0.51685	5.23354	-0.23842	4.00629	17.3599(0.000)
Real Estate Sector	0.40967	6.81492	-1.50342	12.17555	741.971(0.000)
Telecom Sector	0.15369	5.39629	-0.12547	5.13849	64.9059(0.000)
Material Sector	0.43681	5.64977	-0.36437	4.91581	58.8193(0.000)
Consumer Staples	0.67288	3.72463	-0.33537	4.68509	46.0522(0.000)
Health Sector	0.77812	4.41295	-0.35498	3.49552	10.4943(0.000)
Consumer Disc	0.66662	4.99258	-0.48105	4.59075	48.3859(0.000)

Sector					
Utilities Sector	0.31656	4.30485	-0.61305	4.02460	35.7436(0.000)

Note: The probability values for the Jarque-Bera test are in parentheses. The null hypothesis of the test is that series is normally distributed.

As a precondition for the choice of predictive model and estimator, we test for the presence or otherwise of conditional heteroscedascitity and serial correlation tests and the results are presented in Table 3. The Q- and Q^2-Statistics for serial correlation and the ARCH-LM test for heteroscedasticity are used at 5, 10 and 20 lag lengths across the full sample. Considering the results at lag 5, the null hypothesis of no autoregressive conditional heteroscedasticity in the series is rejected for all the series by the ARCH LM test. Although the Q-Stat serial correlation result seems inconclusive, however, the Q^2-Stat test affirms the presence of serial correlations in the series. Meanwhile, at lag 10, conditional heteroscedasticity is absent within consumer staples and health sector stock returns, even though the Q^2– stat test continues to affirm the presence of serial correlations in these series. In addition, at lag 20, only energy sector stock price concedes to the null hypothesis of no autoregressive conditional heteroscedasticity and serial correlation, other sectors are significant. Overall, it can be deduced that whether at 5, 10 or 20 lag length, most of the sectors tend to exhibit the presence of serial correlation and conditional heteroscedasticity.

Table 3: Serial Correlation and Conditional Heteroscedasticity Tests

Lag Structure	**Variables**	**Serial Correlation Test**		**Heteroscedasticity Test**
	Exchange Rates	**Q-stat**	**Q-stat^2**	**ARCH LM**
	CAD/USD	1583.9***	1304.9***	647.2840***
	GBP/USD	1280.9***	1153.3***	572.7871***
	EUR/USD	1464.9***	1239.0***	678.2953***
	Stock Returns			
	Aggregate	25.940***	261.67***	35.60068***
	Financial Sector	8.0127	143.74***	18.78130***
(5)	Info Tech Sector	4.6831	147.06***	21.50297***
	Industry Sector	5.0027	95.120***	12.57115***
	Energy Sector	2.0314	12.073**	2.091398*
	Real Estate Sector	23.368***	78.448***	9.324750***
	Telecom Sector	6.9807	67.890***	9.537534***
	Material Sector	0.8250	44.167***	8.868076***
	Consumer Staples	6.7203	15.831***	3.192984***
	Health Sector	10.217*	18.959***	2.883981**
	Consumer Disc Sector	6.9051	50.374***	6.410336***
	Utilities Sector	4.3998	53.064***	8.363415***

(10)	**Exchange Rates**			
	CAD/USD	2989.1***	2089.5***	313.7052***
	GBP/USD	1972.3***	1596.0***	287.5067***
	EUR/USD	2601.8***	2112.2***	364.1229***
	Stock returns			
	Aggregate	32.330***	540.86***	28.08331***
	Financial Sector	18.676**	163.94***	9.832792***
	Info Tech Sector	9.0837	234.25***	12.58394***
	Industry Sector	14.054	105.72***	6.307623***
	Energy Sector	4.3989	24.304***	1.956362**
	Real Estate Sector	43.876***	92.590***	6.730785***
	Telecom Sector	16.534*	113.88***	7.946232***
	Material Sector	10.777	58.875***	5.016295***
	Consumer Staples	12.478	17.300*	1.447256
	Health Sector	24.504***	20.419**	1.548003
	Consumer Disc Sector	9.8108	70.356***	4.133559***
	Utilities Sector	13.016	85.890***	4.944683***
(20)	**Exchange Rates**			
	CAD/USD	5292.3***	2688.6***	152.2077***
	GBP/USD	2493.3***	1676.7***	150.7896***
	EUR/USD	4054.9***	2708.2***	183.7547***
	Stock Returns			
	Aggregate	63.329***	820.48***	17.38812***
	Financial Sector	30.444*	169.20***	5.063442***
	Info Tech Sector	26.768	351.19***	7.616129***
	Industry Sector	22.051	124.71***	4.370445***
	Energy Sector	8.0495	28.212	1.253995
	Real Estate Sector	69.258***	93.701***	3.347378***
	Telecom Sector	27.405	131.09***	4.116003***
	Material Sector	17.591	63.289***	2.744807***
	Consumer Staples	26.073	60.181***	2.343539***
	Health Sector	33.310**	57.864***	2.385431***
	Consumer Disc Sector	24.993	87.073***	2.403131***
	Utilities Sector	19.545	112.96***	2.722238***

Note: ***, ** and * denote 1, 5 and 10% levels of significance respectively. The serial correlation test conducted involves the use of both Q-stat and Q-stat^2 of Ljung-Box. The underlying null hypothesis for the test is that there is no serial correlation. The ARCH-LM test of Engle (1982) is used to test for conditional heteroscedasticiy. The null hypothesis is that there is no ARCH effect, in other words, there is no presence of conditional heteroscedasticity. The F-statistic is reported for the ARCH-LM test. Both Serial Correlation and Conditional Heteroscedasticty tests are conducted at different lag orders of 5, 10, and 20 for robustness.

Table 4: Testing for persistence in the predictors (Stock Returns)

Stock Returns	**Exchange Rates**		
	Persistence test		
	GBP/USD	**EUR/USD**	**CAD/USD**
Aggregate	0.995623***	0.995623***	0.995623***
Consumer Disc	0.997863***	0.997863***	0.997863***
Consumer Staples	0.994763***	0.994763***	0.994763***
Energy	0.993996***	0.993996***	0.993996***
Finance	0.991114***	0.991114***	0.991114***
Health	0.995885***	0.995885***	0.995885***

Industries	0.995194***	0.995194***	0.995194***
Info Tech	0.995151***	0.995151***	0.995151***
Materials	0.992347***	0.992347***	0.992347***
Real Estate	0.978039***	0.978039***	0.978039***
Telecom	0.983495***	0.983495***	0.983495***
Utility	0.992093***	0.992093***	0.992093***

Note: The persistence test is conducted by regressing a first order autoregressive process for the predictor: $s_t = \omega + \rho s_{t-1} + \upsilon_t$ using OLS estimator. The first order autocorrelation coefficient (ρ) captures the persistence effect and is reported in Table 4 for each of the sectors across the three exchange rates. There is presence of persistence effect if ρ is statistically significant and the closer the value to zero the higher the degree of persistence. In fact, the LW (2004) and WN (2014) estimators are more suitable for predictors with high persistence effects. *** denotes 1% level of significance.

To arrest potential biases inherent in the predictors due to persistence effects common to most high frequency data, it is important to carry out a formal test to avoid spurious conclusions. Even though unit root tests may attest to absence of non stationarity, absence of unit root test is not sufficient to prove absence of persistence in the predictors. Table 4 presents these results, the AR(1) coefficients estimated for the predictors (Stock returns) are declared to be very close or equal to 1 revealing high level of persistence in the predictors regardless of sample size and exchange rates. Therefore, all the statistical features (persistence and conditional heteroscedasticity) put together justify the consideration of the WN (2014) estimator.

5.0 Discussion of results

As previously noted, we examine how much of information in stock prices can be exploited to predict US exchange rates namely CAD/USD, EUR/USD and GBP/USD. We account for persistence and conditional heteroscedasticity and in the process, adopt the WN estimator. The analyses are also extended to capture the asymmetric response of these exchange rates to changes in stock prices. We assess the in-sample and out-of-sample predictability of the specific industry stock price for forecasting exchange rates and compare results for the symmetric and asymmetric exchange rate predictive models. The analyses involving the symmetric predictive model of exchange rates stem from Tables 5 to 11 while the discussions of the asymmetric exchange rates predictive model cover Tables 12 to 15.

5.1 The Linear (Symmetric) Predictive Model

5.1.1 In-Sample Predictability

We begin the discussion of results by examining the symmetric in-sample predictability of stock prices of various sectors of the US economy, namely finance, information technology, industrial, energy, real estate, telecommunication, materials, consumer staples & disc, health and utilities as well as the aggregate stock price for predicting US exchange rates. This information is contained in Table 5. Results show positive nexus between these exchange rates and US stock prices, individually at industry level and collectively at aggregate level. This result is intuitive in that it validates the thesis of this study which claims that in an economy like the US with dominance effects in the international markets, exchange rate is endogenously determined, and can be predicted with changes in stock market fundamentals. This claim is not only verified for the aggregate stock prices but also for the sectoral stock prices.

The result in the light of portfolio balance theory (views espoused by Black, 1973; Dornbusch, 1975; Boyer, 1977; Branson, et al. 1977; Kouri and de Macedo, 1978; Allen and Kenen, 1980; Branson, 1983 and others) indicates that risk averse investors in Canada, United Kingdom and countries in the Euro area tend to obtain higher returns on their US portfolio assets compared with domestic stocks, hence higher demand for US stocks and its currency appreciation.

Our result is an improvement on the findings of studies like Kutty (2010), Lin(2012), Ibicioglu (2012), Ding and Ma(2013), Tsagkanos and Siriopoulos (2013), and Khan and Abbas(2015) which affirm evidence for portfolio balance theory but with evidence of causation running from stock prices to exchange rate. Specifically, Tsagkanos and Siriopoulos, (2013) adopt structural nonparametric cointegration technique to provide evidence of relationship between stock returns and exchange rate to validate the portfolio balance theory for EU and the US. In a related study on the Asian emerging markets, Lin (2012) also suggests that the channel of co-movement between exchange rates and stock prices runs from stock price shocks to exchange rates but the co-movement was stronger during the financial crisis. More specifically, results from Ismail et al. (2017) also support the nexus between exchange rate and sectoral stock prices but the study departs from the present study as it examines the impact of exchange rate on sectoral stock prices. Our result also somewhat agrees with the findings from Wong (2017). Examining the relationship between real exchange rate and real stock price returns with a DCC-MGARCH model, Wong (2017) finds a negative nexus for Malaysia, Singapore, Korea and UK and insignificant relationship for Phillipines, Japan and Germany.

Table 5: In-sample predictability of stock price – exchange rate nexus

Predictor	GBP/USD	EUR/USD	CAD/USD
Aggregate	0.0653*** (0.0104)	0.2266*** (0.0132)	0.1745*** (0.0076)
Financial Sector	0.0059*** (0.0081)	0.1894*** (0.0109)	0.1452*** (0.0050)
Info Tech Sector	0.0328*** (0.0062)	0.1329*** (0.0085)	0.0916*** (0.0055)
Industry Sector	0.0768*** (0.0105)	0.2461*** (0.0136)	0.1861*** (0.0071)
Energy Sector	0.0943*** (0.0145)	0.3313*** (0.0172)	0.2434*** (0.0107)
Real Estate Sector	0.1580*** (0.0171)	0.1762*** (0.0377)	0.2102*** (0.0233)
Telecom Sector	0.0532*** (0.0123)	0.2044*** (0.0190)	0.1586*** (0.0126)
Material Sector	0.1257*** (0.0218)	0.3246*** (0.0378)	0.3375*** (0.0183)
Consumer Staples	0.0638*** (0.0122)	0.2235*** (0.0184)	0.1988*** (0.0082)
Health Sector	0.0495*** (0.0086)	0.1884*** (0.0109)	0.1409*** (0.0063)
Consumer Disc Sector	0.0777*** (0.0106)	0.2500*** (0.0136)	0.1895*** (0.0072)
Utilities Sector	0.1742*** (0.0226)	0.4655*** (0.0337)	0.3118*** (0.0254)

Note: The in-sample predictability is obtained by estimating the equation $e_t = \mu + \delta s_{t-1} + \eta\left(s_t - \rho s_{t-1}\right) + \xi_t$ with the FQGLS estimator and the coefficient δ is used to test for predictability. In other words, the coefficients reported in Table 5 are the respective $\hat{\delta}$'s for all the sectors across the three exchange rates. The values reported in parentheses are standard errors while ***, ** and * denote 1%, 5% and 10% levels of statistical significance respectively.

5.1.2 In-Sample Forecast Evaluation

The in-sample predictability results presented in Table 5 and discussed in the previous section suggest that the sectoral information on US stock prices can predict exchange rates implying that the foreign exchange market could actually respond to fundamentals in the US stock markets. While this has partly validated our research hypothesis of a strong nexus between stock price and exchange rate, a further analysis that compares the forecast performance of the proposed model to the conventional autoregressive models often used in forecasting exchange rate is imperative. As emphasized previously, it has become a tradition to compare forecast performance of theoretically motivated predictive models with the statistical models such as the Autoregressive models when dealing with financial time series forecasting including exchange rate (see for example, Moosa and Burns, 2012, 2014a,b,c; and Moosa and Burns, 2016; for a review of the literature on exchange rate forecasting). Also, this consideration is motivated by the findings of the extant studies on exchange rate forecasting. Most of these studies find that exchange rate models such as the Messe-Rogoff model (Meese and Rogoff, 1983), the Frenkel–Bilson model (Frenkel, 1976; Bilson,1978), the Dornbusch–Frankel model (Dornbusch, 1976; Frankel, 1979), and Hooper-Morton Model (Hooper and Morton, 1982), among others, only seem to outperform the autoregressive models if they (the former models) are specified in form of the latter (the AR models) (see Moosa and Burns, 2014a,b,c). For instance, Moosa and Burns (2014b) express scepticism of the claims that dynamic models outperform the random walk in terms of the RMSE because these claims are invariably based on the introduction of dynamics, hence a random walk component, typically without testing for the statistical significance of the difference between RMSEs (Moosa and Burns, 2014c). They further argue that even if proper hypothesis testing reveals that a dynamic model outperforms the random walk, this amounts to beating the random walk (a special case of AR models) by a random walk with the help of some explanatory variables (Moosa and Burns, 2014c). In other words, including a lagged dependent variable as a regressor in the predictive model for exchange rate may enhance its forecast performance and by implication enables it to outperform the autoregressive models. Morever, Moosa and Burns (2014c) find that most of the forecast comparisons only rely on the RMSE and where the values for two different models are very close, using this forecast measure may lead to wrong conclusions.

We however take a clear departure from the existing literature in two ways. First, our predictive model does not include the lagged dependent variable. Thus, our forecast comparison involves an economic model against a statistical model which differs from the observation of Moosa and Burns (2014b,c) where most of the exchange rate models analysed in the literature are seen as statistical (autoregressive) in nature and such comparison such with AR models may not be valid. Secondly, we consider other relevant forecast measures including Diebold and Mariano test used to test for the equality of forecast accuracy between two models. Thus, we are also able to test whether the forecast performance of our proposed model differs significantly from that of the AR models.

Specifically, our in-sample forecast evaluation compares the in-sample forecast accuracy of our stock price-exchange rate (symmetric) predictive model with AR(1) and AR(2) models. To execute this task, we employ the Campbell-Thompson (C-T) test (see Table 6) and Diebold and Mariano (D-M) test (see Table 7). In the ensuing analysis, a positive C-T statistic indicates that the predictive (economic) model outperforms the relevant AR (statistical) model while the reverse holds if the statistic is negative. Further, the D-M test ascertains whether the result suggested by the C-T testis statistically significant. We approach the analysis by discussing the forecast evaluation for each of the symmetric exchange rate models i.e. CAD/USD, EUR/USD and GBP/USD.

We have convincing evidence to affirm that our symmetric model for GBP/USD exchange rate outperforms each of AR(1) and AR(2) models in in-sample forecast evaluation. This result is consistent for all the sectors of the US stock markets given the consistent positive values of the C-T coefficients across the predictors. This result is further supported by the significant values across all the D-M test statistics; thus, we reject the null hypothesis that the forecast accuracy of the predictive model of stock price - GBP/USD exchange rate nexus is not different from either of the autoregressive models. Similarly, the forecast results for the stock price – EUR/USD exchange rate nexus also outperform the two autoregressive models for the in-sample forecast evaluation. Findings also clearly show positive values for C-T and rejection of null hypothesis for the D-M tests across aggregate and sectoral stock price indexes.

In a different scenario however, our forecast results for the stock price–CAD/USD exchange rate nexus are somewhat mixed. Unlike, the EUR/USD and GBP/USD, the AR(1) and AR(2) models were able to outperform our models but only in three(3) and four(4) cases respectively. For instance, while the results from aggregate, finance, industrial, energy, material, consumer staples & disc, and health sectors show that our model consistently outperforms both AR(1) and AR(2) models, the reverse is the case when stock prices from information technology, real estate, telecommunication, utility sectors are used as the predictors. Nonetheless, our model still records substantial success relative to the autoregressive models with 8:3 and 7:4 ratios for AR(1) and AR(2) models respectively.

Table 6: In-sample forecast evaluation using Campbell-Thompson (C-T) test

Predictor	GBP/USD		EUR/USD		CAD/USD	
	AR[1]	AR[2]	AR[1]	AR[2]	AR[1]	AR[2]
Aggregate	0.1064	0.1335	0.4367	0.4214	0.1844	0.1714
Financial Sector	0.1249	0.1611	0.4348	0.4194	0.3215	0.3107
Info Tech Sector	0.0790	0.1069	0.4039	0.3877	0.0046	-0.0113
Industry Sector	0.1295	0.1559	0.4437	0.4285	0.2642	0.2525
Energy Sector	0.0942	0.1217	0.4627	0.4481	0.1553	0.1418
Real Estate Sector	0.1840	0.2088	0.1049	0.0806	-0.4347	-0.4575
Telecom Sector	0.0672	0.0955	0.2805	0.2609	-0.2282	-0.2477
Material Sector	0.0999	0.1272	0.2147	0.1933	0.0642	0.0493
Consumer Staples	0.0784	0.1063	0.3129	0.2942	0.2132	0.2007
Health Sector	0.0714	0.0996	0.4152	0.3993	0.1115	0.0973
Consumer Disc Sector	0.1440	0.1699	0.4542	0.4393	0.2835	0.2721
Utilities Sector	0.1359	0.1621	0.3331	0.3149	-0.2589	-0.2789

Note: The unrestricted model in the C-T test reported in Table 6 is our (symmetric) model while the unrestricted is the autoregressive model. Thus, a positive statistic implies that the Portfolio Balance theory based exchange rate model outperforms the autoregressive model while the reverse holds if the statistic is negative.

Table 7: Diebold and Mariano (In-Sample) Test

	GBP/USD		EUR/USD		CAD/USD	
	AR[1]	AR[2]	AR[1]	AR[2]	AR[1]	AR[2]
Aggregate	2.976*** (0.003)	3.528*** (0.000)	8.3356*** (0.000)	8.1122*** (0.000)	4.056*** (0.000)	3.707*** (0.000)
Financial Sector	3.318*** (0.001)	3.766*** (0.000)	8.121*** (0.000)	7.876*** (0.000)	5.775*** (0.000)	5.544*** (0.000)
Info Tech Sector	2.808*** (0.005)	3.526*** (0.000)	8.328*** (0.000)	8.034*** (0.000)	0.124 (0.902)	-0.254 (0.799)
Industry Sector	3.143*** (0.002)	3.633*** (0.000)	7.999*** (0.000)	7.799*** (0.000)	5.333*** (0.000)	5.023*** (0.000)
Energy Sector	2.654*** (0.008)	3.284*** (0.001)	8.225*** (0.000)	8.089*** (0.000)	3.088*** (0.002)	2.732*** (0.006)
Real Estate Sector	4.651*** (0.000)	5.007*** (0.000)	3.778*** (0.000)	2.893*** (0.004)	-7.657*** (0.000)	-7.861*** (0.000)
Telecom Sector	2.846*** (0.004)	3.712*** (0.000)	6.521*** (0.000)	6.010*** (0.000)	-3.441*** (0.001)	-3.606*** (0.000)
Material Sector	2.772*** (0.006)	3.295*** (0.001)	6.534*** (0.000)	6.095*** (0.000)	1.557 (0.119)	1.147 (0.251)
Consumer Staples	2.566** (0.010)	3.222*** (0.001)	7.307*** (0.000)	7.160*** (0.000)	4.092*** (0.000)	3.770*** (0.000)
Health Sector	2.191** (0.028)	2.871*** (0.004)	7.572*** (0.000)	7.402*** (0.000)	1.927* (0.054)	1.611 (0.107)
Consumer Disc Sector	3.551*** (0.000)	3.987*** (0.000)	8.538*** (0.000)	8.324*** (0.000)	5.954*** (0.000)	5.661*** (0.000)
Utilities Sector	3.639*** (0.000)	4.126*** (0.000)	6.249*** (0.000)	5.871*** (0.000)	-3.295*** (0.000)	-3.471*** (0.001)

Note: The Diebold and Mariano test is used to for equality of forecast accuracy between two models. In this case, we are testing whether the forecast accuracy of our model differs from that of the autoregressive models. Both the test statistics and the corresponding probability values are reported in Table 7. The probability values are in parenthesis. The underlying null hypothesis is that the forecast accuracy is equal implying that the forecasts are not statistically different from each other. As a consequence, rejecting the null hypothesis implies that the forecasts from the two models differ statistically.

5.1.3 Out-of-Sample Forecast Evaluation

Having established evidence for the stock prices of different sectors of the US economy in the symmetric models for the relevant exchange rates, the next task is to evaluate the predictive models for out-of-sample evaluation since evidence of in-sample predictability does not necessarily translate into out-of-sample predictive accuracy. We utilize 50 per cent of the full sample for the out-of-sample forecast evaluation and multiple forecast horizons are considered for robustness. Thus, the out-of-sample forecasts are produced for 12-month (h=12) and 24-month (h=24) ahead forecasts. The results obtained are presented in Tables 8 and 9 for the C-T test and Table 10 for the D-M test.

Starting with the predictive model for EUR/USD exchange rate, the harmony of the C-T and D-M tests reveal that the exchange rate model consistently outperforms each of the autoregressive models across the predictors in the 12-period ahead out-forecast. Remarkably, the result of the good predictability of the 12-period horizon forecast model is in agreement with findings reported for the in-sample predictability evaluation where our predictive model consistently outperforms the benchmark autoregressive models. However, the out-of-sample forecast power of the exchange rate model diminished for the 24-period. For this forecast horizon, the EUR/USD exchange rate predictive model outperforms the AR(1) and AR(2) models for the aggregate and sectoral stock price predictors except in cases where energy, real estate and material sectors were captured as predictors.

For the stock - GBP/USD exchange rate predictive model over the 12-period ahead forecast horizon, we find that the model has a better out-of-sample predictive power over AR(1)and AR(2) models judging by the C-T test. However, the D-M test for the same forecast horizon suggests that the forecast accuracy seems the same with AR(1) and AR(2) models in seven(7) and three(3) cases respectively. However, for the 24-period ahead forecast, the GBP/USD exchange rate outperforms each of AR(1) and AR(2) in out-of-sample predictability in only two sectors; telecom and utilities.

Results of the predictive model for the stock price – CAD/USD exchange rate indicate that for the 12-period ahead forecast horizon, the model surpasses AR(1) model for the aggregate, financial, industrial and consumer staples sectors. Still on the 12-period ahead forecast horizon, the model transcends the AR(2) model for the aggregate and two other sectors; financial and industrial sectors. Further results for the 24-period the predictive model underperform both the AR(1) and AR(2).

The understanding of the reaction of exchange rates to sectoral stock price predictability offers key evidence to policy makers to target monetary and fiscal policies effectively, and to analysts and investors to maximize returns or minimize risk as regards the stock market sectors to choose from. The major implication of the findings for policy makers, analysts and investors is that the results indicate the viability of the relevant US sectors abroad; thus, profits and shares prices of these sectors are revealed to be competitive. Thus, investors in US and relevant foreign countries concerned with hedging decisions should take advantage of investment opportunities in these competitive US sectors. The implication of our result for policy makers is that the competitiveness of these sectors has a way to spur future economic growth because high stock prices tend to induce consumers' and investors' confidence in the sectors and thereby boost aggregate consumption and investments.

However, for some of these firms/sectors that are export oriented, exchange rate depreciation boosts exportation, improves profit and share prices. On the other hand, some of these sectors that rely heavily on importation especially for their inputs, exchange rate depreciation increases cost of production, hence, profits and share prices of the sectors. The converse is expected to be obtainable in the event of exchange rate appreciation. Thus, the nexus between exchange rate and stock prices may not be asymmetric. This brings us to the discussion of the asymmetric predictability model of exchange rate – stock price nexus in the next section.

Table 8: Out-of-Sample forecast performance using Campbell-Thompson statistic for h=12

Predictor	GBP/USD		EUR/USD		CAD/USD	
	AR[1]	AR[2]	AR[1]	AR[2]	AR[1]	AR[2]
Aggregate	0.0974	0.1241	0.4229	0.4072	0.1569	0.1443
Financial Sector	0.1171	0.1432	0.4042	0.3879	0.2343	0.2228
Info Tech Sector	0.0736	0.1009	0.3960	0.3795	0.0009	-0.0142
Industry Sector	0.1164	0.1425	0.4250	0.4093	0.2194	0.2076
Energy Sector	0.0820	0.1091	0.4384	0.4231	0.1132	0.0998
Real Estate Sector	0.1505	0.1756	0.0982	0.0735	-0.4445	-0.4663
Telecom Sector	0.0687	0.0962	0.2778	0.2581	-0.2111	-0.2293
Material Sector	0.0880	0.1149	0.2068	0.1852	0.0343	0.0197
Consumer Staples	0.0686	0.0962	0.2993	0.2802	0.1645	0.1519
Health Sector	0.0605	0.0882	0.3913	0.3746	0.0672	0.0531
Consumer Disc Sector	0.1282	0.1540	0.4287	0.4131	0.2196	0.2078
Utilities Sector	0.1369	0.1624	0.3286	0.3103	-0.2425	-0.2612

Note: The unrestricted model in the C-T test reported in Table 6 is our (symmetric) model while the unrestricted is the autoregressive model. Thus, a positive statistic implies that the Portfolio Balance theory based exchange rate model outperforms the autoregressive model while the reverse holds if the statistic is negative.

Table 9: Out-of-Sample forecast performance using Campbell-Thompson statistic for h=24

Predictor	GBP/USD		EUR/USD		CAD/USD	
	AR[1]	AR[2]	AR[1]	AR[2]	AR[1]	AR[2]
Aggregate	-0.0095	0.0089	0.2524	0.2348	-0.0301	-0.0398
Financial Sector	-0.0332	-0.0144	0.1764	0.1570	-0.0984	-0.1088
Info Tech Sector	0.0051	0.0232	0.2819	0.2650	-0.0273	-0.0371
Industry Sector	-0.0291	-0.0103	0.2063	0.1876	-0.0765	-0.0867
Energy Sector	-0.0886	-0.0687	0.0983	0.0770	-0.3104	-0.3228
Real Estate Sector	-0.7778	-0.0581	0.0265	0.0035	-0.4352	-0.4488
Telecom Sector	0.0615	0.0787	0.2698	0.2525	-0.0577	-0.0677
Material Sector	-0.0671	-0.0476	0.0525	0.0301	-0.2905	-0.3027
Consumer Staples	-0.0277	-0.0090	0.1570	0.1371	-0.0708	-0.0809
Health Sector	-0.0334	-0.0146	0.2126	0.1940	-0.0988	-0.1092
Consumer Disc Sector	-0.0254	-0.0067	0.2015	0.1826	-0.0851	-0.0954
Utilities Sector	0.0761	0.0930	0.2757	0.2586	-0.1411	-0.1519

Note: The unrestricted model in the C-T test reported in Table 6 is our (symmetric) model while the unrestricted is the autoregressive model. Thus, a positive statistic implies that the Portfolio Balance theory based exchange rate model outperforms the autoregressive model while the reverse holds if the statistic is negative.

Table 10: Diebold & Mariano (Out-of-Sample) test

	GBP/USD				EUR/USD				CAD/USD			
	Out-of-Sample				Out-of-Sample				Out-of-Sample			
	H=12		H=24		H=12		H=24		H=12		H=24	
	AR[1]	AR[2]	AR[1]	AR[2]	AR[1]	AR[2]	AR[1]	AR[2]	AR[1]	AR[2]	AR[1]	AR[2]
Aggregate	1.715*	2.264**	-0.310	0.224	6.877***	6.633***	4.401***	4.144***	4.056***	3.707***	-0.683	-0.946
	(0.086)	(0.024)	(0.756)	(0.823)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.494)	(0.344)
Financial	1.438	1.917*	-0.873	-0.405	5.685***	5.394***	2.749***	2.453**	1.923*	1.713*	-1.442	-1.605
Sector	(0.150)	(0.055)	(0.383)	(0.686)	(0.000)	(0.000)	(0.006)	(0.014)	(0.054)	(0.087)	(0.149)	(0.109)
Info Tech	1.786*	2.472**	0.225	0.865	7.271***	6.982***	5.610***	5.341***	-0.306	-0.672	-1.067	-1.427
Sector	(0.074)	(0.013)	(0.822)	(0.387)	(0.000)	(0.000)	(0.000)	(0.000)	(0.759)	(0.501)	(0.286)	(0.154)
Industry	1.637	2.131**	-0.769	-0.294	6.280***	6.046***	3.214***	2.952***	2.775***	2.496**	-1.239	-1.431
Sector	(0.102)	(0.033)	(0.442)	(0.769)	(0.000)	(0.000)	(0.001)	(0.003)	(0.006)	(0.013)	(0.215)	(0.153)
Energy	0.856	1.466	-0.209**	-1.619	5.919***	5.711***	1.200	0.959	0.477	0.188	-2.968***	-3.082***
Sector	(0.392)	(0.143)	(0.036)	(0.105)	(0.000)	(0.000)	(0.229)	(0.338)	(0.634)	(0.851)	(0.003)	(0.002)
Real Estate	1.327	1.770*	-1.585	-1.194	2.677***	1.804*	0.857	0.035	-8.648***	-8.856***	-9.809***	-10.011***
Sector	(0.184)	(0.077)	(0.113)	(0.232)	(0.007)	(0.071)	(0.391)	(0.972)	(0.000)	(0.000)	(0.000)	(0.000)
Telecom	3.223***	3.976***	3.611***	4.180***	6.486***	6.005***	6.509***	6.098***	-2.845***	-2.991***	-1.012	-1.127
Sector	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.003)	(0.312)	(0.259)
Material	0.943	1.5054	-1.731*	-1.213	4.632***	4.137***	1.144	0.653	-0.014	-1.332	-3.511***	-3.658***
Sector	(0.346)	(0.132)	(0.083)	(0.225)	(0.000)	(0.000)	(0.253)	(0.514)	(0.311)	(0.183)	(0.000)	(0.000)
Consumer	1.076	1.754*	-1.009	-0.340	5.657***	5.435***	3.196***	2.918***	1.688*	1.398	-1.313	-1.548
Staples	(0.282)	(0.079)	(0.313)	(0.734)	(0.000)	(0.000)	(0.001)	(0.004)	(0.091)	(0.162)	(0.188)	(0.122)
Health	0.751	1.426	-1.173	-0.528	5.812***	5.596***	3.549***	3.312***	0.190	-0.097	-1.974**	-2.223**
Sector	(0.453)	(0.154)	(0.241)	(0.598)	(0.000)	(0.000)	(0.000)	(0.001)	(0.8492)	(0.923)	(0.048)	(0.026)
Consumer	1.744*	2.210**	-0.665	-0.207	6.255***	5.994***	3.164***	2.887***	2.295**	2.036**	-1.359	-1.546
Disc Sector	(0.081)	(0.027)	(0.506)	(0.836)	(0.000)	(0.000)	(0.002)	(0.004)	(0.022)	(0.042)	(0.174)	(0.122)
Utilities	3.851***	4.264***	2.745***	3.104***	6.146***	5.789***	5.290***	4.982***	-2.837***	-2.999***	-2.412**	-2.563**
Sector	(0.000)	(0.000)	(0.006)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.003)	(0.016)	(0.010)

Note: The Diebold and Mariano test is used to for equality of forecast accuracy between two models. In this case, we are testing whether the forecast accuracy of our model differs from that of the autoregressive models. Both the test statistics and the corresponding probability values are reported in Table 7. The probability values are in parenthesis. The underlying null hypothesis is that the forecast accuracy is equal implying that the forecasts are not statistically different from each other. As a consequence, rejecting the null hypothesis implies that the forecasts from the two models differ statistically.

5.2 Nonlinear (Asymmetric) predictive model: Positive vs. Negative changes in stock price

5.2.1 In-Sample Predictability

The major aim of this study is to evaluate whether sectoral stock prices can serve as good predictors in our exchange rate forecasting models. While some studies approached the analyses of the stock price-exchange rate nexus from the perspective of a symmetric relationship, others (for example Koutmos and Martin, 2007; Hsu et al., 2009; Naifar and Al Dohaiman, 2013; Dieci and Westerhoff, 2013; Ali et al. 2015; Bahmani-Oskooee and Saha, 2016) have suggested that the relationship between financial and foreign exchange markets are nonlinearly interwoven, hence, we assess the asymmetric nexus between exchange rate dynamics and US stock prices. In order to circumvent aggregation bias, we assess the asymmetric nexus between exchange rates and stock prices in 11 sectors of the US economy. We show the direction and magnitude of the asymmetric response of exchange rates to shocks in aggregate and sectoral stock prices in the economy (see Table 11).

Our analysis indicates that exchange rates respond differently to changes in sectoral stock prices, depending on the magnitude and the direction of the asymmetry (i.e. positive or negative). We find that positive changes to the stock prices (aggregate and sectoral) cause the three exchange rates to appreciate in favour of US dollar while the negative changes to the predictors (aggregate and sectoral stock prices) cause the US dollar exchange rates to depreciate (see Table 11). Further, we find that positive changes to stock prices are larger than the negative shocks, hence, the greater tendency for currency appreciation. The result of the greater positive impact of the predictors is consistent with the symmetric predictive model and also partly supports findings from other contemporary studies (for example Chkili and Nguyen, 2012; Ali, et al. 2015; Bahmani-Oskooee and Saha, 2016; Stillwagon, 2016; Zivkov, et al. 2016; Kisswani and Elian, 2017). However, most of these studies are limited to asymmetric cointegration analysis and those that consider sectoral analysis (such as Bahmani-Oskooee and Saha, 2016; Kisswani and Elian, 2017) are concerned with predictive model of stock prices. The related study, Stillwagon

(2016) that finds evidence of asymmetric response of dollar-pounds and dollar-yen exchange rates to fundamentals (money supply, inflation, interest rate and foreign trade) leaving out stock price.

In all, our findings give support for using nonlinear asymmetric models of exchange rate relationship with stock prices as the models contribute to better understanding of the exchange rate dynamics, hence, aiding investment decision and policymaking. The foregoing findings accentuate hedging opportunities for investors in the US foreign exchange market and the viable sectors of the economy. Harmonising the foregoing result of asymmetric predictive model with findings obtained from the symmetric predictive models, nationals and foreigners seeking for optimal portfolio asset decision will be able to reduce portfolio risk by diversifying portfolio investments possibly towards holding more stocks in the US sectors. We provide more support for the results in the next section.

Table 11: In-Sample predictability of stock price – exchange rate nexus

	GBP/USD		EUR/USD		CAD/USD	
	Positive	**Negative**	**Positive**	**Negative**	**Positive**	**Negative**
Aggregate	0.03407*** (0.006026)	-0.02311*** (0.007708)	0.129827*** (0.010076)	-0.09143*** (0.015257)	0.063950*** (0.004151)	-0.06312*** (0.006348)
Financial Sector	0.026075*** (0.004386)	-0.03538*** (0.006016)	0.100828*** (0.007243)	-0.12263*** (0.011010)	0.049295*** (0.002869)	-0.07210*** (0.004773)
Info Tech Sector	0.017930*** (0.003168)	-0.00744** (0.003275)	0.058296*** (0.005700)	-0.03116*** (0.006453)	0.028155*** (0.002266)	-0.02427*** (0.002670)
Industry Sector	0.032931*** (0.005595)	-0.02558*** (0.007251)	0.123736*** (0.009452)	-0.09938*** (0.014142)	0.061535*** (0.003773)	-0.06582*** (0.005989)
Energy Sector	0.036178*** (0.006038)	-0.03189*** (0.007682)	0.134843*** (0.010140)	-0.13302*** (0.014770)	0.066070*** (0.004011)	-0.07674*** (0.005612)
Real Estate Sector	0.022031*** (0.005040)	-0.03128*** (0.007310)	0.104410*** (0.008489)	-0.12780*** (0.011432)	0.050539*** (0.003199)	-0.06054*** (0.004699)
Telecom Sector	0.025550*** (0.005233)	-0.006005 (0.004620)	0.097815*** (0.009445)	-0.03405*** (0.009391)	0.048841*** (0.003864)	-0.02955*** (0.004030)
Material Sector	0.029394*** (0.005384)	-0.02974*** (0.005651)	0.110578*** (0.009785)	-0.09846*** (0.010774)	0.057896*** (0.003888)	-0.05590*** (0.004444)
Consumer Staples	0.036579*** (0.006274)	-0.04586*** (0.008420)	0.142951*** (0.010189)	-0.16502*** (0.015830)	0.076066*** (0.003949)	-0.08699*** (0.006639)
Health Sector	0.029181*** (0.004872)	-0.03316*** (0.007308)	0.114275*** (0.007867)	-0.14443*** (0.013858)	0.055945*** (0.003166)	-0.07813*** (0.005494)
Consumer Disc Sector	0.029718*** (0.005221)	-0.02819*** (0.006757)	0.113721*** (0.008893)	-0.10246*** (0.013209)	0.058792*** (0.003646)	-0.06651*** (0.005662)
Utilities Sector	0.040261*** (0.006244)	-0.008932 (0.005970)	0.131421*** (0.011368)	-0.05410*** (0.012415)	0.066292*** (0.004352)	-0.04099*** (0.005010)

Note: The in-sample predictability is obtained by estimating the equations for positive and negative stock price changes given as $e_t = \mu^+ + \delta^+ s_{t-1}^+ + \gamma^+ \left(s_{t-1}^+ - \rho^+ s_{t-1}^+\right) + \xi_t^+$ and $e_t = \mu^- + \delta^- s_{t-1}^- + \gamma^- \left(s_{t-1}^- - \rho^- s_{t-1}^-\right) + \xi_t^-$ respectively. The coefficients δ^+ and δ^- are used to test for the predictability of positive and negative stock price changes in the exchange rate model respectively and are reported in Table 12. The values reported in parentheses are standard errors while ***, ** and * denote 1%, 5% and 10% levels of statistical significance respectively.

5.2.2 In-Sample Forecast Evaluation

The in-sample predictability results of our asymmetric models suggest that the exchange rates in question respond in a nonlinear fashion to sectoral US stock prices where the positive impacts of sectoral stock prices seem to outweigh the negative changes. We then proceed to validate this finding to show whether the predictive model with positive stock price changes outperforms the one with negative changes. For this purpose, we compare the in-sample forecast accuracy of the two asymmetric predictive models using the C-T test and the D-M test. In the resulting analysis, a positive C-T statistic indicates that the predictive model with positive shock outperforms the other with negative shock (see Table 12). Further, the D-M test ascertains whether the result suggested by the Campbell-Thompson statistic is statistically significant (see Table 14). We approach the analysis by discussing the forecast evaluation for each of the exchange rate models.

For the stock price - GBP/USD exchange rate predictive model, the forecast performance for the positive stock price asymmetry largely outperforms the negative variant as the C-T statistic is positive for all the sectors including the aggregate stock price (see Table 13). The superiority of the positive asymmetry model is also attested to by the D-M test where there is statistical significance in eight of 12 cases including the aggregate. The finding is consistent with the results for EUR/USD and CAD/USD. For instance, C-T statistics are consistently positive for all the considered cases for CAD/USD and just two are negative for EUR/USD (see Table 12). Similarly, the D-M test suggests that the forecast accuracy of the positive and negative asymmetries significantly differs for both EUR/USD and CAD/USD (see

Table 14). These findings thus confirm that US exchange rates respond asymmetrically to changes in stock price both in terms of impact and forecast.

Table 12: In-sample forecast evaluation using Campbell-Thompson statistic

Predictor	GBP/USD	EUR/USD	CAD/USD
Aggregate	0.11996641	0.28487301	0.33552811
Financial Sector	0.03308891	0.00157304	0.19088221
Info Tech Sector	0.12471702	0.36897039	0.24845746
Industry Sector	0.09247208	0.19633486	0.30955397
Energy Sector	0.04975223	0.05938552	0.20173400
Real Estate Sector	0.05191235	0.11732979	0.02448775
Telecom Sector	0.15080601	0.39942388	0.30487513
Material Sector	0.02260394	0.05759370	0.19085926
Consumer Staples	0.01350867	-0.11153873	0.34597365
Health Sector	0.02876741	-0.06112635	0.21817898
Consumer Disc Sector	0.08640882	0.20543000	0.26628299
Utilities Sector	0.16040498	0.35943014	0.29583144

Note: The positive asymmetry is used as the reference predictor. Thus, a positive statistic implies that the positive shock outperforms the negative while the reverse holds if the statistic is negative.

5.2.3 Out-of-Sample Forecast Evaluation

Like the symmetric case, we also evaluate the out-of-sample forecast performance of the asymmetric predictive models using the C-T test (see Table14) and the Diebold and Mariano test (see Table 15). Also, the forecast evaluation is done for 12- and 24-period ahead forecasts (i.e. h = 12 and h = 24).

If we harmonise both the Campbell-Thompson and Diebold-Mariano tests, the results indicate that in the GBP/USD exchange rate predictive model, positive shocks to aggregate, industry, real estate, telecom, consumer disc and utilities outperform negative shocks in 12-period ahead out-of-sample forecast horizon. However, the null hypothesis for D-M test for the 24-period forecast horizon is largely valid implying equality for forecast accuracy between the positive and negative stock price asymmetries although the positive C-T statistics seem more prominent that the negative.

For the EUR/USD asymmetric predictive model, the C-T statistics are positive in 9 of 12 cases and the D-M test shows some level of superiority of the forecast performance of the positive asymmetry over the negative variant. However, in the 24-period horizon, the D-M test largely suggests equality of forecast horizon as the null hypothesis cannot be rejected in about 7 of 12 cases (see Table 14) although the negative C-T statistics appear dominant than the positive (see Table 13).

For the CAD/USD exchange rate, the evidence of asymmetry is in fact stronger for both in-sample and out-of-sample forecasts. As shown in Table 14, the forecast accuracy for the positive asymmetry remains dominant even for the 24-period forecast horizon (see Table 14). This also corroborated by the C-T test where all the statistics are found to be positive with the exception of real estate sector for 24-period ahead forecast.

Table 13: Out-of-Sample forecast accuracy using C-T statistic for h=12 and h=24

Predictor	GBP/USD		EUR/USD		CAD/USD	
	H=12	H=24	H=12	H=24	H=12	H=24
Aggregate	0.10479	0.01206	0.21391	-0.0013	0.28151	0.11524
Financial Sector	0.03367	0.01567	-0.0093	-0.0417	0.15115	0.05913
Info Tech Sector	0.10323	-0.0038	0.29220	0.05735	0.21244	0.09845
Industry Sector	0.07982	0.00017	0.13696	-0.0452	0.25460	0.08647
Energy Sector	0.04198	-0.0172	0.03288	-0.0950	0.16369	0.02890
Real Estate Sector	0.04653	0.01013	0.09143	0.02086	0.00585	-0.02165
Telecom Sector	0.12922	0.00227	0.32079	0.05291	0.26195	0.10817
Material Sector	0.02183	-0.0024	0.02496	-0.0699	0.14834	0.02158
Consumer Staples	0.02104	0.02641	-0.0840	-0.0484	0.27884	0.11132
Health Sector	0.02549	0.00896	-0.0499	-0.0238	0.18112	0.09671
Consumer Disc Sector	0.07640	0.00855	0.14437	-0.0257	0.21522	0.07292
Utilities Sector	0.13041	-0.0293	0.27616	0.00029	0.24489	0.07660

Note: The positive asymmetry is used as the reference predictor. Thus, a positive statistic implies that the positive shock outperforms the negative while the reverse holds if the statistic is negative.

Table 14: Diebold and Mariano test: Positive asymmetry vs. Negative asymmetry

	GBP/USD			EUR/USD			CAD/USD		
	In-sample	Out-of-Sample		In-sample	Out-of-Sample		In-sample	Out-of-Sample	
		H=12	H=24		H=12	H=24		H=12	H=24
Aggregate	-3.034*** (0.002)	-2.059** (0.039)	-0.514 (0.607)	-5.767*** (0.000)	-2.778*** (0.005)	0.034 (0.9725)	-7.598*** (0.000)	-6.350*** (0.000)	-4.401*** (0.000)
Financial Sector	-1.333 (0.183)	-1.498 (0.134)	-1.397 (0.162)	-0.036 (0.971)	0.956 (0.339)	2.391** (0.017)	-6.251*** (0.000)	-5.934*** (0.000)	-5.238*** (0.000)
Info Tech Sector	-2.920*** (0.004)	-1.598 (0.110)	0.140 (0.888)	-8.449*** (0.000)	-4.473*** (0.000)	-1.426 (0.154)	-8.131*** (0.000)	-6.536*** (0.000)	-4.644*** (0.000)
Industry Sector	-2.599*** (0.009)	-1.678* (0.093)	-0.008 (0.993)	-3.958*** (0.000)	-1.480 (0.139)	1.241 (0.215)	-7.324*** (0.000)	-6.148*** (0.000)	-3.623*** (0.000)
Energy Sector	-1.725* (0.085)	-0.969 (0.332)	1.022 (0.307)	-1.361 (0.174)	0.411 (0.681)	3.045*** (0.002)	-6.852*** (0.000)	-5.792*** (0.000)	-1.596 (0.111)
Real Estate Sector	-2.220** (0.026)	-1.830* (0.067)	-0.782 (0.434)	-4.837*** (0.000)	-3.365*** (0.001)	-1.701* (0.089)	-1.147 (0.251)	0.689 (0.490)	2.454** (0.014)
Telecom Sector	-4.162*** (0.000)	-2.443** (0.015)	-0.081 (0.935)	-9.402*** (0.000)	-4.799*** (0.000)	-1.125 (0.261)	-8.309*** (0.000)	-6.582*** (0.000)	-3.857*** (0.000)
Material Sector	-1.352 (0.176)	-0.966 (0.334)	0.291 (0.771)	-1.892* (0.058)	0.673 (0.501)	3.149*** (0.002)	-6.650*** (0.000)	-4.649*** (0.000)	-1.161 (0.246)
Consumer Staples	-0.484 (0.628)	-1.248 (0.212)	-1.994** (0.046)	1.953* (0.051)	2.055** (0.039)	2.468** (0.014)	-7.185*** (0.000)	-6.624*** (0.000)	-5.580*** (0.000)
Health Sector	-0.874 (0.382)	-0.758 (0.448)	-0.582 (0.561)	1.165 (0.244)	1.349 (0.177)	1.283 (0.199)	-8.005*** (0.000)	-8.664*** (0.000)	-9.745*** (0.000)
Consumer Disc Sector	-3.021*** (0.003)	-2.033** (0.042)	-0.536 (0.592)	-4.945*** (0.000)	-1.789* (0.074)	0.861 (0.389)	-7.472*** (0.000)	-5.904*** (0.000)	-3.818*** (0.000)
Utilities Sector	-3.748*** (0.000)	-1.684* (0.092)	0.837 (0.402)	-8.855*** (0.000)	-3.787*** (0.000)	-0.006 (0.995)	-8.451*** (0.000)	-6.078*** (0.000)	-2.601*** (0.009)

Note: The Diebold and Mariano test is used to for equality of forecast accuracy between two models. In this case, we are testing whether the forecast accuracy of the positive asymmetry model differs from that of the negative. Both the test statistics and the corresponding probability values are reported in Table 14. The probability values are in parenthesis. The underlying null hypothesis is that the forecast accuracy is equal implying that the forecasts are not statistically different from each other. As a consequence, rejecting the null hypothesis implies that the forecasts from the two models differ statistically.

5.3 Simple average combination forecast vs. Individual forecasts

Before we conclude a further test relevant here is to undertake composite forecast evaluation to shed light as to whether combined forecasts of the two asymmetric predictive exchange rate models will outperform the individual forecasts. The results are presented in Table 15. Our evidence suggests that the forecast performance of the positive asymmetry still proves superior particularly for GBP/USD and CAD/USD both for in-sample and 12-ahead forecast as previously observed. However, the combination model appears to dominate the individual forecast for the GBP/USD and EUR/USD exchange rates when the 24-period forecast horizon is considered. These findings further support the D-M test for these exchange rates, where there seems to be equality of forecast accuracy for GBP/USD and EUR/USD exchange rates over the 24-period forecast horizon (see Table 15). Recall that for the CAD/USD, the positive asymmetry remains dominant both for the in-sample and out-of-sample forecasts including 24-period ahead forecast. It is therefore not surprising that the RMSEs for positive asymmetry model for CAD/USD are consistently lower than the combined forecast. Thus, in this case, combining both positive and negative asymmetries will not produce better forecast results particularly when compared with those of the positive asymmetry. In other words, accounting for asymmetries is crucial when dealing with exchange rate forecasting especially from the perspective of Portfolio Balance theory.

Table 15: Combination Forecasts using simple average of RMSE

	GBP/USD			EUR/USD			CAD/USD		
	In-sample	Out-of-Sample		In-sample	Out-of-Sample		In-sample	Out-of-Sample	
		H=12	H=24		H=12	H=24		H=12	H=24
Aggregate	0.0914^{P}	0.0760^{P}	0.0917$^{\wedge}$	0.0643$^{\wedge}$	0.1039$^{\wedge}$	0.1311$^{\wedge}$	0.0998^{P}	0.0758^{P}	0.0942^{P}
Financial Sector	0.0864^{P}	0.0747^{P}	0.0919^{P}	0.0740^{N}	0.1058$^{\wedge}$	0.1357^{N}	0.0778^{P}	0.0669^{P}	0.0889^{P}
Info Tech Sector	0.0945^{P}	0.0770^{P}	0.0921$^{\wedge}$	0.0801^{P}	0.1086^{P}	0.1321$^{\wedge}$	0.1169^{P}	0.0839^{P}	0.0994^{P}
Industry Sector	0.0900^{P}	0.0760^{P}	0.0920$^{\wedge}$	0.0632$^{\wedge}$	0.1051$^{\wedge}$	0.1334$^{\wedge}$	0.0927^{P}	0.0733^{P}	0.0932^{P}
Energy Sector	0.0883^{P}	0.0753^{P}	0.0920^{N}	0.0675^{N}	0.1051$^{\wedge}$	0.1363^{N}	0.0844^{P}	0.0693^{P}	0.0911^{P}
Real Estate Sector	0.0880^{P}	0.0747^{P}	0.0902$^{\wedge}$	0.1156^{P}	0.1119^{P}	0.1395^{P}	0.0660^{N}	0.0605$^{\wedge}$	0.0830^{N}
Telecom Sector	0.0974^{P}	0.0780^{P}	0.0923$^{\wedge}$	0.0855^{P}	0.1122^{P}	0.1350$^{\wedge}$	0.1169^{P}	0.0845^{P}	0.1002^{P}
Material Sector	0.0895^{P}	0.0764^{P}	0.0938$^{\wedge}$	0.0633$^{\wedge}$	0.1081$^{\wedge}$	0.1395^{N}	0.0926^{P}	0.0744^{P}	0.0957^{P}
Consumer Staples	0.0878^{P}	0.0751^{P}	0.0918^{P}	0.0725^{N}	0.1042$^{\wedge}$	0.1338$^{\wedge}$	0.0780^{P}	0.0663^{P}	0.0880^{P}
Health Sector	0.0862$^{\wedge}$	0.0740$^{\wedge}$	0.0906$^{\wedge}$	0.0797^{N}	0.1052$^{\wedge}$	0.1345$^{\wedge}$	0.0746^{P}	0.0649^{P}	0.0870^{P}
Consumer Disc Sector	0.0896^{P}	0.0760^{P}	0.0925$^{\wedge}$	0.0629$^{\wedge}$	0.1068$^{\wedge}$	0.1358$^{\wedge}$	0.0918^{P}	0.0738^{P}	0.0943^{P}
Utilities Sector	0.0937^{P}	0.0770^{P}	0.0921$^{\wedge}$	0.0765^{P}	0.1113^{P}	0.1357$^{\wedge}$	0.1132^{P}	0.0833^{P}	0.1001^{P}

Note: These statistics represent the composite forecast results involving both the positive and negative changes in stock prices. The symbol (^) indicates that the combination forecast outperforms the individual forecasts while the superscript 'p' and 'n' denote that the positive changes and negative changes outperform other forecasts including the combined forecasts.

6.0 Concluding remarks

The literature is replete with papers on exchange rate forecasting using the Dornbusch-Frankel, Frenkel-Bilson and Hooper-Morton models as the theoretical bases for the predictive exchange rate model. Comparing the forecast performance of these theory-based models with the conventional statistical models such as the autoregressive models including random walk prominently reveals the dominance of the latter over the former. Most studies have however attempted to upturn the results by including the lagged dependent variable in the theory-based models which somewhat implies comparing a modified random walk with a traditional random walk.

In this study, we follow a different approach both in terms of theory and methodology. This study examines the predictive role of stock prices in exchange rate modelling to test the predictive power of the Portfolio Balance theory in forecasting US dollar exchange rates. We consider both the aggregate and sectoral stock price data for US and the exchange rates majorly reflect the US currency pairs with the G7 countries. Thus, the data composition is quite extensive enough to enable us offer some useful generalizations about the nexus between stock price and exchange rate. The in-sample predictability is analysed using the Lewellen (2004) and Westerlund and Narayan (2014) estimators that account for the inherent statistical properties of the predictors. The data sample is partitioned into two equal sub-samples; the first half is used for the in-sample analyses while the second half constitutes the out-of-sample period. The latter is conducted for 12-period and 24-period ahead forecast horizons. Owing to the increased evidence in the literature in favour of asymmetries, we further extend our study to account for the role of asymmetries in stock price-exchange rate nexus both for the in-sample and out-of-sample periods.

The result of the symmetric predictive models reveals that changes in aggregate and sectoral stock market prices are good predictors of the US exchange rates. The result of the asymmetric predictive models on the other hand demonstrate that positive changes to the (aggregate and sectoral) stock prices cause the exchange rates to appreciate while the negative changes to the predictors produce exchange rates depreciation. The statistical significance of all the predictors for both the symmetric and asymmetric variants further validates the portfolio balance theory for the US economy where the aggregate and sectoral stock prices consistently turn up as good predictors of various US exchange rates. Contrary to the argument by Moosa and Burns (2014a,b,c), the symmetric model outshines the benchmark autoregressive models for both the in-sample predictability and out-of-sample 12-period ahead forecasts. Thus, it may not be necessary to include the lagged dependent variable in the theory-based exchange rate models proposed in this study, in order to achieve superior forecasts over the autoregressive models.

Acknowledgements

The authors wish to acknowledge the research assistance rendered by Idris Adediran and Ismail Adigun Olayemi.

References

Ahmed, S., Liu, X. and Valente, G. 2016. Can currency-based risk factors help forecast exchange rates? International Journal of Forecasting, 32, 75–97

Ali, H.S., Muktar, U. and Maniam, G.S. 2015. Dynamic Links between Exchange Rates and Stock Prices in Malaysia: An Asymmetric Cointegration Analysis. Journal of Economics and Political Economy, 2:3, 411-417.

Allen, P. and Kenen, P. 1980. Asset Markets, Exchange Rates, and Economic Integration. New York: Cambridge University Press.

Al-Shboul, M and Anwar, S. 2014. Time-varying exchange rate exposure and exchange rate risk pricing in the Canadian Equity Market. Economic Modelling, 37, 451 – 463.

Atems, B., Kapper, D. and Lam, E. 2015. Do Exchange Rates Respond Asymmetrically to Shocks in the Crude Oil Market? Energy Economics, 49, 227-238

Aydemir, O. and Demirhan, E. 2009. The Relationship between Stock Prices and Exchange Rates Evidence from Turkey. International Research Journal of Finance and Economics, 23, 207 – 216

Bacchetta, P. and van Wincoop, E. 2006. Can information heterogeneity explain the exchange rate determination puzzle? American Economic Review, 96, 552–576

Bahmani-Oskooee, M. and Saha, S. 2016. Do exchange rate changes have symmetric or asymmetric effects on stock prices. Global Finance Journal, 31, 57 – 72.

Bannigidadmath, D. and Narayan, P. 2015. Stock return predictability and determinants of predictability and profits. Emerging Markets Review, 26, 153-173

Bilson, J. 1978. The Monetary Approach to the Exchange Rate: Some Evidence. IMF Staff Papers, 25:1, 48-75.

Black, F. 1973. Capital Market Equilibrium with Restricted Borrowing. Journal of Business. 45:3, 444–454

Boyer, R.S. 1977. Devaluation and portfolio balance. American Economic Review, 67:2, 54-63

Boyle, G.W. 1990. Money Demand and the Stock Market in a General Equilibrium Model with variable Velocity. Journal of Political Economy. 98:5, 1039-1053

Branson, W. H. 1983. Macroeconomic determinants of real exchange rates. (Working paper No. 801). Cambridge, UK: The National Bureau of Economic Research.

Branson, W., Halttunen, H. and Masson, P. 1977. Exchange Rates in the Short Run: The Dollar-Deutschemark Rate. European Economic Review, 10:3, 303-324

Breeden, D.T. 1979. An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities. Journal of Financial Economics, 7, 265–296.

Burns, K. and Moosa, I.A. 2015. Enhancing the forecasting power of exchange rate models by introducing nonlinearity: Does it work? Economic Modelling, 50, 27–39

Byrne, J.P., Korobilis, D. and Ribeiro, P.J. 2016. Exchange rate predictability in a changing world, Journal of International Money and Finance, 62, 1-24

Campbell, J.Y. and Thompson, S.B. 2008. Predicting excess stock returns out of sample: can anything beat the historical average? Review of Financial Studies 21, 1509–1531.

Chen, C., Yao, S. and Ou, J. 2016. Exchange rate dynamics in a Taylor rule framework. Journal of international financial markets, institutions & money, 46, 158-173

Cheung, Y., Chinn, M. and Pascual, A. 2005. Empirical exchange rate models of the nineties: are they fit to survive? Journal of International Money & Finance, 24, 1150–1175.

Chih-Chang Hsu, Ruey Y. and Jyun-Yin W. 2009. Asymmetric Exchange Rate Exposure and Industry Characteristics: Evidence from Japanese Data. Hitotsubashi Journal of Economics, 50:1, 57-69.

Chkili, W. and Nguyen, D.K. 2012. Asymmetric effects and long run memory in dynamic volatility relationships between stock returns and exchange rates. Journal of international financial markets, institutions & money, 22:4, 738-737

Dellas, H. and Tavlas, G. 2013. Exchange rate regimes and asset prices. Journal of International Money and Finance, 38, 85 – 97

Devpura, N., Narayan, P.K. and Sharma, S.S. 2017. Is stock return predictability time-varying? Journal of International Financial Markets, Institutions & Money, In press

Diebold, F. and Mariano, R. 1995. Comparing Predictive Accuracy. Journal of Business and Economic Statistics, 13, 134-144.

Dieci, R. and Westerhoff, F. 2013. On the inherent instability of international financial markets: natural nonlinear interactions between stock and foreign exchange markets. Applied Mathematics and Computation, 221, 306–328

Ding, L. and Ma, J. 2013. Portfolio reallocation and exchange rate dynamics. Journal of banking and finance, 37:8, 3100-3124.

Dornbusch, R. 1975. A portfolio balance model of an open economy. Journal of monetary economics, 1, 3-20

Dornbusch, R. 1976. Expectations and Exchange Rate Dynamics. Journal of Political Economy. 84, 1161-1176.

El-Sharif, I., Brown, D., Burton, B., Nixon, B., and Russell, A. 2005. Evidence on the nature and extent of the relationship between oil prices and equity values in the UK. Energy Economics, 27, 819–830.

Engel, C. and West, K. 2005. Exchange rates and fundamentals. Journal of Political Economy, 113, 485‐517.

Engel, C. and West, K. 2006. Taylor rules and the Deutschmark‐Dollar real exchange rate. Journal of Money, Credit & Banking, 38, 1175‐1194

Engel, C., Mark, N. and West, K.D. 2007. Exchange rate models are not as bad as you think, NBER Working Papers, No. 13318

Engel, C., Mark, N.C. and West, K.D. 2008. Exchange rate models are not as bad as you think. NBER Macroeconomics Annual 2007. University of Chicago Press, pp. 381‐441

Engle, Robert F. 1982. Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica. 50:4, 987–1007.

EViews (2017). User's guide on Basic Data Analysis: Forecast Evaluation. http://www.eviews.com/help/helpintro.html#page/content%2Fseries-Forecast_Evaluation.html

Fama, E. F. and French, K. R. 1993. Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics, 33, 3–56.

Fama, E. F. and French, K. R. 1995. Size and Book-to-Market Factors in Earnings and Returns. Journal of Finance, 50,131–156.

Fama, E. F. and French, K.R. 1996. Multifactor Explanations of Asset Pricing Anomalies. Journal of Finance, 51, 55–84.

Fama, E. F. and French, K.R. 2015. A five-factor asset pricing model. Journal of Financial Economics, 116, 1–22.

Fama, E. F. and French, K. R. 2017. International tests of a five-factor asset pricing model. Journal of Financial Economics, 123, 441-463.

Fama, E.F. and French, K.R. 2004. The Capital Asset Pricing Model: Theory and Evidence. Journal of Economic Perspectives, 18:3, 25-46.

Frankel, J. 1983. Monetary and portfolio balance models of exchange rate determination. In: Bhandari, J. Putnam, B. (Eds). Economic interdependence and flexible exchange rates. Cambridge (MA): MIT Press. pp: 84–114.

Frankel, J.A. 1979. On the Mark: a theory of floating exchange rates based on real interest differentials. American Economic Review, 69:4, 610–622.

Frenkel, J. 1976. A Monetary Approach to the Exchange Rate: Doctrinal Aspects and Empirical Evidence. Scandinavian Journal of Economics, 78:2, 200-224.

Friedman, M. 1988. Money and the Stock Market. Journal of Political Economy, 96: 2, 221-245.

Hooper, P. and Morton, J. 1982. Fluctuations in the dollar: A model of nominal and real exchange rate determination. Journal of International Money and Finance, 1, 39-56.

Ince, O., Molodtsova, T. and Papell, D.H. 2016. Taylor rule deviations and out-of-sample exchange rate predictability. Journal of International Money and Finance, 69, 22-44

Ismail, M.T., Yong, L.S. and Ming, L.Y. 2017. Modelling the relationship between Malaysia exchange rate and sectoral stock market indices. Journal of engineering & applied sciences, 12:9, 2525-2531

Jagannathan, R. and Wang, Z. 1996. The Conditional CAPM and the Cross-Section of Expected Returns. Journal of Finance, 51, 3–53

Khan, A. and Abbas, Z. 2015. Portfolio balance approach: An empirical testing. Journal of Economics and International Finance, 7, 137-143

Kilian, L., 2009. Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. American Economic Review, 19, 1053–1069

Kilian, L. and Vigfusson, R.J. 2011. Do Oil Prices Help Forecast U.S. Real GDP? The Role of Nonlinearities and Asymmetries. Journal of Business and Economic Statistics, 31:1, 78-93

Kisswani, K.M. and Elian, M.I. 2017. Exploring the nexus between oil prices and sectoral stock prices: nonlinear evidence from Kuwait stock exchange. Cogent economics & finance, 5, 1-17

Kouri, P. and de Macedo, J. 1978. Exchange Rates and the International Adjustment Process. Brookings Papers on Economic Activity, 1, 111-157

Koutmos, G., and Martin, A.D. 2007. Modelling time variation and asymmetry in foreign exchange exposure. Journal of Multinational Financial Management, 17: 61-74.

Kutty, G. 2010. The Relationship Between Exchange Rates and Stock Prices: The Case of Mexico. North American Journal of Finance and Banking Research, 4 4.

Lansing, K.J. and Ma, J. 2017. Explaining exchange rate anomalies in a model with Taylor-rule fundamentals and consistent expectations. Journal of International Money and Finance, 70, 62–87

Lewellen, J., 2004. Predicting returns with financial ratios. Journal of Financial Economics 74, 209–235.

Lin, C. 2012. The co-movement between exchange rates and stock prices in the Asian emerging markets. International review of economics and finance, 22:1, 161-172

Lintner, J. 1965. The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. Review of Economics and Statistics, 47:1, 13–37.

Litsios, I. 2013. Exchange rate determination and equity prices: Evidence from the UK. The Journal of Economic Asymmetries, 10, 115–128

Makin, A.J., Narayan, P.K. and Narayan, S. (2014). What expenditure does Anglosphere foreign borrowing fund? Journal of International Money and Finance, 40, 63–78.

Mark, N. 2009. Changing monetary policy rules, learning, and real exchange rate dynamics. Journal of Money, Credit & Banking, 41, 1047‑1070.

Meese, R. and Rogoff, K. 1983. Empirical exchange rate models of the seventies: do they fit out of sample? Journal of International Economics, 14, 3–24.

Merton, R.C. 1973. An Intertemporal Capital Asset Pricing Model. Econometrica. 41:5, 867–887.

Merton, R.C. 1990. Continuous-Time Finance. Cambridge, Mass. and Oxford.

Molodtsova, T. and Papell, D.H. 2009. Out-of-sample exchange rate predictability with Taylor rule fundamentals. Journal of International Economics 77, 167–180

Moosa, I. 2013. Why is it so difficult to outperform the random walk in exchange rate forecasting? Applied Economics, 45:23, 3340-3346

Moosa, I. A. and Burns, K. 2012. Can exchange rate models outperform the random walk? Magnitude, direction and profitability as criteria. Economia Internazionale, 65, 473–90.

Moosa, I. and Burns, K. 2014a. The unbeatable random walk in exchange rate forecasting: Reality or myth? Journal of Macroeconomics, 40, 69–81

Moosa, I. and Burns, K. 2014b. Error correction modelling and dynamic specifications as a conduit to outperforming the random walk in exchange rate forecasting. Applied Economics, 46:25, 3107-3118

Moosa, I. and Burns, K. 2014c. A reappraisal of the Meese–Rogoff puzzle, Applied Economics, 46:1, 30-40

Naifar, N. and Al Dohaiman, M.S. 2013. Nonlinear analysis among crude oil prices, stock markets' return and macroeconomic variables. International Review of Economics and Finance, 27, 416–431.

Narayan, P.K. and Bannigidadmath, D. 2015. Are Indian Stock Returns Predictable? Journal of Banking & Finance, 58, 506-531.

Narayan, P.K. and Sharma, S.S. 2014. Firm return volatility and economic gains: The role of oil prices. Economic Modelling, 38, 142–151.

Narayan, P.K., Gupta, R., 2014. Has oil price predicted stock returns for over a century? Energy Economics. 48, 18–23.

Raza, N., Shahzad, S.J., Tiwari, A.K. and Shahbaz, M. 2016. Asymmetric impact of gold, oil prices and their volatilities on stock prices of emerging markets. Resources Policy, 49, 290 – 301

Ross, S.A. 1976. The Arbitrage Theory of Capital Asset Pricing. Journal of Economic Theory, 13:3, 341–360.

Salisu A. A, Ademuyiwa, I. and Isah, K. 2017b. Revisiting the forecasting accuracy of Phillips curve: the role of oil price. Working Papers 022, Centre for Econometric and Allied Research, University of Ibadan.

Salisu A. A, Swaray, R and Oloko, T. F 2017a. A multi-factor predictive model for oil-US stock nexus with persistence, endogeneity and conditional heteroscedasticity effects - Centre for Econometric and Allied Research, University of Ibadan Working Papers Series, CWPS 0024.

Salisu, A.A. and Isah, K.O. 2017a. Predicting US CPI-Inflation in the presence of asymmetries, persistence, endogeneity, and conditional heteroscedasticity.

Working Papers 026, Centre for Econometric and Allied Research, University of Ibadan.

Salisu, A.A. and Isah, K.O. 2017b. Revisiting the oil price and stock market nexus: A nonlinear Panel ARDL approach. Economic Modelling, 66, 258-271.

Salisu, A.A. and Oloko, T.F. 2015. Modelling spillovers between stock market and FX market: evidence for Nigeria. Journal of African Business, 16:1-2, 84-108

Sharpe, W.F. 1964. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. Journal of Finance, 19:3, 425–442

Shin, Y., Yu, B.C. and Greenwood, N. 2014 Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications, eds. by R. Sickels and W. Horrace: Springer, 281-314.

Smith, C. 1992. Stock Markets and the Exchange rate: A Multi-Country Approach. Journal of Macroeconomics, 14:4, 607-629.

Stillwagon, J.R. 2016. Non-linear exchange rate relationships: An automated model selection approach with indicator saturation. North American Journal of Economics and Finance, 37, 84–109

Stulz, R.M. 1995. The cost of capital in internationally integrated markets: the case of Nestle. European Financial Management 1, 11 -22.

Stulz, R.M. 1981a. On the effects of barriers to international investment. The Journal of Finance, 36:4, 923 – 934.

Stulz, R.M. 1981b. A model of international asset pricing. Journal of Applied Corporate Finance, 12, 8 – 25.

Swaray, R and Salisu A. A 2017. The impact of crude oil prices on stock prices of oil firms: Should upstream-downstream dichotomy in supply chain be ignored? - Centre for Econometric and Allied Research, University of Ibadan Working Papers Series, CWPS 0021.

Taylor, J.B. 1993. Discretion versus policy rules in practice. Carnegie-Rochester Conference Series on Public Policy, 39, 195–214.

Timmermann, A. 2013. Forecast Combinations. Updated version of the Chapter in Handbook of Economic Forecasting, in Graham Elliott, Clive W.J. Granger and Allan Timmermann (eds.), Oxford.

Tsagkanos, A. and Siriopoulos, C. 2013. A long run relationship between stock price index and exchange rate: A structural nonparametric cointegration regression approach. Journal of international financial markets, institutions & money, 25, 106-118

Tsai, I.C. 2012. The relationship between stock price index and exchange rate in Asian markets: A quantile regression approach. Journal of International Financial Markets, Institutions & Money, 22: 609–621

Ülkü, N., & Demirci, E. 2012. Joint dynamics of foreign exchange and stock markets in emerging Europe. Journal of International Financial Markets, Institutions and Money, 22, 55-86.

Wang, J. and Wu, J.J. 2012. The Taylor rule and forecast intervals for exchange rates. Journal of Money, Credit & Banking, 44, 103–144.

Wang, R., Morley, B. and Ordonez, J. 2016. The Taylor rule, wealth effects and the exchange rate. Review International Economics, 24:2, 282–301.

Westerlund, J. and Narayan, P. K. 2014. Testing for Predictability in Conditionally Hetoroscedasticity Stock Returns. Journal of Financial Econometrics, 13, 342-375

Wilde, Wolfram. 2012. The Influence of Taylor Rule Deviations on the Real Exchange Rate. International Review of Economics & Finance 24, no. 1:51-61

Wong, H.T. 2017. Real exchange rate returns and real stock price returns. International review of economics & finance, 49, 340-352

Wright, J.H. 2008. Bayesian Model Averaging and exchange rate forecasts. Journal of Econometrics, 146, 329-341

Zivkov, D., Njegic, J. and Mirovic, V. 2016. Dynamic Nexus Between Exchange Rate and Stock Prices in the Major East European Economies. Prague Economic Papers, 25 06, 686 – 705

Zubair, A. 2013. Causal Relationship between Stock Market Index and Exchange Rate: Evidence from Nigeria. CBN Journal of Applied Statistics, 4, 87-110