Forecasting Exchange Rate with MIDAS: A Case study on Thailand

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ABSTRACT

This study aims to develop an efficient exchange rate forecasting model using quarterly and monthly data spanning from 2000 to 2022 for Thailand. Our methodology involves several approaches, including Autoregressive Moving Average (ARMA) for the random walk model (RW), Ordinary Least Squares (OLS) for purchasing power parity (PPP), and the monetary model with flexible prices (MMF), all using the same frequency data (quarterly). Additionally, we employ Mixed Data Sampling (MIDAS) for PPP and MMF when dealing with mixed-frequency data. We then perform a comprehensive comparative analysis of these models, both statistical (e.g., random walk) and theoretical (e.g., PPP and MMF), using performance indices such as Root Mean Squared Error (RMSE) and Mean Squared Error (MSE). Our findings indicate that while the RW outperforms PPP, however RW demonstrates lower predictive performance compared to MMF. Notably, MIDAS, a crucial component of our methodology, proves effective, as both PPP and MMF estimations using MIDAS outperform those obtained through OLS estimation.

Keywords: MIDAS, PPP, Monetary Model, Random Walk.

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1. INTRODUCTION

Exchange rates are crucial in the economy as they indicate the price of international transactions between countries. These transactions include the exchange of goods and services, financial and investment activities. Therefore, changes in exchange rates have an impact on the transaction costs for those involved. Exchange rates play a pivotal role in the global economy, serving as a crucial mechanism for facilitating international trade, and investment. Exchange rates significantly influence a country's balance of trade. A weaker domestic currency can make exports more competitive, potentially boosting a nation's exports and economic growth. Conversely, a stronger currency may make imports cheaper, impacting the trade balance. Furthermore, certain studies suggest that inadequate management of exchange rates can affect the growth of trade and the economy. For instance, Hamid & Mir (2017) have shown that an excessively overvalued exchange rate is the primary cause of efficiency loss in international trade competition. Furthermore, exchange rates, as key macroeconomic variables, continue to significantly affect commodity (copper and oil) and asset markets (bond). Ernanto et al. (2023) show that fluctuations in copper prices are influenced not only by supply and demand but also by movements in macroeconomic variables such as GDP, CPI, and exchange rates. Sohhel and Rao (2023) reviewed the high susceptibility of Russia’s export revenue to the volatility of the RUB/USD exchange rate, noting that the exchange rate tends to positively correlate with oil prices. Obalade et al. (2023) study the macroeconomic variables that influence the performance

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of the South African bond market in different market regimes and found that volatility of bond is explained by changes in fiscal balance, inflation, domestic debt, GDP per capita, exchange rate and interest rate. Consequently, policymakers often implement specific policies to regulate exchange rates due to their significant impact on various aspects of the economy.

Since Thailand allowed the Thai Baht to float in 1997, Thailand's exchange rate has been operating within a system known as a "managed float." In this system, policymakers at the Bank of Thailand monitor and manage changes in the exchange rate to ensure that it remains at a level that does not excessively impact those engaged in international transactions and Thailand asset markets.

The study of determining and forecasting exchange rates holds substantial significance in macroeconomics. There are numerous models for estimating or forecasting exchange rates. These models fall into two main categories: statistical models, which use historical data and adopt the random walk approach, as demonstrated by Meese and Rogoff in 1983, and theoretical macroeconomic models, which establish relationships between macroeconomic variables and exchange rates to aid in estimation and forecasting. The theoretical macroeconomic models include concepts such as Purchasing Power Parity (PPP) (Samuelson, 1964; Frankel, 1990) and monetary models that employ monetary approaches to balance of payments (Mundell, 1968; Dornbusch, 1973, 1979; Frenkel, 1976; Frenkel and Mussa, 1985; Rogoff, 1999).

There are numerous studies that attempt to find the long-term relationships between various macroeconomic variables and exchange rates using various econometric methods. These methods include linear estimation as well as non-linear approaches. These methods encompass both linear estimation models, as exemplified by Mark (1995) and Stock and Watson (1993), and non-linear models, such as those proposed by Meese and Rose (1991) and Chinn (1991). From the various modeling and estimation techniques mentioned above, Meese and Rogoff (1983) demonstrated that a random walk model can provide better out-of-sample forecasts for exchange rates than monetary models. This finding was further corroborated by Cheung, Chinn, and Pascual (2005). In contrast to the findings of Meese and Rogoff (1983), some economists argue that it is possible theoretical exchange rate models outperform the random walk (using the root mean square error and similar metrics as criteria) in the medium or long run (Mark, 1995; Chinn and Meese, 1995; MacDonald, 1999; Mark and Sul, 2001)

One common aspect of all the models mentioned above is that they require data with the same frequency. If the data has different frequencies, statistical methods such as interpolation are used to transform the data to have the same frequency. For example, transforming quarterly GDP data into monthly data. However, Friedman (1962), Denton (1971), Chow and Lin (1971), and Wright and Salazar (2005) raised the question of whether interpolation results in the best-quality data. Additionally, using such methods may lead to the loss of information from the original dataset, and there is a risk of misspecification due to the data frequency issue. Ghysels et al. (2004, 2007) addressed this problem by introducing the Mixed Data Sampling (MIDAS) technique, which allows for the handling of mixed-frequency data. The concept is that using short-term information available in high-frequency data to forecast the current values (nowcasting) of low-frequency data can improve the efficiency of model forecasting.

In the context of Thailand, upon reviewing the literature, no prior work has been found that utilizes the Mixed Data Sampling (MIDAS) method for estimating and forecasting long-term exchange rates adhering to theoretical frameworks or economic models. Additionally, Thailand's economy, as an emerging market in Southeast ASEAN, is internationally connected through its manufacturing, agriculture, and tourism sectors, as well as its asset markets. This

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makes the exchange rate of the Baht an important indicator of economic health and investor sentiment in the region. This complexity allows for a comprehensive analysis, making it a compelling case for sophisticated forecasting techniques. Therefore, the objective of this study is to test efficiency of the theoretical frameworks model compare to statistic model to forecast exchange rates. Additionally, we compare traditional estimation as OLS with the MIDAS approach, which allows for the estimation of data with mixed frequencies. Specifically, we will use high-frequency data (monthly) such as price index, money supply, and interest rates to estimate and forecast low-frequency data (quarterly) which is long-term exchange rates (Cheung et al., 2005, 2019).

The paper is organized into five sections. Section 1 is the introduction, providing an overview of the study's objectives and some literatures review. Section 2 is dedicated to the methodology, where we demonstrate the definitions and concepts underpinning the random walk process, the purchasing power parity, and the flexible price monetary model of the exchange rate. Section 3 encompasses the scope of data and their statistics. In Section 4, we present the results of our analyses and investigations. Finally, Section 5 is the conclusion and recommendation, summarizing the key findings and recommendations for policy and further study.

2. METHODOLOGY

In this paper, we estimate three distinct models: the Random Walk Model, the Purchasing Power Parity Model, and the Monetary Model with flexible price. We select these two theoretical models since the potential impact of a managed float exchange rate system can be captured by both the monetary model and the purchasing power parity (PPP) model. The monetary model of exchange rate determination posits that exchange rates are primarily influenced by the money supply, income levels, and interest rates. The PPP model suggests that exchange rates adjust to equalize the price levels of a basket of goods and services between two countries. In the context of a managed float exchange rate system, central bank actions to stabilize the currency can influence domestic inflation, money supply, income levels, and interest rates. In practice, combining insights from both models can provide a more comprehensive understanding of the exchange rate dynamics under a managed float system. The details of these models are elaborated as follows:

2.1 Random Walk Model

The current exchange rate movements are essentially unpredictable and follow a random pattern. According to the model, the best forecast for the current exchange rate is simply past rate. The model can be shown as follows:

$$s_t = s_{t-1} + \varepsilon_t \tag{1}$$

The error terms, ε_t is white noise processes and should be independent and normally distributed

2.2 Purchasing Power parity

Purchasing Power Parity (PPP) is an economic concept that helps to explain how exchange rates are determined. In theory, exchange rates are determined by the relative prices of a basket of goods and services between two countries. The PPP concept is based on the law of one price. The law of one price states that in competitive markets free of transportation costs and official barriers to trade (such as tariffs), identical goods sold in different countries must sell for the same price when their prices are expressed in terms of the same currency. Given these assumptions, if the law of one price holds, then the exchange rate between two currencies should equal the ratio of the prices of an identical basket of goods in each country. For example,

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if a good costs $10 in the United States and the same good costs Baht350 in Thailand, the law of one price suggests that the exchange rate should be adjusted to make the prices equal. In this case, the implied exchange rate would be 1 USD = 35Baht.

Based on the PPP concept, we can express the exchange rate equation as follows:

$$s_t = \alpha + \beta\left(p_t - p_t^*\right) + \varepsilon_t \tag{2}$$

where s is the nominal exchange rate measured in units of domestic currency per unit of foreign currency, p is the domestic price level, and p^* is the foreign price level, all variables in logarithms.

2.3 Monetary Model

The basic flexible price monetary model was developed by Frankel (1976) and Bilson (1978). The model uses monetary factors to predict the adjustment of the exchange rate based on PPP. Specifically, the model use the assumption that PPP holds both in short-run and long-run since changes in demand and supply of money results instantaneously in price level leading to immediately adjustment in exchange rate to maintain PPP. The basic flexible-price monetary model (MMF) is specified as

$$s_t = \alpha + \eta\left(i_t - i_t^*\right) + \phi\left(y_t - y_t^*\right) + \left(m_t - m_t^*\right) \tag{3}$$

where s, as before, is the exchange rate, m is the domestic money supply, y is domestic output, i represents domestic interest rates. Additionally, all variables with superscripts '*' indicate the same variables but for foreign counterparts.

In this paper, we employ a range of methodologies to analyze and estimate economic models related to exchange rates. Firstly, we use the Auto-Regressive Moving Average (ARMA) model to estimate the Random Walk (RW) model, using quarterly data. The Random Walk model assumes that future exchange rates can be predicted by their past values as mentioned above. Secondly, we apply Ordinary Least Squares (OLS) to estimate both the Purchasing Power Parity model (PPP) and the flexible price Monetary Model (MMF), again using quarterly data. OLS is a common statistical method for linear regression, widely employed in economic modeling. Lastly, we employ a Mixed Frequency Sampling Data approach (MIDAS), which involves using high-frequency data (e.g., price, money supply, and interest rate) to estimate low-frequency data, specifically quarterly exchange rates. These methodologies enable a comprehensive examination of exchange rate forecasting and allow for a comparison between traditional statistical estimation and innovative mixed-frequency data estimation.

When assessing the performance of model estimations, common criteria are employed for performance comparison. These criteria include RMSE (Root Mean Square Error : $RMSE(i) = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(s_{t_q} - \hat{s}_{t_q}\right)^2}$), MSE (Mean Square Error : $MSE(i) = \frac{1}{n}\sum_{t=1}^{n}\left(s_{t_q} - \hat{s}_{t_q}\right)$), and MAE (Mean Absolute Error : $MAE(i) = \frac{1}{n}\sum_{t=1}^{n}\left|s_{t_q} - \hat{s}_{t_q}\right|$). The notation s_{t_q} is actual value and $\hat{s}_{t_q}$ is predicted value. Based on these indices, the lower the better. So the lowest value among these performance indices is considered the most predictive in terms of forecasting exchange rates.

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3. DATA

The study incorporates data spanning from 2000 to 2022, encompassing both Thailand and the United States. The dataset used in this study comprises two quarterly variables. One of these variables is the quarterly exchange rate of the Thai Baht against the USD, which serves as a measure of the long-term exchange rate. This exchange rate is transformed into its natural logarithm form, and changes in the natural logarithm values are employed to indicate the rate of change. The other is quarterly real GDP included as an independent variable within the MMF model. The concept of relative inflation, denoted as "inf" is introduced to represent Thailand's inflation (inf_th) relative to that of the United States (inf_us). Furthermore, "ms" signifies the relative money supply, indicating Thailand's money supply relative to that of the United States. Lastly, "int" represents the relative interest rate, with "int_th" standing for the Thai interest rate and "int_us" representing the US interest rate. Descriptive statistics for these variables are presented in Table 1.

Table 1 Descriptive Statistics

Monthly data								
	n	mean	Sd.	median	min	max	skew	kurtosis
i_th	267	2.87	1.22	2.75	1.0	6.5	0.86	0.98
inf_th	267	0.17	0.52	0.15	-3.01	2.18	-0.79	7.29
ms_th	267	12.74	0.55	12.88	11.84	13.55	-0.26	-1.37
i_us	267	1.63	1.88	1.0	0.05	6.54	1.18	0.17
inf_us	267	0.2	0.39	0.2	-1.92	1.34	-0.69	3.25
ms_us	267	16.05	0.41	16	15.36	16.89	0.21	-0.94
inf	267	-0.04	0.42	-0.02	-2.61	1.34	-0.86	6.31
int	267	1.24	1.48	1.55	-3.54	3.93	-1.12	1.85
ms	267	-4.23	0.43	-4.11	-5.49	-3.74	-1.75	2.53
Quarterly Data								
	n	mean	sd	median	min	max	skew	kurtosis
rgdp_th	89	11.40	0.22	10.96	11.71	0.74	-0.44	-1.00
rgdp_us	89	15.24	0.12	15.03	15.46	0.44	-0.03	-0.99
rgdp	89	-3.84	0.11	-4.08	-3.70	0.38	-0.64	-0.84

The interest rate in Thailand has an average value of 2.87%, with a maximum value of 6.5% and a minimum value of 1.0%. The standard deviation is 1.22. The inflation rate in Thailand has an average value of 0.17%, with a maximum value of 2.18% and a minimum value of -3.01%. Meanwhile, the logarithm of Thailand's money supply has an average value of 12.74, with a maximum value of 13.55 and a minimum value of 11.84. For the data of the United States, the interest rate in the United States has a maximum value of 6.54% and a minimum value of 0.05%. Meanwhile, the inflation rate for the United States has a maximum value of 1.34% and a minimum value of -1.92%. The quantity of money in log form has an average value of 16.05, with a maximum value of 16.89 and a minimum value of 15.36.

When considering relative variables, relative inflation (inf) has a maximum value of 1.34% and a minimum value of -2.61%. It has a standard deviation of 0.42, with an average at -0.04, this indicates that overall, Thailand's inflation rate is lower than that of the United States by 0.04%. Regarding the relative interest rate (int), it has a maximum value of 3.93% and a minimum value of -3.54%. The average of relative interest rate is 1.24%. This shows that, on

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average, Thailand's interest rates are 1.24% higher than those of the United States. The relative money supply (ms) has a maximum value of -3.74% and a minimum value of -5.49%. The average of relative quantity of money is -4.23. This indicates that Thailand's quantity of money in log form is lower than that of the United States.

4. RESULTS

4.1 In-sample Forecast

The results are divided into two parts. In the first part, the estimated models are conducted using data with the same frequency, employing ARMA for RW model and the OLS method for PPP and MMF models and the results are shown in Table2. Subsequently, we calculate the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Square Error (MSE) for each model as shown in Table 3 to compare error indices. This comparison is made between the theoretically driven models (PPP and MMF) and the statistical model (RW).

Table 2 Estimation' results for ARMA and OLS Model for Quarterly Data with Full Sample (2002-2022)

Model	**Random Walk**	**PPP**	**MMF**
AR1	-0.059		
	(0.105)		
Intercept		-0.002	-0.044
		(0.004)	(0.173)
inf		-0.002	
		(0.006)	
dummy		0.001	0.002
		(0.010)	(0.011)
int			-0.002
			(0.003)
ms			-0.002
			(0.042)
output			-0.010
			(0.072)
AIC	-349.970		
BIC	-344.993		
Log Likelihood	176.985		
Num. obs.	89	89	89
R^2		0.001	0.013

Notes: 1. the parentheses indicate standard errors. 2. "inf", "ms", "int", and "output" represent relative value of inflation, money supply, interest rate, and output, respectively. Dummy represents the period when the USA changed the definition of money supply.

Based on the objective of this study, to investigate the efficient model to forecast exchange rates through the utilization of various models and estimation techniques, followed by a comparative analysis of their performance. Consequently, the presentation of study results does not encompass an exhaustive discussion of the estimation outcomes. However, we do employ the estimated models to generate predicted values and subsequently calculate performance indices, including RMSE, MSE, and MAE. The model that exhibits the lowest value among these performance indices is considered the most predictive in terms of forecasting exchange rates.

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The results for efficiency indices with full-sample data and baseline estimation are presented in Table 3. Based on the baseline estimation, which employs ARMA for Random Walk (RW) and OLS for Purchasing Power Parity (PPP) and the Monetary Model with flexible price (MMF), RW model outperforms the PPP model in forecasting the exchange rate by a slight margin of 0.027% [(0.033131 - 0.033122)/0.033131*100)]. However, the most efficient model for exchange rate forecasting is MMF, as indicated by the lowest MSE at 0.001085. It outperforms RW and PPP by 1.09% [(0.001097-0.001085)/0.001907*100] and 1.18% [(0.001098-0.001085)/0.001098*100, respectively.

Table 3: Efficiency Indices for Quarterly Data – ARMA and OLS with Full Sample (2002-2022)

Model	RMSE	MAE	MSE
RW	0.033122	0.026245	0.001097
PPP	0.033131	0.025808	0.001098
MMF	0.032939	0.025746	0.001085

Source: Author

In the second part, mixed-frequency data is utilized, specifically monthly data, which is particularly valuable for forecasting long term exchange rates (quarterly). We employ the MIDAS regression method, as introduced by Ghysels et al. (2004, 2007). This approach is chosen because the inclusion of high-frequency or more current data may enhance the accuracy of exchange rate forecasts

To compare the efficiency of the model, we estimated the same model using mixed-frequency data, except for the RW model. The results are presented in Table 4. Then, we calculate efficiency indices as shown in Table 5 for comparison with the quarterly model. Notably, the MMF model demonstrates greater efficiency in forecasting exchange rates compared to the PPP model. Furthermore, mixed-frequency estimation surpasses OLS in efficiency, as evidenced by the lower RMSE, MAE, and MSE for both PPP and MMF models.

Table 4: Estimation' results for Mixed-Frequency Data with Full sample (2002-2022)

	PPP	MMF
(Intercept)	-0.002	-0.103
	(0.004)	(0.104)
inf(-1)	0.006	
	(0.014)	
inf(-2)	0.006	
	(0.007)	
inf(-3)	0.005	
	(0.010)	
dummy	0.012	0.003
	(0.011)	(0.010)
int(-1)		0.001
		(0.015)
int(-2)		-0.016
		(0.025)
int(-3)		0.015
		(0.013)
ms(-1)		-0.824 ***
		(0.151)

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ms(-2)		0.172
		(0.297)
ms(-3)		0.673 **
		(0.207)
output		-0.045
		(0.043)
Rsquare	0.027	0.531
Num. obs.	89	89

Source: Author

Note: 1. the parentheses indicate standard errors.

2"inf", "ms", "int", and "output" represent relative value of inflation, money supply, interest rate, and output, respectively. Dummy represents the period when the USA changed the definition of money supply.

3. (-1), (-2), and (-3) represent the value at lag 1 (last month of the quarter; March, June, September, December), lag 2 (second month of the quarter; February, May, August, November), and lag 3 (first month of the quarter; January, April, July, October), respectively.

Table 5 Efficiency Indices for Mixed-Frequency Data with Full sample (2002-2022)

Model	RMSE	MAE	MSE
PPP	0.032702	0.025106	0.001069
MMF	0.022695	0.017431	0.000515

According to the RMSE index, both the PPP and MMF models estimated through the MIDAS method exhibit superior performance compared to the OLS estimation. In the case of the PPP model, MIDAS estimation outperforms OLS estimation by 1.294% [(0.033131 - 0.032702) / 0.033131 * 100]. For the MMF model, MIDAS estimation outperforms OLS estimation by 31.08% [(0.032939 - 0.022695) / 0.032939 * 100]. Additionally, for the other two indices (MAE and MSE), also lead to the same conclusion that MIDAS outperforms OLS.

Considering that exchange rates function as prices determined by the fundamental forces of supply and demand, it becomes evident that the Monetary Model with Flexible Prices (MMF), which incorporates variables from money supply and demand, should be regarded as the most efficient model. Our study's findings strongly support the pivotal role of this model in understanding and forecasting exchange rates.

4.2 Out-of-Sample Forecast

For out-of-sample forecasting, the model estimation period is divided into a training set (2000q1-2018q4) and a testing set (2019q1-2022q4). Table 6 shows the estimation results of training model. Table 7 shows the efficiency indices for the training set estimation. It's noteworthy that, based on MSE, out-of-sample forecasting (2019q1-2022q4) exhibits less effectiveness compared to in-sample forecasting (2000q1-2018q4). As indicated in Table 8, the MSE for the out-of-sample forecast is 0.00241, which is higher than the in-sample MSE of 0.00091. This difference in performance may be attributed to inconsistencies in the data splitting process between the training (2000q1-2018q4) and testing sets (2019q1-2022q4). In the training data, there were no events like COVID-19, but the forecasting in the testing data relied on estimation derived from the training data, which did not account for the occurrence of the COVID-19 event.

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Table 6 Estimation' results for Mixed-Frequency Data with Full sample (2000-2018)

	PPP	MMF
(Intercept)	-0.002	-0.036
	(0.005)	(0.096)
inf(-1)	0.016	
	(0.011)	
inf(-2)	0.017 *	
	(0.008)	
inf(-3)	-0.003	
	(0.010)	
dummy	0.021	0.017
	(0.020)	(0.015)
int(-1)		-0.005
		(0.016)
int(-2)		-0.011
		(0.026)
int(-3)		0.014
		(0.015)
ms(-1)		-0.727 ***
		(0.129)
ms(-2)		0.046
		(0.319)
ms(-3)		0.697 **
		(0.238)
output		-0.023
		(0.040)
Rsquare	0.103	0.542
Num. obs.	76	76

Source: Author

Note: Notations are consistent with those in Table 4.

Table 7 Efficiency Indices for Mixed-Frequency Data with Subsample (2002-2018)

Model	RMSE	MAE	MSE
PPP	0.030189	0.023256	0.000911
MMF	0.021569	0.016505	0.000465

Source: Author

Table 8: Efficiency Indices for Mixed-Frequency Data - In-Sample and Out-of-Sample

Model	MSE. Out-of-sample	MASE Out-of-sample	MSE. In-sample	MASE In-sample
PPP	0.00241	0.67085	0.000911	0.65580
MMF	0.00111	0.48812	0.000465	0.46542

Source: Author

Figures 1 and 2 show the actual and forecasted value for purchasing power parity and monetary model for out of sample forecasting.

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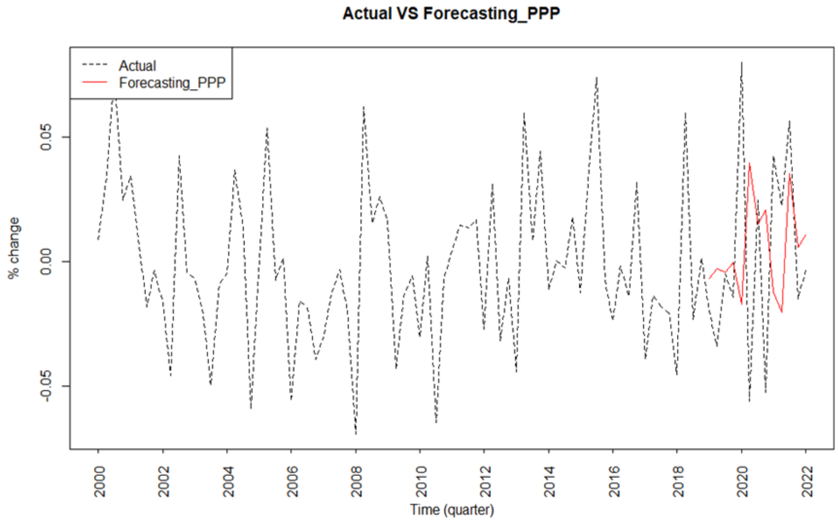

Figure 1 Actual and Forecasting of Exchange rate from PPP Model
Source: Author

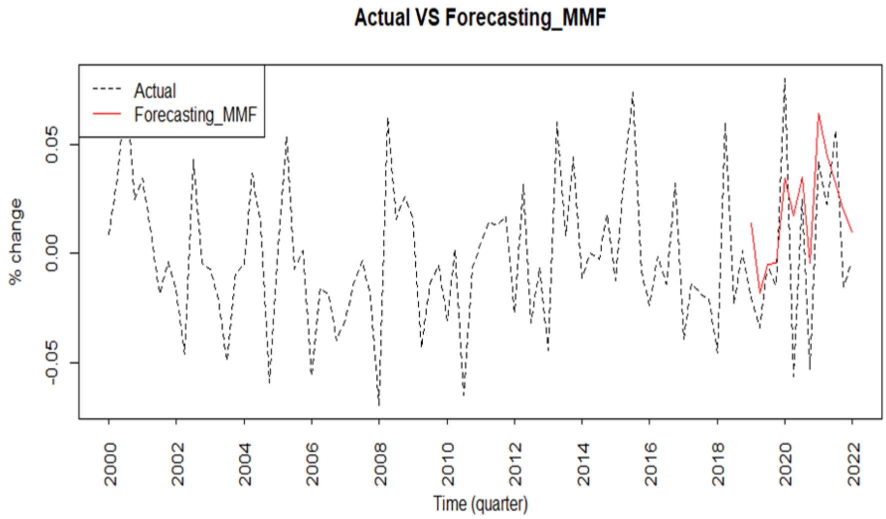

Figure 2 Actual and Forecasting of Exchange rate from MMF Model
Source: Author

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The objective of this paper is to investigate the efficiency of exchange rate models, encompassing the Random Walk Model (RW), the Purchasing Power Parity Model (PPP), and the Monetary Model with flexible price (MMF), while utilizing ARMA, Ordinary Least Squares (OLS), and Mixed Frequency Estimation (MIDAS) techniques. When considering ARMA and OLS models with data of the same frequency, the findings indicate that the RW model exhibits superior predictive performance for exchange rate forecasting compared to the theoretical model as PPP model. However, RW demonstrates lower predictive performance compared to the MMF. In this study, the MMF model, grounded in the dynamics of money supply and demand, has emerged as the most effective model for forecasting exchange rates,

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which represent the prices for international transactions. This reaffirms the importance of basing exchange rate models on economic theory. Furthermore, based on in-sample forecast, when comparing both the PPP and MMF models estimated using OLS and MIDAS techniques, the results indicate that MIDAS outperforms OLS in both the PPP and MMF.

5.2 Recommendation

From the results, it has become evident that mixed frequency data techniques offer enhanced accuracy and robustness when dealing with datasets characterized by varying sampling frequencies. Then the policy maker should consider the regular collection and integration of data from various sources and frequencies to improve the quality of information available for analysis and forecasting. This not only aligns with the findings of this study but also emphasize the significance of data quality and frequency in enhancing the efficiency of exchange rate models.

Future research can explore additional factors and models to further enhance exchange rate prediction accuracy and inform robust economic decision-making strategies. The comparison of accuracy in this study is just one method of evaluating the performance of the model. However, it is important to consider accuracy alongside other attributes such as forecasting speed, adjustment mechanism to equilibrium, and the ability to handle data with unique characteristics in various frequencies to achieve the most suitable and efficient forecasts.

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