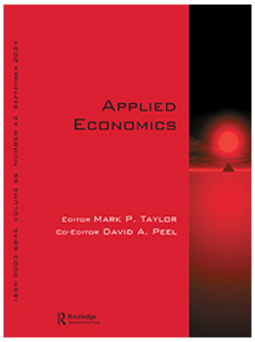

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Forecasting the future: applying Bayesian model averaging for exchange rates drivers in Ghana

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ABSTRACT
Exchange rate forecasts and stability have been a challenge for developing economies. This study analyses the possible exchange rate predictors in Ghana that are needed for policymaking. We perform an out-of-sample exchange rate forecast for the Ghana Cedis (GHS) per the United States dollar (USD) and the Euro (EUR) and the nominal effective exchange rate (NEER) using the Bayesian model averaging for 1, 3 and 6-month horizons. We observed that domestic predictors largely drive the exchange rates in Ghana with the stock market index and fiscal operations exhibiting the strongest predictive power followed by the Taylor rule, and the real economic sector. Moreover, there is an international spillover from the US economy to Ghana's exchange rate. Finally, we noticed that forecast accuracy improved at the 3-month-ahead.

KEYWORDS
Exchange rate; factor; weighted average; Bayesian model averaging; out-of-sample forecasting

JEL CLASSIFICATION
F31; F37; F47; G15

I. Introduction

Exchange rates are believed to be one of the major driving forces behind sustainable economic growth, necessitating efficient forecasting to study the market dynamics (Arratibel et al. 2011). However, since Meese and Rogoff (1983) the predictive imperiousness of the random walk model than the exchange rate determinants in forecasting has been well known. Identifying economic variables that predict or correlate with exchange rates has been controversial and difficult, a term known as 'exchange rate disconnect' (Itskhoki and Mukhin 2024; Lilley et al. 2022; Manzur 2018). A simple implication is that the exchange rate is hard to forecast.

Nevertheless, a survey by Rossi (2013) reveals that exchange rates are predictable. The predictive power depends on the choice of predictor, forecast horizon, model and evaluation approach. Unfortunately, most of the existing literature on exchange rate predictability has focused on advanced economies (Alquist and Chinn 2008; Beckmann and Schüssler 2016; Cheung et al. 2019; Eichenbaum, Johannsen, and Rebelo 2021; etc.), leaving developing economies facing the weak and inconsistent connection between macroeconomic fundamentals, government spending and exchange rates (Liu et al. 2019; Sarno 2005). There is still a debate on identifying effective predictors for exchange rates in developing economies (Lilley et al. 2022; Liu et al. 2019; Manzur 2018).

Ghana is a heavily import-dependent economy that continues to buy foreign currencies to meet its import demands, hence adopting an inflation-targeting flexible exchange rate regime in 2007 to ensure price stability. This affects the foreign reserves of the country leading to exchange rate pressure. Also, the economy is exposed to external shocks, through fluctuations in commodity prices (gold, cocoa and crude oil) and the recent global crises such as COVID-19 and the Russia-Ukraine war. Although, historically, the Ghana Cedis (GHS) has been one of the strongest in Africa, it has lately observed a significant depreciation of the GHS against major currencies like the USD and EUR (check Figure 16) making it one of the worst-performing currencies in the world (Bloomberg 2022). Adusei and Gyapong (2017) find that inflation, monetary policy rate, annual GDP growth rate and the total external debt explain 82% of

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GHS's fluctuations, hitherto comprehensive forecasting analysis on this subject is scanty.

Against this backdrop, this research aims to forecast the changes in the exchange rates in Ghana using 33 predictors. The study's motivation is to provide a broader spectrum of predictors that are relevant in forecasting the future exchange rates not only in Ghana but developing economies at large. We contribute to the existing literature by extracting categories of indices that are imperative for the exchange rate forecast. The predictability explains how these economic variables reconnect with the exchange rate. To achieve this, we employ principal component analysis and equal-weighted average techniques which help in reducing predictor parameters for effective forecasting. Our forecast is performed on three sets of exchange rates: GHS per USD and the EUR and the nominal effective exchange rate (NEER).[1]

The study addresses these questions: Can the exchange rates in Ghana be forecasted? What drives the exchange rate in Ghana? Bayesian model averaging (BMA) is applied in out-of-sample forecasting due to its ability to incorporate several predictors while minimizing the model uncertainties (Byrne, Korobilis, and Ribeiro 2018; Wright 2008). The forecast performance is examined for the 1, 3 and 6-month horizon. We explore the predictive improvement of the exchange rate changes by employing both a random walk without drift and an autoregressive model (Rossi 2013). Monthly data from 2017M5 to 2022M6 is used for the forecast exercise. The forecast performance of the models is evaluated using the Root Mean Squared Forecast Error (RMSFE) and the forecast accuracy of the exchange rate predictors is tested using the Clark and West (2007) adjusted statistics. To the best of our knowledge, this is the first study to perform an out-of-sample exchange rate forecast for multiple horizons for the largely unexplored GHS market.

Our empirical findings suggest that Ghana's exchange rate is highly driven by domestic predictors, with the domestic stock market index (FSI) and government fiscal operations exhibiting the strongest predictive power on the exchange rates. The other domestic predictors such as the Taylor rule, and the real economic sector are also proven to be strong predictors of the exchange rate. Moreover, we noticed the S&P500 and the US real economic sector to be the most international variables that have predictive power on the exchange rate. Even though the forecast is time-dependent, we find that the forecast accuracy is improved at the 3-month-ahead and a lower forecast performance at the 1-month-ahead.

The remaining study is structured as follows: the next subsection reviews the existing literature. Section II discusses the exchange rate predictors and the data. Section III reports the econometric methodology whereas Section IV presents the empirical results. Section V discusses the results and the policy implications and Section VI concludes.

Literature review

The exchange rate economics has received extant literature that has applied the uncovered interest rate parity (UIP) model to establish the predictability of the exchange in the short run while long-run predictability is proven using the purchasing power parity (PPP) (Alquist and Chinn 2008). A review by Manzur (2018) finds that the connection between the exchange rate and economic fundamentals is breaking new ground. Also, Nor et al. (2020) find macroeconomic fundamentals such as imports, money supply, domestic prices, and hot money matter in managing exchange rate volatility in Somalia.

Recent literature reviews have highlighted the evolving connection between exchange rates and bonds (Engel and Wu 2023; Lilley et al. 2022). An enormous amount of literature has engrossed on the Taylor rule monetary policy. Following this, for instance, Molodtsova and Papell (2009) and Panopoulou and Souropanis (2019) emphasize the importance of Taylor rule fundamentals in predicting the exchange rates.

Several studies have examined the relationship between exchange rates and factors such as reserve balance, fiscal operations, and external impacts. For instance, Kuncoro (2015) indicates that credible fiscal policies can help stabilize exchange rates. Also, using a sample of 82 countries, Calderón and Kubota (2018) find trade composition and financial openness play

[1]USD and EUR are chosen as currency pairs of GHS because of their dominance as major trading currencies in the international markets (Gopinath et al. 2020).

important roles in stabilizing real exchange rate volatility. In line with the dominant currency paradigm of the US dollar, Gopinath et al. (2020) explain the correlations between some trade segments and the US dollar exchange rates. Also, Alessandria and Choi (2021) find that exporting decisions, pricing-to-market, and trade cost shocks can determine the dynamics of the US trade balance, real exchange rate, and trade integration.

Moreover, studies employing Bayesian model averaging have shown promise in forecasting exchange rates (Byrne, Korobilis, and Ribeiro 2018; Wright 2008). These approaches incorporate various predictors into the BMA model, including UIP, PPP, and sticky price monetary models (Lam, Fung, and Yu 2008; Wada 2022). Moreover, Beckmann and Schüssler (2016) allow for both model coefficient uncertainty and find that strong shrinkage is required in exchange rate forecasting.

In addition, studies focusing on specific regions like Ghana have employed different models to understand exchange rate fluctuations. These studies have examined factors such as monetary policy rates, GDP growth rates, external debt, and stock market indices (Adusei and Gyapong 2017; Owusu Junior et al. 2018; Sarpong 2019). Gyamerah and Moyo (2020) employ machine learning techniques to predict the exchange rate probability density. Also, Adekoya et al. (2021) applied the Long Short-Term Memory Network to predict the weekly exchange rate of the GHS against the USD, British Pound, and EUR.

Ongoing discussions continue to explore the drivers of exchange rates, including the impact of US monetary policy, Chinese economic growth, and financial shocks (Itskhoki and Mukhin 2024; Liu et al. 2019). By investigating various drivers and categories of predictors, our study aims to enhance the understanding of exchange rate dynamics, particularly in developing economies.

II. Exchange rate predictors and data

Exchange rate predictors

Several economic variables influence the dynamics of the exchange rates. The outstanding contribution this research gives is that we generate and discuss the essential data background and economic variables that commonly drive exchange rate dynamics. These are categorized as:

Real economic sector

The study examines how the dynamics of economic activities affect the changes in the exchange rate. We measure the real economic sector through the composite index of real economic activities (CIE) which is a weighted average of the real GDP. This aggregates all the monthly economic activities that take place in the economy. We also consider the real survey index data which comprises the consumer confidence index (CCI). The CCI indicates households' consumption and savings, hence, an increase in CCI projects growth in economic activities. The study terms these variables as real economic sector variables, which are expected to generate a negative impact on the exchange rate.

Real money market rates

We investigate the impact of money market rates on exchange rates, drawing on recent research that links asset yields, such as treasury bonds, to currency valuations (Jiang, Krishnamurthy, and Lustig 2021). Particularly, we employ the treasury instrument (3-month treasury bill) (I) and credit market (Commercial average lending rate) (L) as short-term nominal interest rates and the 10-year bond rate (B) as the long-term rate. By examining both short- and long-term dynamics, we gain a comprehensive understanding of how exchange rates respond to changes in the money market. The relationship between money market rates and exchange rates suggests that higher domestic interest rates typically lead to higher exchange rates, resulting in the devaluation of the domestic currency, especially in economies with inflation-targeting regimes. To accurately capture the impact of price developments in the money market, we adjust the nominal rates for expected inflation (Z_t - $E_t\pi_t$), where Z_t is a vector of the market rates and $E_t\pi_t$ is the expected inflation rate, providing us with the real Treasury bill rate (r), real average lending rate (lr) and real bond rate (br) predictors.

Commodity market returns

In the 2000s, rising commodity prices significantly impacted various sectors, including exchange rates,[2] with a more pronounced effect over the long term (Beckmann, Czudaj, and Arora 2020). This trend is particularly relevant for commodity-dependent economies like Ghana. To explore this relationship, we examine the returns of Ghana's top three exports: cocoa, gold, and crude oil. Given Europe's importance as Ghana's largest trading partner, we focus on Brent crude oil, the European benchmark. We denote these returns as: (cp_t, gp_t, op_t), where cp_t, gp_t, op_t are log returns: $ln(P_t)$ - $ln(P_{t-1})$ of cocoa, gold and Brent crude oil respectively. The expectation is that an increase in commodity returns will lead to a short-run fall in the exchange rate of the exporting country.

External sector developments

This study investigates the effect of an economy's engagement in external activities on the behaviour of the exchange rate (Alessandria and Choi 2021; Calderón and Kubota 2018). We employ the trade balance and international reserves as proxies for the external sector. This sector contributes immensely to the fluctuations in the exchange rate in developing economies.[3] Similarly, international reserve, being an import cover, has been a major factor contributing to the exchange rate in major economies. The central bank has been using the international reserve to offset imports when there is a shortfall in export revenue. The external sector generates a negative impact on the exchange rate.

Government fiscal operations

It became a debate in the middle of the 1980s about why the USD was appreciating relative to the other currencies amidst the US federal budget deficit and the rising government debt. Feldstein (1986) supported the idea that increasing US debt to finance the deficit led to USD appreciation. Subsequently, other literature challenged this conventional view. For instance, Evans (1986) used the Ricardian equivalence approach to show that government deficits actually caused USD depreciation. Similarly, McMillin and Koray (1990) confirmed that US debt shock causes a temporal depreciation of the USD. Considering the continuous budget deficit and increasing government debt in Ghana, the study sought to examine the impact of government fiscal operations in forecasting the changes in the nominal exchange rate. We employ the three major fiscal operation tools which include; the overall balance of the central government budget (CGB) which is a cash basis and both external and domestic public debt (ED, DD). All these fiscal variable tools are a percentage of GDP. Previous research suggests that government debt adversely affects currencies in developing countries (Kuncoro 2015).

Banking sector

The health of the banking sector affects the success of the domestic currency. We assess this using three key predictors: total assets annual growth (TAG), capital adequacy ratio (CAR) and core liquid assets to short-term liabilities (LASL). TAG acts as a proxy for the central bank's aggregate balance sheet. CAR measures the financial soundness of the economy, while LASL explains liquidity's effect on the exchange rate. We examine the banking sector because they are relevant drivers the central banks apply to form unconventional policies. In reaction to the global financial crisis, the major central banks set short-term interest rates to a Zero Lower Bound and adopted unconventional monetary policies. Inoue and Rossi (2019) confirm that unconventional monetary policy tools have recently become more frequent in the international financial market and potentially influence global market dynamics, including foreign exchange rates.

Stock market index

Another predictor that the study employs to forecast the exchange rate is the stock market returns. This is a leading indicator that projects the performance or growth of companies at the economy level. Essentially, the stock market can indicate the direction of the economy; when the stock market index of a country rises, it suggests increasing company earnings and overall economic growth, and vice versa. An increase in the stock market index increases the demand for the local currency leading to

[2]Manzur (2018) finds the world commodity prices as alternative fundamental instruments that influence the exchange rate economics in recent studies.

[3]Even though Ghana has been experiencing a trade surplus since 2017, the GHS has depreciated against the USD due to the higher proportion of primary exports and increased value of manufactured imports (Agyapong and Suleman 2022).

a fall in the exchange rate (Owusu Junior et al. 2018). In this study, the Financial Stock Index is used as the best proxy for the stock market index.

Taylor rule

A strand of exchange rate literature has emphasized the application of the Taylor rule as a monetary policy to capture the set of fundamentals imperative for comprehending exchange rate movements (Beckmann and Wilde 2013; Byrne, Korobilis, and Ribeiro 2018; Molodtsova and Papell 2009; Panopoulou and Souropanis 2019). This is a monetary policy often used by the central bank. Although recent studies have demonstrated that the Taylor rule has not been effective in predicting the exchange rate after the 2008 financial crisis due to the interest rate reaching the zero-lower bound (Agyapong 2021). Currently, the fundamentals used in the Taylor rule have become global issues due to higher inflation resulting from the energy crisis. In this regard, the study examines if the Taylor rule has the predictive power to explain the exchange rate movement. The calibration of the Taylor rule is given below:

$$TRF_t = 1.5\pi_t + 0.5y_t, \tag{1}$$

where π_t and y_t denote the inflation rate and output gap.

Data

Given the availability of monthly frequency data our sample runs from 2017M5 to 2022M6 which includes two critical periods such as the prevailing COVID-19 crisis and the Russia-Ukraine war which is affecting several indicators of the economy. Our target variables are the change in exchange rates – Ghana Cedis (GHS) per the USD and the Euro (EUR) and the nominal effective exchange rate (NEER). Ghana is the domestic country. The study applies a total number of 19 predictors at the domestic level and 14 comparable predictors at the international level for the robustness analysis (see Table A1 in Appendix A for the details on the data variables, abbreviations and sources.). The data used in our study are very important as it contains all the key economic data that the monetary policy committee of the Bank of Ghana considered prior to their policy decision. We apply the annual inflation rate measured as the 12-month percentage difference of the consumer price index (CPI). The output gap is measured as the percent deviation of GDP from its trend.

There are two indices we extract in this study to further examine the exchange rate predictors. Firstly, we apply the principal component analysis (PCA) to generate predictor factors. These are categorized as the real economic sector factor (factor1); real money market rates factor (factor2); commodity market returns factor (factor3); external sector developments factor (factor4); government fiscal operations factor (factor5); and banking sector factor (factor6).

We also compute the equal-weighted average as the second index approach. This is measured below:

$$GEP_t = \frac{\sum_{i=1}^{N} ERP_{i,t}}{N}, \tag{2}$$

where GEP_t is the category of the exchange rate predictor explained in section 2.1. $ERP_{i,t}$ represents the predictor within the category at time t. N denotes the number of predictors within the category. We termed GEP_t as real economic sector weighted average (avreecon); real money market rates weighted average (avmarrate); commodity market returns weighted average (avcompric); external sector developments weighted average (avexternal), government fiscal operations weighted average (avfiscal); and banking sector weighted average (avbanking). These categories of predictors are generated at both domestic and international levels. The importance of creating these indices is to help reduce the number of parameters to estimate in our model. The financial stock index (FSI) and Taylor rule which are single predictors are added to the two sets of indices.

III. Econometric methodology

Bayesian model averaging

Ordinary Least Squares (OLS) regression has been widely used as a good estimating model for forecasting (Rossi 2013). However, estimating OLS regression could face the challenge of model uncertainty as the predictor variables increase. Thus, the in-sample is overfitted when too many predictors are used. In the case of out-of-sample forecast analysis, the in-sample over-fitting reduces the forecast performance. It's in this vein Learner (1978) proposes the Bayesian model. Given our dependent variable as $\Delta e_{t+h} \equiv e_{t+h} - e_t$ representing the h-step-ahead change in the log of the nominal exchange rate and the several predictors,[4] we employ the Bayesian model averaging (BMA).

The BMA mitigates the problem of model uncertainty which instigates from increasing predictors. An econometric application of BMA to the linear regression models is made by Raftery et al. (1997); Hoeting et al. (1999). The BMA works through a model selection exercise that extracts a single 'best' model. This model is presented as the true model and inference is made from it. The selection is performed by creating a weighted average on all the models. For better understanding, let's assume we have q potential predictor variables of X, 2^q predictor combinations and models could be estimated. For simplicity, let's have all the predictor models considered in this study as $M = M_{1,\ldots,}M_q$ where all the probabilities are conditional. If Y is the future observation thus, in this study Δe_{t+h} given the data Z then we predict Y using a posterior distribution in the form

$$Pr(Y|Z) = \sum_{i=1}^{q} Pr(Y|M_q, Z) Pr(M_q|Z), \tag{3}$$

where $Pr(M_q|Z)$ is the posterior model probability of M_q which is expressed as

$$Pr(M_q|Z) = \frac{Pr(Z|M_q)Pr(M_q)}{\sum_{j=1}^{q} Pr(Z|M_j)Pr(M_j)}. \tag{4}$$

The posterior model probability is relevant in selecting the best model for the estimation which involves the researcher's prior knowledge about the data. Hence, the prior probability that M_q is a true representation of the model has to be known which is denoted as $Pr(M_q)$. The $Pr(Z|M_q)$ represents the marginal likelihood which is constant over all the models in M and it's given in the Equation (5) below:

$$Pr(Z|M_q) = \int Pr(Z|\theta_q, M_q) Pr(\theta_q|M_q) d\theta_q, \tag{5}$$

where θ_q contains the coefficients of the model M_q and $Pr(Z|\theta_q, M_q)$ explains the likelihood. $Pr(\theta_q|M_q)$ denotes the prior density of θ_q.

The model average resulting from each model weighted under the posterior model probabilities $Pr(M_q|Z)$ in Equation (4) is termed the BMA that enhances predictive performance. In so doing, the BMA generates the prior and posterior inclusion probabilities for the individual predictor. To explain further, a prior inclusion probability provides the probability that a predictor is included in the model before accessing the data. This is computed by adding up the prior model probabilities of all models which encompass that predictor. The posterior inclusion probability on the other hand gives the probability that a predictor is included in the model after seeing the data. We compute this by totalling up the posterior model probabilities of all models that cover that predictor.

In computing BMA, two approaches are usually considered in simulating from the posterior. These include Occam's window and Markov Chain Monte Carlo Model Composition (MCMC). However, according to Raftery et al. (1997), Occam's window is relevant for analysing the relationship between variables whereas the MCMC is useful for predictions. Therefore, since this study involves an out-of-sample forecasting exercise, the MCMC as suggested by Raftery et al. (1997) would be applied. We apply BMA to estimate the train data (in-sample data) under a rolling window where the estimates are used to generate a robust forecast which is not included in the in-sample estimation.

Benchmark and forecast comparison

Benchmark selection is imperative in determining the predictability of a model (Rossi 2013). A strand of literature applies the random walk without drift (RW) as the benchmark. However, for robust analysis, this study employs both RW and the univariate Autoregressive (AR) models which are widely used by professionals and forecast analysts. The

[4] To avoid endogeneity problem, we use the lag form of the predictors.

random walk model means that the exchange rate cannot be forecasted, hence, the most current exchange rate is used to measure the accurate forecast value as represented below.

$$e_{t+h} = e_t + \varepsilon_t, \tag{6}$$

where e denotes the nominal exchange rate at time t or $t + h$.

In the case of the RW, the out-of-sample forecast cannot be applied to the exchange rate. From Equation (6), the RW error becomes the change in the realized exchange rate ($\varepsilon_t = e_{t+h} - e_t \equiv \Delta e_{t+h}$). This makes it difficult for a model to accurately outperform the RW. Hence, according to Rossi (2013), the RW is a good benchmark model to judge the forecasting accuracy of a model.

The alternative benchmark model the study employs is the first-order univariate autoregressive model (AR(1)). From the econometric perspective, AR(1) allows for mean revision and it explains that the best forecast of the exchange rate stems from its previous value:

$$\Delta e_{t+h} = \beta_0 + \beta_1 \Delta e_{t+h-1} + \varepsilon_t, \tag{7}$$

As depicted in Equation (7), the recent lag value of the nominal exchange rate changes Δe_{t+h-1} is the only predictor in the AR(1) model. We then apply the out-of-sample forecast to generate the forecast values and errors.

In analysing the forecasting ability of our exchange rate predictors, we compare the out-of-sample forecasts from BMA with the two benchmarks. There are several statistical models for evaluating the forecast performance against the benchmarks. However, in this study, we employ the Root Mean Squared Forecast Error (RMSFE) which is recognized by Meese and Rogoff (1983) as an effective forecast evaluation tool:

$$RMSFE = \sqrt{P^{-1} \sum_{t=T-P+1}^{T} (y_{t+\tau} - \hat{y}_{t,t+\tau})^2}, \tag{8}$$

where $y_{t+\tau}$ and $\hat{y}_{t,t+\tau}$ are the realized and forecasted exchange rates respectively at time $t + \tau$. The error term is obtained from the difference between the realized and forecasted value. $(T + 1)$ denotes the sample observations and P is the number of forecasts.

A comparison of the forecasts of our models and the two benchmarks is performed by computing the ratio of the RMSFE of the benchmarks to the RMSFE of the exchange rate predictors. This is termed Theil's U-statistics:

$$Theil'sU = \frac{RMSFE_B}{RMSFE_M}, \tag{9}$$

where $RMSFE_B$ and $RMSFE_M$ denote the RMSFE of the benchmarks and the RMSFE of the exchange rate predictors respectively. The premise is that, if Theil's U is greater than 1 then the exchange rate predictors perform better than the benchmark model in forecasting the nominal exchange rate change. The forecast evaluation in certain cases is not enough to conclude the forecast performance against the benchmarks. As the study focuses more on which sector of the economy largely affects the dynamics of the exchange rate, we extend the evaluation to compare the forecast accuracy.

We compare the forecasting accuracy of our model using the adjusted statistics by Clark and West (2007) (CW-Test). This statistical test is appropriate for nested models. Using CW-Test, we test the forecast accuracy through a hypothesis that the coefficients of our Bayesian model are not zero hence the exchange rate change can be predicted by our models.[5]

IV. Empirical results

Some preliminary analysis

Descriptive analysis

The trend of the change in the nominal exchange rates is illustrated in Figure A1 in Appendix A. Table A2 reports a brief description of all the variables in the study. Most of the predictors have their standard deviations lower than their means which indicates that the predictors do not largely change from their average values. In other words, it implies that the variables display some form of certainty.

[5]There could be a serial correlation in the residuals for the multiple forecast horizons. To solve this problem, we apply the Newey – West robust variance estimator (Newey and West 1987) to the Clark and West test statistics.

Unit root tests

We first tested for stationarity for all the predictors using the Augmented Dickey-Fuller test. As presented in Table A2 it is evident that most variables are not stationary at the levels. However, taking their first difference we find all the predictors to be stationary. Hence, to avoid spurious regression demands to use the first difference of the variables in the model.

Linear correlation

The correlation between the predictors and the exchange rate is reported in Table A3. Averagely, the highest positive correlation between the exchange rate and the domestic variables is external debt (ED) (0.8770). For the international predictors, the US trade balance (TB) is found to have the highest negative correlation (−0.8426) with the exchange rate. We observe that the factors and equal-weighted predictors generally have a low correlation with the exchange rate. This might be due to the first different form that is used. However, this is not evidence that the predictors do not have predictive power over the exchange rate.

Marginal inclusion probability in-sample analysis

We begin with employing only the domestic predictors. The study applies a rolling window from 2017M5 - 2019M12 for the in-sample estimation. The remaining observations (2020M1 - 2022M6) are used for the forecast evaluation and comparison. To obtain the posterior and model statistics, Bayesian averaging sampling (BAS) which apportions a uniform prior distribution to all the models is used. This generates the marginal posterior inclusion probabilities (PIP) for the individual covariates and we dwell on this to analyse the in-sample predictive power of the model.

The marginal inclusion probability explains the predictors that are capable of influencing the changes in the exchange rate. The hypothesis is that the predictors with a PIP greater than 0.5 are relevant for predicting the changes in the exchange rate and vice versa. We present the PIP for the two categories of predictors, namely, All factors, FSI and Taylor rule; and All equal-weighted averages, FSI and Taylor. Each category has 8 predictors giving 256 potential models to select from. The motivation of this section is that it helps to address the question of what drives the exchange rate changes in Ghana. Note that the diagrams below illustrate the marginal inclusion probabilities with the red bar displaying the predictors that drive the changes in the exchange rate.

As illustrated in Figure 1, we observe that all the predictors are relevant determinants of the exchange rate across all the forecast horizons except the real money market rates and the external sector developments. The real economic sector, government fiscal operations and FSI exert the strongest predictive power on the exchange rate changes based on its higher marginal inclusion probability (note: details of all the predictors are displayed in Figure B1). This implies that these economic variables reconnect with the exchange rate (Lilley et al. 2022). Our results support Adusei and Gyapong (2017), who find some macroeconomic variables including the annual GDP growth rate and the total external debt explain 82% of the variance in the GHS per USD exchange rate. It also aligns with Itskhoki and Mukhin (2024), who find that financial shock influences the exchange rate behaviour. The predictive power of these predictors is greatest at $h = 6$, and $h = 3$.

Out-of-sample forecast

We report Theil's U statistics with the two benchmarks – random walk without drift and AR(1) models to analyse the forecast performance for 1-month, 3-month and 6-month ahead in Table 1 using only the domestic predictors.

Theil's U statistics show that the two benchmark models perform better than employing all the predictors at $h = 1$, $h = 3$ and $h = 6$. However, the CW-Test finds all the predictors to be significantly accurate in forecasting the exchange rate as the horizon increases against the RW. All the predictors accurately forecast the exchange rate when the forecast horizon is 3 months and 6 months at 10% and 1% significance respectively. When we applied all the principal component factors, stock prices and the Taylor rule, we found these predictors to outperform the two benchmark models at a 6-month-ahead forecast. Nevertheless, it becomes difficult for these predictors to beat the two

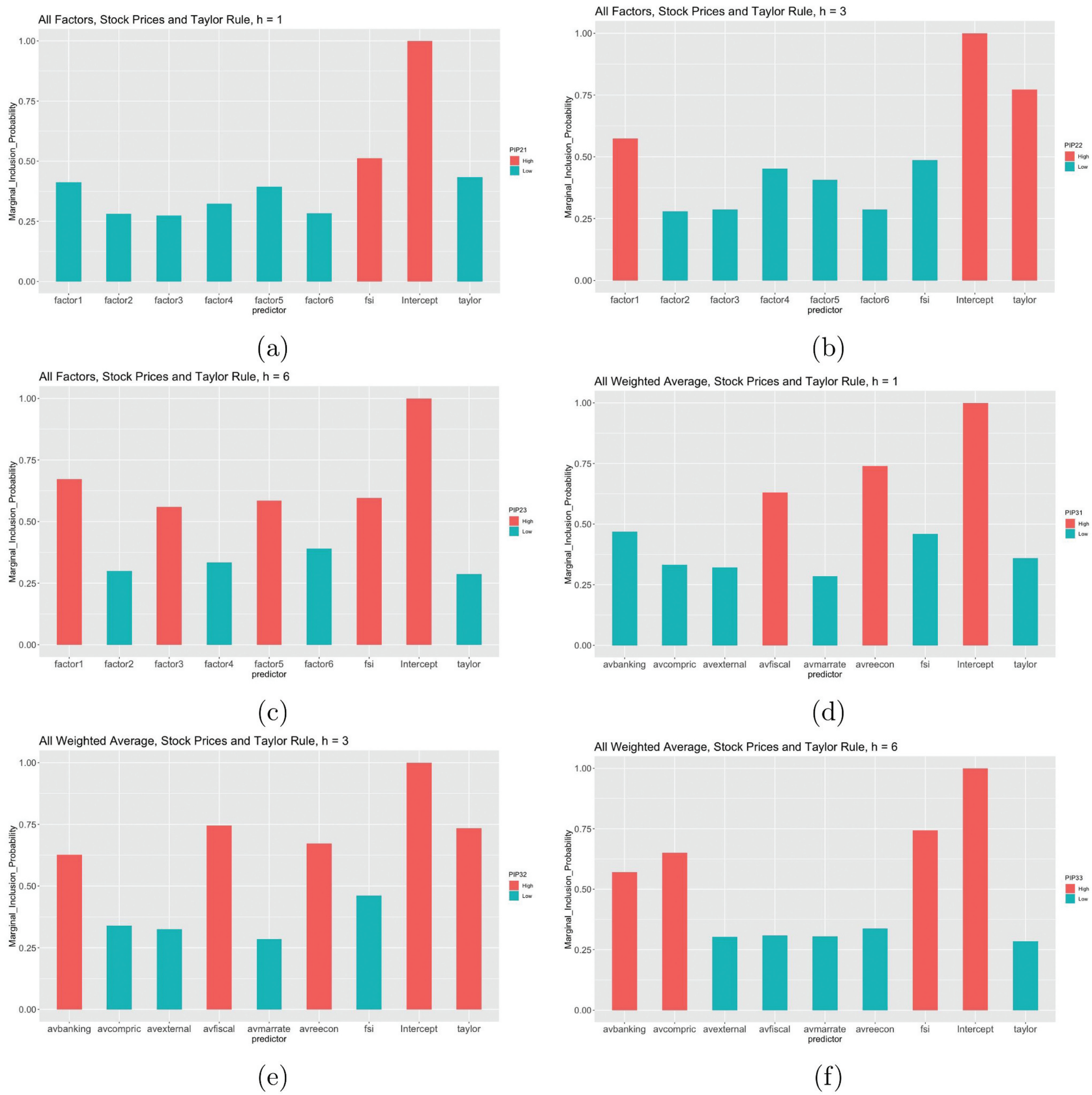


Figure 1. Marginal inclusion probability for only domestic predictors.

Table 1. Out-of-sample forecast using domestic predictors.

	With Random Walk Benchmark			With AR(1) Benchmark		
Forecast Horizon	h = 1	h = 3	h = 6	h = 1	h = 3	h = 6
Predictors	Theil's U	Theil's U	Theil's U	Theil's U	Theil's U	Theil's U
All Predictors	0.8220	0.9582*	0.9298***	0.8406	0.8510	0.8840
All Factors, Stock Prices and Taylor Rule	0.9130	0.9892**	1.0282**	0.9095	0.8854	1.0099
All Weighted Averages, Stock Prices and Taylor Rule	1.0078**	1.0441**	0.8320	1.0287	0.9360	0.9036

The table presents Theil's U values and Clark and West's forecast accuracy test. Theil's U greater than 1 implies that the model outperforms the benchmark. The estimation window is 2017M5 - 2019M12 and the remaining observations (2020M1 - 2022M6) are used for the forecast evaluation and comparison. The Newey–West robust variance estimator (Newey and West 1987) is applied to solve the serial correlation in the residuals for the multiple forecast horizons. ***; **; * represent the statistical significance of Clark and West's forecast accuracy of the model at 1%, 5% and 10% respectively.

benchmark models at a shorter horizon, specifically $h = 1$ and $h = 3$. With the CW-Test, we observe the principal component factors, stock prices and Taylor rule predictors to significantly (5%) accurately forecast the exchange rate at $h = 3$ and $h = 6$ against the RW. We also observe all the equal-weighted averages, stock prices and Taylor rule predictors to outperform the random walk at $h = 1$ and $h = 3$ and accurately forecast the exchange rate at a 5% significant level. Considering the AR(1) benchmark, all the equal-weighted averages, stock prices and Taylor rule predictors better forecast exchange rate $h = 1$ than the benchmark. Generally, our results find no accurate forecast for the different sets of predictors against the AR(1) benchmark.

Controlling for international (US) predictors

The concept of the exchange rate as domestic currency exchanged for a foreign currency opens a challenge that using only the domestic predictors would not be enough to justify the forecast performance of the exchange rate changes. There could be an international influence on the exchange rate. We address this by controlling for international (US) predictors. Knowing that Ghana is a small open economy and trades currency with the US which is a large open economy, we add similar predictors of the US (see Table A1 in Appendix A for details) in a heterogeneous approach.

Next, we follow Engel and West (2005) to assume that the central bank targets the domestic currency through its purchasing power in the international market. That is, the central bank monitors whether the nominal exchange rate appreciates or depreciates from the PPP. To consider this adjustment we include the real exchange rate (rer) which is defined as $rer_t = e_t + p_t^* - p_t$. where e_t is the log of the nominal exchange rate. p_t and p_t^* are logs of the domestic and US consumer price index respectively. $rer_t > 1$ implies that the domestic currency is depreciating and $rer_t < 1$ shows that the domestic currency is appreciating. In equilibrium, $rer_t = 1$ to make PPP hold.

After running the BAS for the three forecast horizons, the PIP from Figure 2 confirms that the predictors have predictive power except for the real money market rates and external sector developments while the commodity market also loses its predictive power. The in-sample analysis finds the domestic and international financial stock index: FSI and S&P 500 obtain the highest PIP. This is consistent with Lilley et al. (2022), who demonstrate that the S&P 500 comoves with the exchange rates. This is followed by both the domestic and US Taylor rules. Moreover, the PIP attained for the real exchange rate, real economic sector of the US and the domestic government fiscal operations indicate that they are plausible predictors of the exchange rate. This is consistent with Liu et al. (2019), who find US monetary policy having a significant impact on emerging market exchange rate growth fluctuations.

We proceed to analyse the out-of-sample forecast of the exchange rate using both the domestic and international predictors. The Theil's U results in Table 2 evaluate that, none of the predictors could outperform the two benchmarks. Nevertheless, the CW-Test shows that using all the predictors accurately forecasts the changes in exchange against the RW benchmark at a significance of 10% for $h = 1$ and 1% for $h = 6$. More so, using the principal component factors, stock prices and Taylor rule predictors is significant at a 10% level for $h = 1$ against the RW. This is robust even after adding the real exchange rate. The forecast accuracy generated at the international level with all the equal-weighted averages, stock prices and Taylor rule predictors is consistent with using only domestic predictors at a 5% significant level against the RW. The inclusion of the real exchange rate reduces the statistical significance for $h = 1$ to 10%.

Robustness check

Exchange rate against Euro

In this section, we show that our results are not restricted to the Ghana Cedis (GHS) and the US dollar exchange rate. We conduct a robustness analysis by examining GHS relative to the Euro which is the second largest international trading currency (Gopinath et al. 2020). This data is extracted from the International Monetary Fund (IMF) on a monthly frequency. Since the earlier results prove the dominance of the

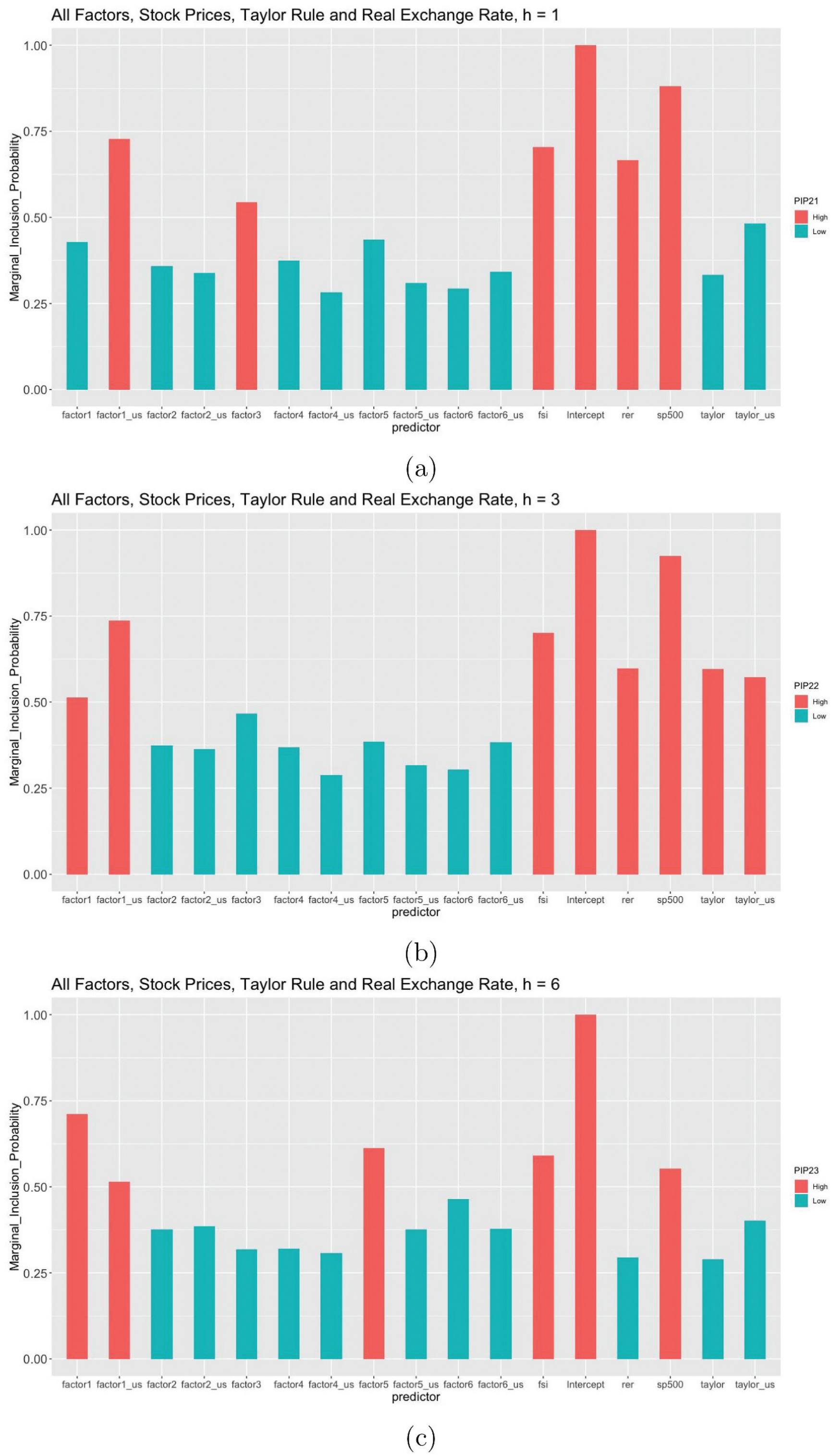
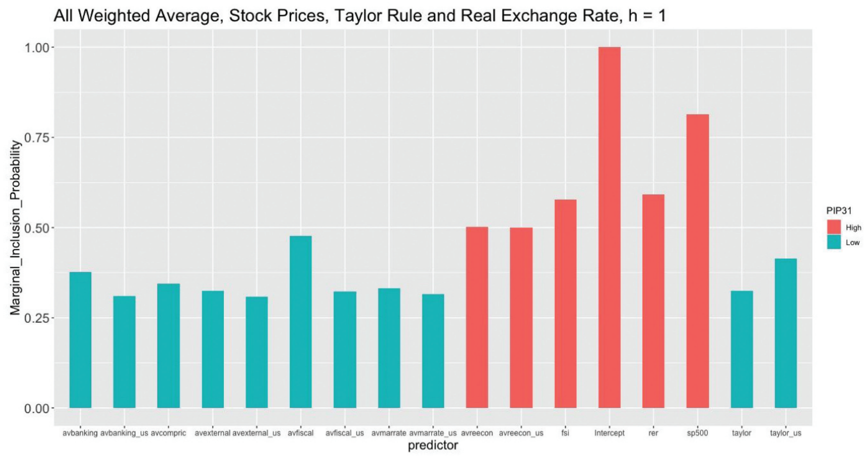


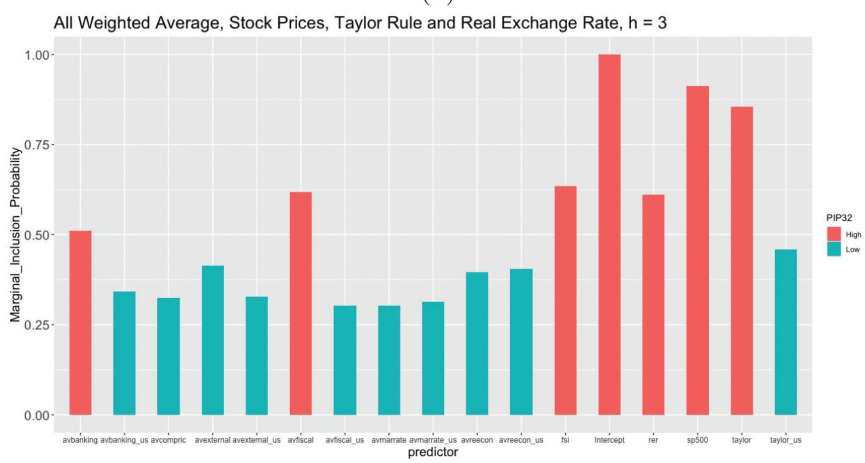
Figure 2. Marginal inclusion probability for both domestic and international predictors.

domestic predictors in forecasting the exchange rate, we use only the domestic predictors to forecast the changes in the exchange rate against the Euro.

From the PIP results in Figures B2 and B3 we find the FSI to exhibit the most predictive power on the exchange rate changes. This is proceeded by the real economic sector, Taylor rule and



(d)



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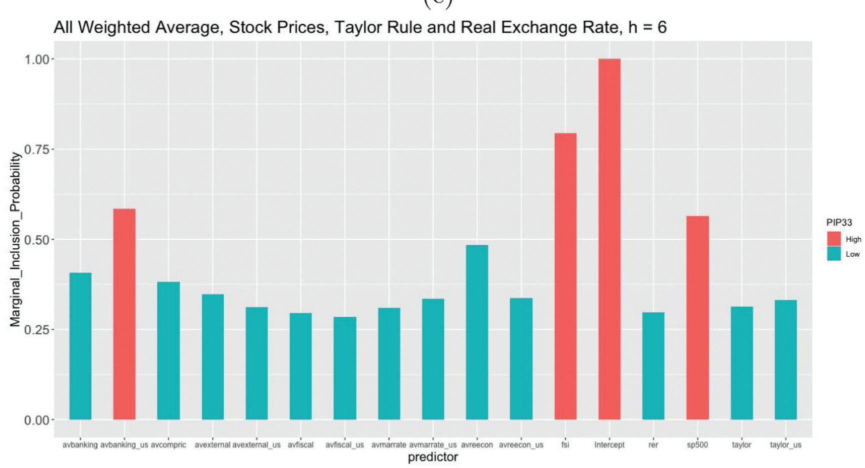

(f)

Figure 2. Marginal inclusion probability for both domestic and international predictors.

government fiscal operations which is consistent with the previous results. The out-of-sample forecast results in Table B1 show that even though it is difficult to beat the two benchmark models, we find at least a 10% statistically significant level of forecast accuracy. The accuracy of the predictors is improved when the AR(1) model benchmark is employed.

Table 2. Out-of-sample forecast using both domestic and international predictors.

	With Random Walk Benchmark			With AR(1) Benchmark		
Forecast Horizon	h = 1	h = 3	h = 6	h = 1	h = 3	h = 6
Predictors	Theil's U	Theil's U	Theil's U	Theil's U	Theil's U	Theil's U
All Predictors	0.8220	0.9582*	0.9298***	0.8406	0.8510	0.8840
All Factors, Stock Prices and Taylor Rule	0.8474*	0.7878	0.8286	0.8500	0.6905	0.8037
All Factors, Stock Prices, Taylor Rule and Real Exchange Rate	0.8262*	0.7826	0.8263	0.8244	0.6796	0.7996
All Weighted Averages, Stock Prices and Taylor Rule	0.8958**	0.8581**	0.7231	0.8606	0.7915	0.7375
All Weighted Averages, Stock Prices, Taylor Rule and Real Exchange Rate	0.8884*	0.8646**	0.7175	0.8492	0.8006	0.7255

The table presents Theil's U values and Clark and West's forecast accuracy test. Theil's U greater than 1 implies that the model outperforms the benchmark. The estimation window is 2017M5 - 2019M12 and the remaining observations (2020M1 - 2022M6) are used for the forecast evaluation and comparison. The Newey–West robust variance estimator (Newey and West 1987) is applied to solve the serial correlation in the residuals for the multiple forecast horizons. ***; **; * represent the statistical significance of Clark and West's forecast accuracy of the model at 1%, 5% and 10% respectively.

Nominal effective exchange rate

One can further ask, do you find results that are otherwise absent using a different currency pair? This question could be a major concern in international economics. To address this we employ the IMF nominal effective exchange rate (NEER) for Ghana which measures the value of GHS against a weighted average of several foreign currencies. Both the PIP and out-of-sample forecast results are presented in Figures B4 and B5 and Table B2. Again our previous results hold even when we extend GHS against the basket of foreign currencies. Although our conclusions do not change, we find that the depreciation of the GHS against the basket of other foreign currencies is largely influenced by the government's fiscal operations.

V. Economic discussions and policy implications

The study applies Bayesian model averaging to forecast exchange rates at 1, 3, and 6-month horizons, revealing varying degrees of accuracy across different timeframes. Notably, both the in-sample and out-of-sample analyses show that the 3-month-ahead forecast demonstrates the highest accuracy, followed by the 6-month-ahead forecast, while the 1-month-ahead forecast shows lower performance.

The inclusion of US predictors enhances the forecast accuracy of domestic predictors, suggesting the potential impact of foreign real variability, particularly US spillover shocks, on Ghana's exchange rate dynamics (Verdelhan 2018). We noticed the S&P 500 and the US real economic sector to have higher predictive power on the exchange rate in Ghana. Despite facing external economic fluctuations, the study finds that domestic predictors exert significant influence, implying a self-inflicting depreciation of the domestic currency.

Among the predictors, the domestic Stock Market Index and government fiscal operations emerge as the strongest predictors of the exchange rate. Notably, government fiscal operations exhibit a positive correlation with the exchange rate (check Table A3), aligning with theories such as Ricardian equivalence (Evans 1986; McMillin and Koray 1990). To ensure currency stability, the study recommends prudent fiscal management and measures to reduce public debt (Aryeetey and Fenny 2017; Kuncoro 2015). The budget deficit contributes to the increased external indebtedness of countries causing currency depreciation either through reserves depletion or interest payment.

Additionally, factors such as the Taylor rule, real economic sector performance, and banking sector stability are identified as robust predictors of the exchange rate. The Taylor rule is shown to positively correlate with the exchange rate. Following this, the study underscores the importance of controlling inflation to alleviate pressure on the exchange rate. Moreover, the study advocates for policies promoting growth in the domestic stock market and real economic sector which causes domestic currency stabilization. For instance, during this global crisis, unconventional monetary policy tools such as forward guidance and quantitative easing complement the conventional monetary policy in achieving a lower interest rate.[6]

Furthermore, commodity prices, particularly gold and oil, are identified as accurate determinants of exchange rates at different forecast horizons (see Figure B1). These commodities are means of storing currency value. Considering the current energy crisis stemming from geopolitical tensions, policymakers are encouraged to explore mechanisms such as commodity exchange agreements to manage exchange rate fluctuations effectively.

VI. Conclusions and recommendation

Exchange rate stability remains a critical concern for developing economies, especially amidst global crises (Liu et al. 2019; Velasco 2000). This study addresses this challenge by providing a comprehensive out-of-sample exchange rate forecast for Ghana for the 1, 3 and 6-month horizon, incorporating both domestic and international predictors through Bayesian model averaging. This is imperative in circumventing the depreciating currency in Ghana and proposing appropriate policy implications to stabilize the exchange rate.

Our findings underscore the significant influence of domestic predictors on exchange rate dynamics, particularly the domestic stock market index and government fiscal operations. This implies that these economic variables most reconnect with the exchange rate (Lilley et al. 2022). To mitigate currency depreciation, we recommend the establishment of a National Fiscal Council to manage fiscal operations (Eichengreen, Hausmann, and Von Hagen 1999) and emphasize attention to the stock market (Itskhoki and Mukhin 2024). The other domestic predictors such as the Taylor rule, the real economic sector and the Banking sector are also proven to be strong predictors of the exchange rate.

Moreover, our analysis reveals the impact of international spillovers, with variables such as S&P 500 and the US real economic sector showing substantial predictive power on exchange rates which supports Verdelhan (2018). By leveraging insights from this study and addressing data limitations, policymakers and researchers can better understand and manage exchange rate fluctuations in developing economies, fostering economic stability and growth. Also, following the discussions of Beckmann et al. (2021), we advocate for further research to explore the effects of fiscal operations on the real economic sector, considering the time-dependent nature of forecast accuracy and data availability constraints.

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[6]The reduction in the lending rates lowers the cost of borrowing which boosts investment, consumption, access to capital and puts downward pressure on the exchange rate (Agyapong and Suleman 2022).

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Appendices

Appendix A

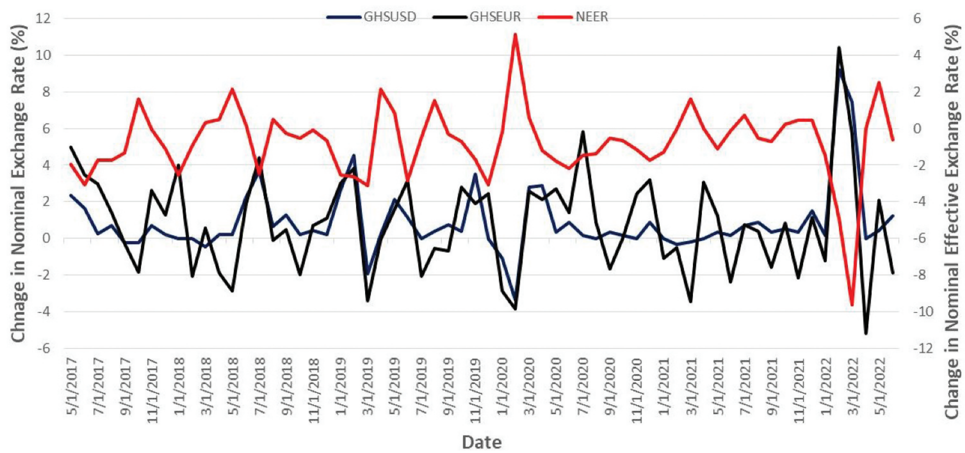


Figure A1. Change in exchange rates in Ghana.

Table A1. Data description and sources.

Data Variables	Abbreviation	Data Source
Domestic		
Exchange Rate		
Ghana Cedi per US dollar (Nominal)	GHSUSD	DataStream
Ghana Cedi per Euro (Nominal)	GHSEUR	International Monetary Fund
Effective Exchange Rate (Nominal)	NEER	International Monetary Fund
Real Exchange Rate (For GHSUSD)	RER	Authors' Own Computation
Real Economic Sector		
Composite Index of Real Economic Activities	CIE	Bank of Ghana
Consumer Confidence Index	CCI	DataStream
Real Money Market Rates		
3-Month Treasury Bill Rate	I	DataStream
Commercial Average Lending Rate	L	DataStream
10-Year Bond Rate	B	Bank of Ghana
Commodity Market		
Cocoa Price	CP	DataStream
Gold Price	GP	International Monetary Fund
Brent Oil Price	OP	US Energy Information Administration
External Sector		
Trade Balance	TB	DataStream
International Reserve	IR	DataStream
Government Fiscal Operations		
Overall Balance of Central Government Budget	CGB	Bank of Ghana
External Public Debt	ED	Bank of Ghana
Domestic Debt	DD	Bank of Ghana
Banking Sector		
Total Assets Annual Growth	TAG	Bank of Ghana
Capital Adequacy Ratio	CAR	Bank of Ghana
Core Liquid Assets to Short-Term Liabilities	LASL	Bank of Ghana
Stock Market		
Financial Stock Index	FSI	Bank of Ghana
Price Developments		
Ghana Consumer Price Index	CPI GH	DataStream
Gross Domestic Product	GDP	DataStream
International (U.S.A.)		
Real Economic Sector		
Composite leading indicator	CLI	OECD
Consumer Confidence Index	CCI	Fred DataBase
Real Money Market Rates		
Fed Fund Rate	I	Fred DataBase
Prime Lending Rate	L	Fred DataBase
10-Year Bond Rate	B	Fred DataBase
External Sector		
Trade Balance	TB	Fred DataBase
International Reserve	IR	International Monetary Fund
Government Fiscal Operations		
Overall Balance of Central Government Budget	CGB	Data Stream
US Total Debt Outstanding	ED	Data Stream
Banking Sector		
Total Assets Annual Growth	TAG	Data Stream
Capital Adequacy Ratio	CAR	Data Stream
Core Liquid Assets to Short-Term Liabilities	LASL	Data Stream
Stock Market		
S&P500 Stock Index	S&P500	Yahoo Finance
Price Developments		
US Consumer Price Index	CPI US	DataStream
Gross Domestic Product	GDP	DataStream

Table A2. Data descriptive analysis.

Data Variables	Mean	Std. Dev	Min.	Max.	Stationary Test Level	Stationary Test First Diff.
Domestic						
GHSUSD	5.3484	0.7447	4.2900	7.2300	1.3940	−5.8770***
GHSEUR	6.1455	0.7757	4.8100	7.9000	−0.8690	−7.5110***
NEER	33.0508	3.7641	25.3300	40.5600	−0.7670	−5.6330***
RER	12.1374	0.4941	11.1480	13.7473	−1.8700	−6.8160***
factor1	$2.85e-09$	1.0000	−2.5443	3.4476		−9.2700***
avreecon	1.2924	14.0767	−36.1950	39.8100		−8.4680***
CIE	652.3761	74.6293	536.5100	791.0200	−1.0360	−9.0020***
CCI	8.9355	27.1637	−47.0000	59.0000	−2.4020	−8.7520***
factor2	$5.17e-09$	1.0000	−2.8370	2.4269		−5.8400***
avmarrate	−0.0346	1.0968	−2.1031	5.9701		−10.3020***
r	4.0224	2.4032	−1.2792	8.5229	−1.3940	−6.6080***
lr	13.0936	3.5725	−0.1200	17.2800	3.7830	−4.9340***
br	9.7346	3.0863	1.4719	16.9646	−1.9300	−6.6170***
factor3	$-8.11e-10$	1.0000	−4.2714	2.1901		−6.3910***
avcompric	0.7152	5.5549	−23.5400	16.9772		−6.0620***
CP	7.7464	0.0811	7.5589	7.9070	−3.0380**	−7.1570***
GP	7.3325	0.1704	7.0888	7.5848	−0.7610	−5.9550***
OP	4.1339	0.3195	2.9113	4.8098	−1.2690	−5.7630***
factor4	$1.65e-09$	1.0000	−3.0459	3.4120		−9.7460***
avexternal	11.1329	393.8930	−436.8200	1810.5300		−9.1040***
TB	139.8181	158.0412	−178.2400	704.5000	−5.0680***	−10.6140***
IR	8470.1940	1371.8020	6309.9700	11442.5100	−2.0980	−8.5950***
factor5	$1.13e-09$	1.0000	−4.1898	1.3027		−7.8840***
avfiscal	0.1281	0.5200	−1.4600	1.5400		−7.8490***
CGB	−4.2581	2.6375	−11.7000	−0.4000	−3.3860**	−8.2780***
ED	32.1765	4.3558	24.8700	40.5000	−0.8380	−8.0720***
DD	31.0874	5.8069	23.0700	40.8300	−0.7300	−7.1230***
factor6	$2.40e-09$	1.0000	−3.1137	2.2809		−9.6800***
avbanking	−0.0584	1.1475	−3.6900	2.1500		−8.2150***
TAG	18.7145	4.9140	7.2000	32.9000	−2.5300	−7.4570***
CAR	19.5473	1.9450	14.5300	23.8900	−3.0000**	−9.9040***
LASL	29.7047	2.8847	24.1900	36.6700	−2.5420	−11.3270***
FSI	2111.4810	355.5954	1651.2000	3200.8000	−1.5660	−5.7020***
Taylor Rule	15.1134	6.0829	7.8970	41.2020	5.3670	−3.3620**
International (U.S.A.)						
factor1	$-2.60e-09$	1.0000	−5.8752	2.2537		−6.3990***
avreecon	−0.1576	4.2059	−18.9325	9.3620		−7.4600***
CLI	99.6587	1.5318	92.4843	101.0773	−2.0010	−5.7680***
CCI	117.5919	14.6155	84.8000	138.4000	−2.0010	−7.5900***
factor2	$-2.43e-09$	1.0000	−3.4388	3.0994		−4.3380***
avmarrate	−0.0803	0.3995	−1.4545	1.1582		−4.3380***
r	−1.8035	2.4700	−7.8811	0.9391	1.1160	−4.6290***
lr	1.3287	2.4482	−4.7111	4.0291	1.0920	−4.6240***
br	−0.8908	2.0295	−5.4846	1.1928	0.5330	−4.6790***
factor4	$2.61e-09$	1.0000	−3.0826	5.5357		−9.0360***
avexternal	528.8765	7544.3090	−9918.2200	55544.1900		−8.5210***
TB	−56697.3400	15226.2200	−106917.0000	−38684.0000	−1.0040	−11.4150***
IR	71110.1100	42850.6200	49976.2100	165663.8000	−0.5700	−7.9190***
factor5	$3.61e-09$	1.0000	−4.1755	3.0226		−7.5120***
avfiscal	0.1956	6.5016	−14.2035	21.0536		−14.4460***
CGB	−7.3236	10.2761	−48.4517	15.4844	−6.3180***	−13.6030***
TD	113.8149	10.2348	103.0058	134.8353	−1.0190	−4.0020***
factor6	$1.58e-09$	1.0000	−1.8978	3.3553		−2.5530***
avbanking	0.0170	1.8177	−4.9301	8.4708		−3.2910***
TAG	9.7987	19.1038	−12.7803	46.1425	−0.9800	−3.7050***
CAR	14.5886	0.6805	13.8000	15.7000	−0.9800	−2.6930***
LASL	86.3940	8.8124	72.9420	100.1760	−0.4590	−3.1000**
S&P500	3285.9220	704.7504	2411.8000	4766.1800	−1.1860	−8.3510***
Taylor Rule	4.2869	4.0538	−0.5994	16.1865	3.3760	−3.4410***

Table A3. Linear correlation.

Domestic		International	
	Nominal Exchange Rate		Nominal Exchange Rate
factor1	−0.0800	factor1	−0.1646
avreecon	−0.1975	avreecon	−0.1812
CIE	0.8060	CLI	−0.1575
CCI	−0.3462	CCI	−0.5445
factor2	−0.0990	factor2	−0.0387
avmarrate	0.0148	avmarrate	−0.0386
r	−0.1696	r	−0.7351
lr	−0.8173	lr	−0.7275
br	0.1416	br	−0.7959
factor3	−0.0261		
avcompric	−0.0342		
CP	0.5089		
GP	0.8543		
OP	0.2985		
factor4	0.1125	factor4	0.0269
avexternal	−0.0087	avexternal	−0.0597
TB	0.2219	TB	−0.8426
IR	0.5341	IR	0.6768
factor5	−0.1693	factor5	−0.1195
avfiscal	0.1207	avfiscal	−0.0213
CGB	−0.3365	CGB	−0.1187
ED	0.8770	TD	0.7318
DD	0.8321		
factor6	−0.0620	factor6	−0.0368
avbanking	0.1095	avbanking	0.0641
TAG	0.1534	TAG	0.4831
CAR	0.5582	CAR	0.6615
LASL	−0.7035	LASL	0.2793
FSI	−0.4238	S&P500	0.8083
Taylor Rule	0.5104	Taylor Rule	0.6412
RER	0.8247		

The table reports the correlation between the predictors and the Ghana Cedis per US dollar nominal exchange rate.

Appendix B

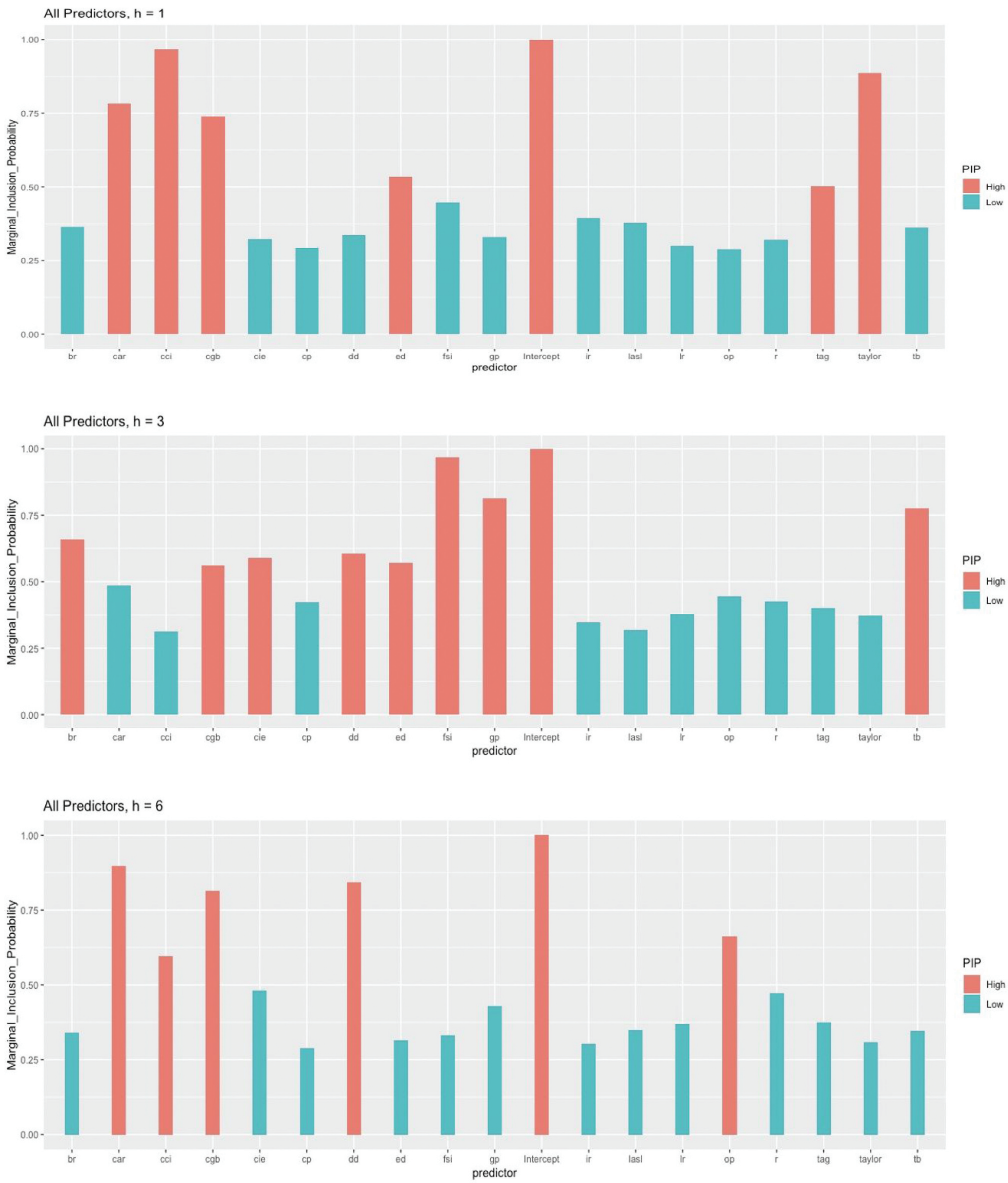


Figure B1. Marginal inclusion probability for all the domestic predictors.

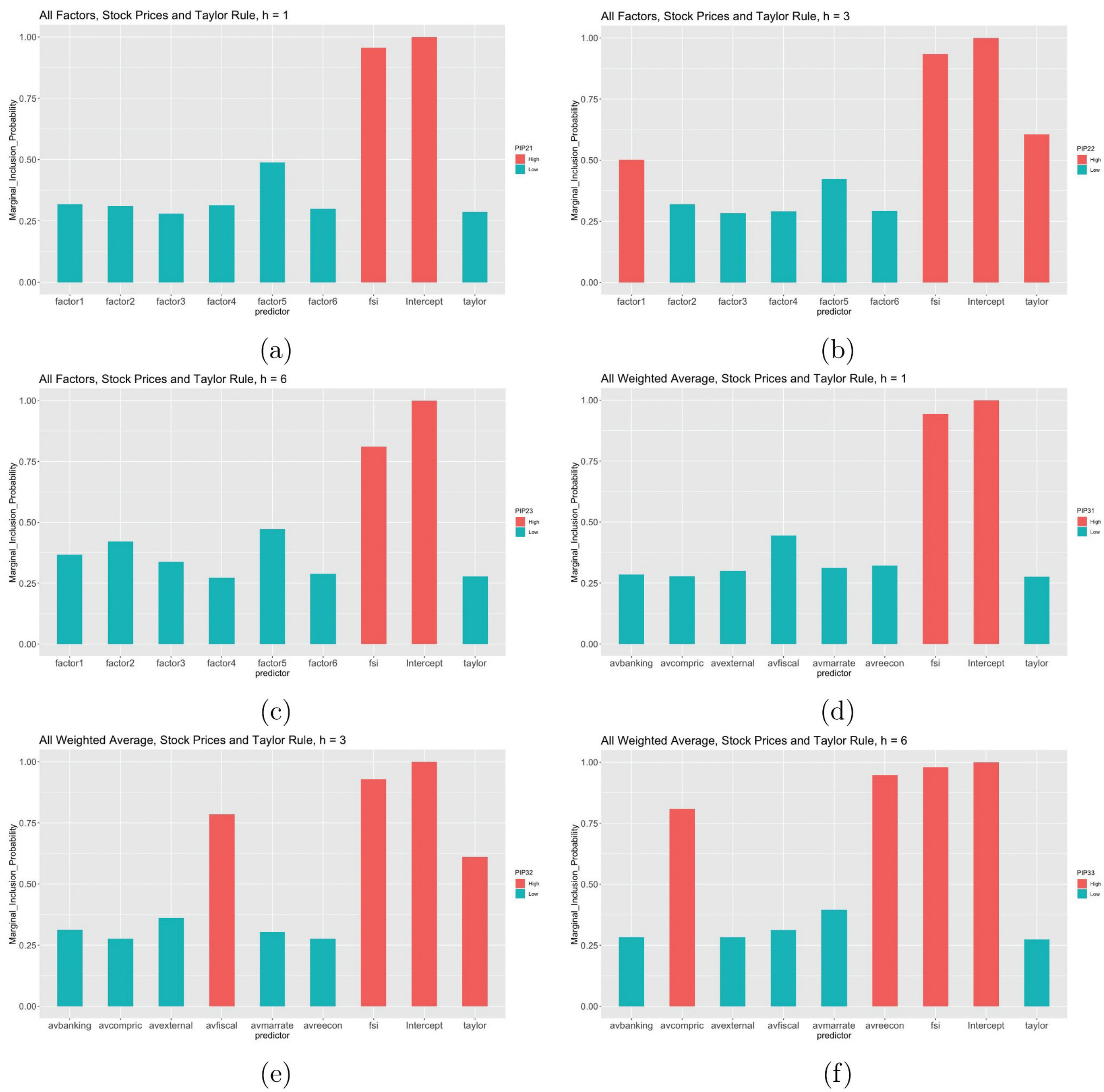


Figure B2. Marginal inclusion probability for Ghana's exchange rate against the Euro. The marginal inclusion probability greater than 0.5 shows the relevance of the predictors in forecasting the changes in the exchange rate and vice versa.

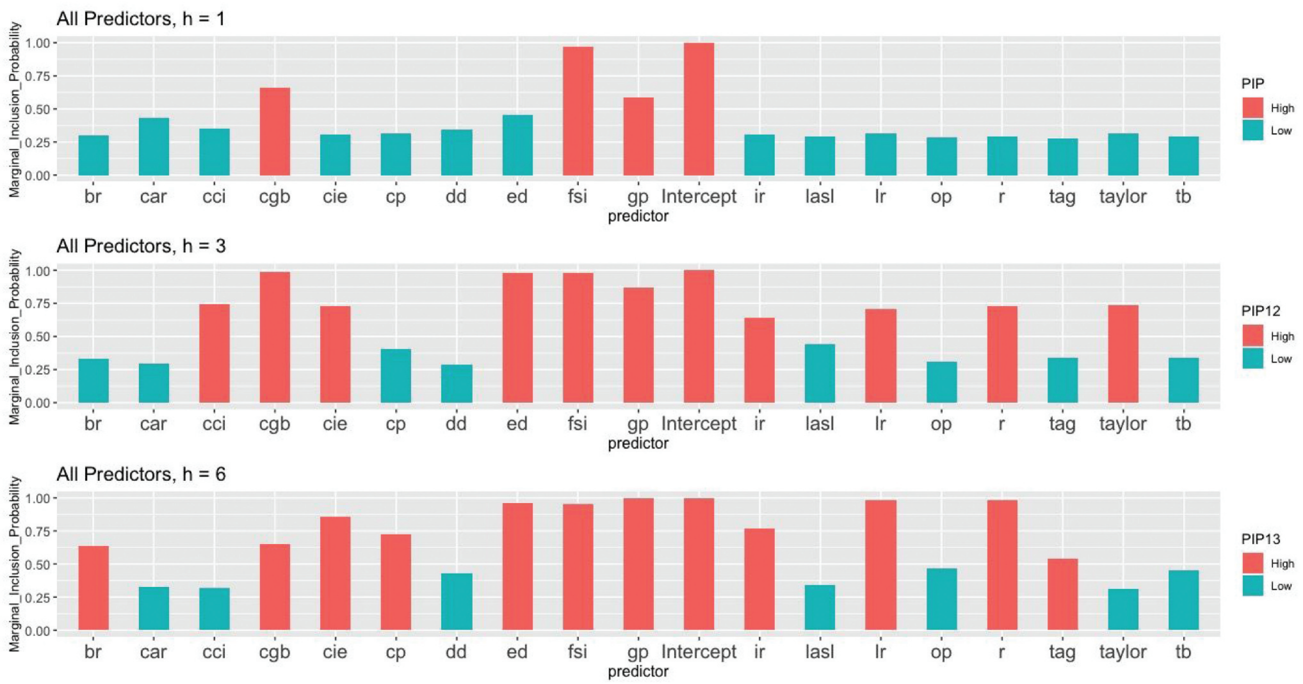
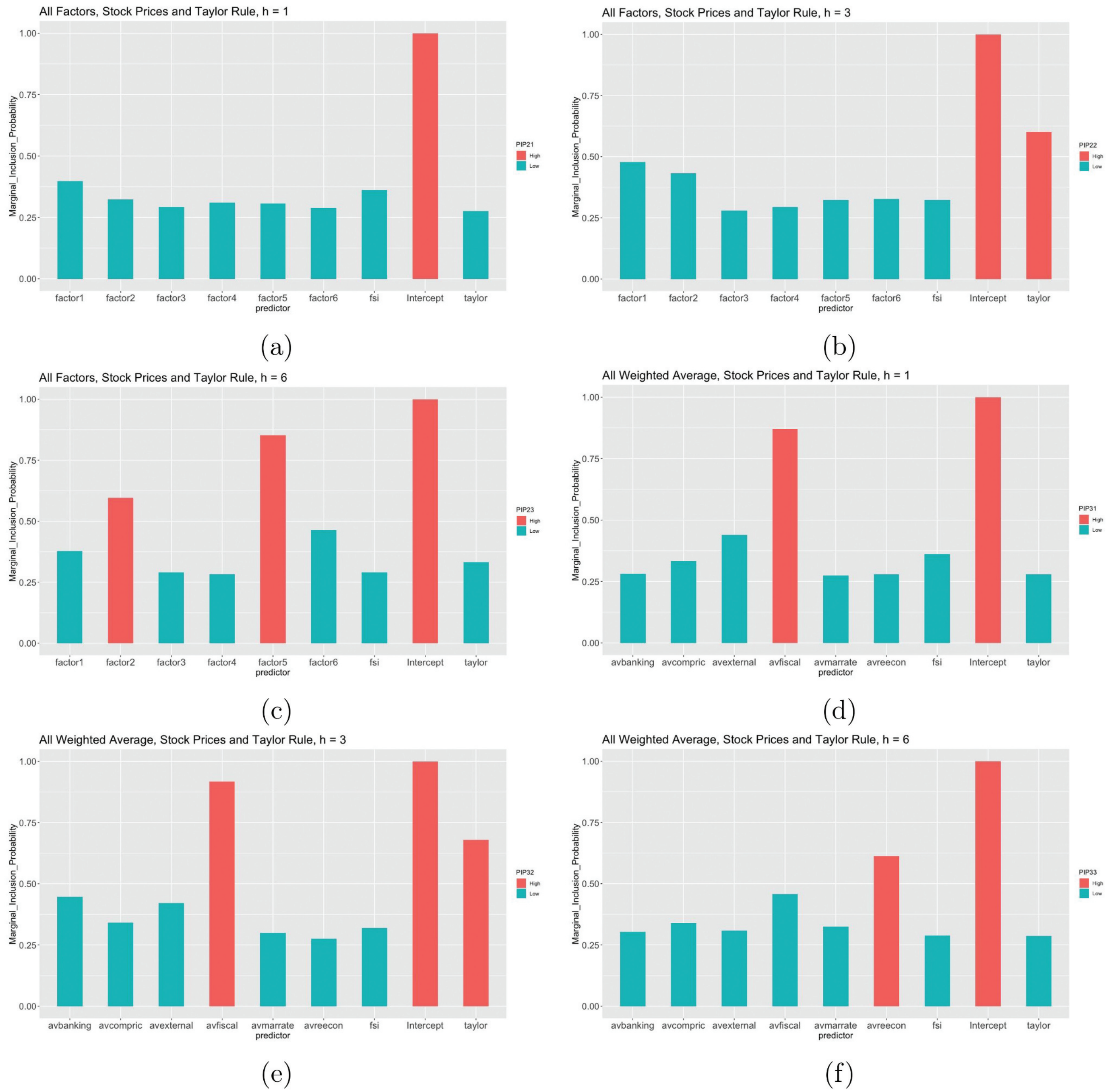


Figure B3. Marginal inclusion probability for Ghana's exchange rate against the Euro using all predictors. The marginal inclusion probability greater than 0.5 shows the relevance of the predictors in forecasting the changes in the exchange rate and vice versa.



(a) (b) (c) (d) (e) (f)

Figure B4. Marginal inclusion probability for Ghana's nominal effective exchange rate. The marginal inclusion probability greater than 0.5 shows the relevance of the predictors in forecasting the changes in the exchange rate and vice versa.

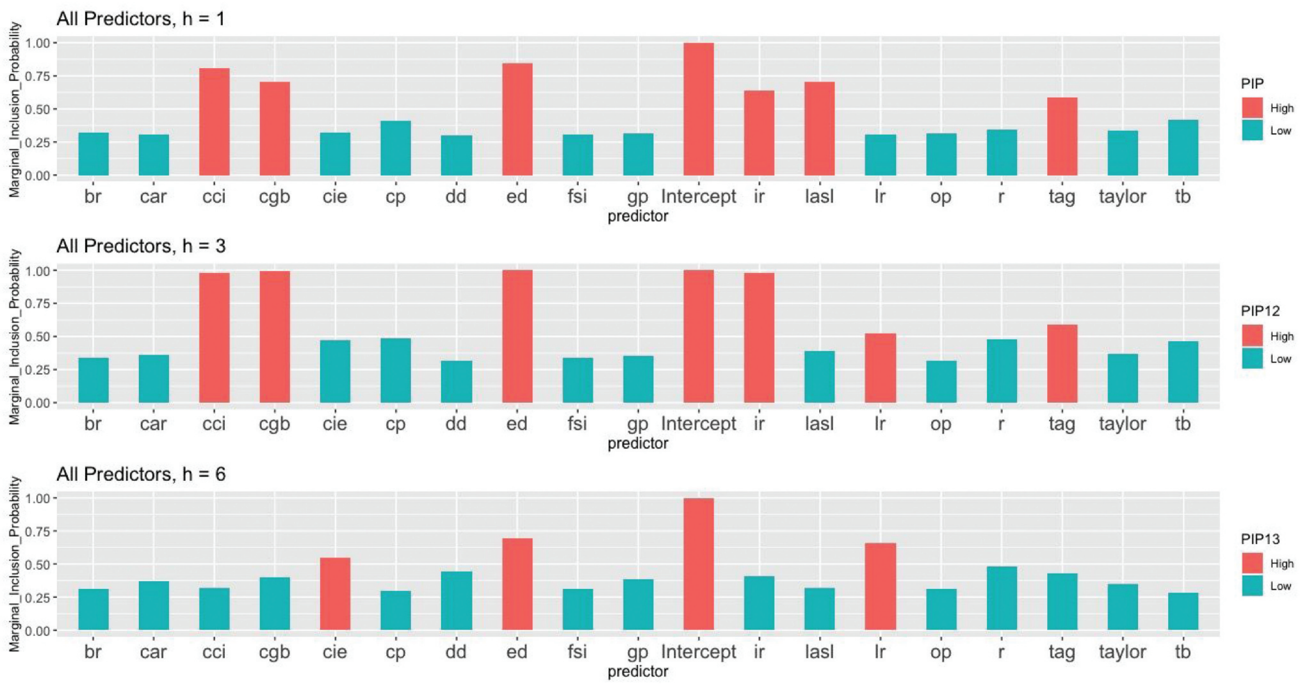


Figure B5. Marginal inclusion probability for Ghana's nominal effective exchange rate using all predictors. The marginal inclusion probability greater than 0.5 shows the relevance of the predictors in forecasting the changes in the exchange rate and vice versa.

Table B1. Out-of-sample forecast of Ghana's exchange rate against the Euro using domestic interaction variables.

	With Random Walk Benchmark			With AR(1) Benchmark		
Forecast Horizon	h = 1	h = 3	h = 6	h = 1	h = 3	h = 6
Predictors	Theil's U	Theil's U	Theil's U	Theil's U	Theil's U	Theil's U
All Predictors	0.6799	0.6219	0.6355	0.6511**	0.6071***	0.6198***
All Factors, Stock Prices and Taylor Rule	0.9491	1.0080*	1.0323*	0.9702	0.9840	1.0067
All Weighted Averages, Stock Prices and Taylor Rule	0.8355	0.7821	0.8439	0.8770	0.7635*	0.8230**

The table presents Theil's U values and Clark and West's forecast accuracy test of Ghana cedis relative to the Euro (GHSEUR). Theil's U greater than 1 implies that the model outperforms the benchmark. The estimation window is 2017M5 - 2019M12 and the remaining observations (2020M1 - 2022M6) are used for the forecast evaluation and comparison. The Newey – West robust variance estimator (Newey and West 1987)is applied to solve the serial correlation in the residuals for the multiple forecast horizons. ***; **; * represent the statistical significance of Clark and West's forecast accuracy of the model at 1%, 5% and 10% respectively.

Table B2. Out-of-sample forecast of the nominal effective exchange rate using domestic interaction variables.

	With Random Walk Benchmark			With AR(1) Benchmark		
Forecast Horizon	h = 1	h = 3	h = 6	h = 1	h = 3	h = 6
Predictors	Theil's U	Theil's U	Theil's U	Theil's U	Theil's U	Theil's U
All Predictors	0.7354	0.8993*	1.0045	0.7587**	0.8020**	0.8693
All Factors, Stock Prices and Taylor Rule	0.8936	0.9907**	1.0474*	0.9200	0.8836	0.9064
All Weighted Averages, Stock Prices and Taylor Rule	0.9595	0.9767*	0.9928	1.0099	0.8710	0.8592

The table presents Theil's U values and Clark and West's forecast accuracy test of Ghana's nominal effective exchange rate. Theil's U greater than 1 implies that the model outperforms the benchmark. The estimation window is 2017M5 - 2019M12 and the remaining observations (2020M1 - 2022M6) are used for the forecast evaluation and comparison. The Newey – West robust variance estimator (Newey and West 1987) is applied to solve the serial correlation in the residuals for the multiple forecast horizons. ***; **; * represent the statistical significance of Clark and West's forecast accuracy of the model at 1%, 5% and 10% respectively.