

An Investigation of Exchange Rate Volatility using Econometric Model: Evidence from Cambodia

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Abstract

The examination of foreign exchange dynamics was performed utilizing the Autoregressive Integrated Moving Average (ARIMA) model, which integrates both Autoregressive (AR) and Moving Average (MA) components. The analysis focused on the monthly exchange rate between the Khmer Riel and the US dollar, spanning from December 2018 to September 2024, to assess the variations in exchange rates. According to the results of the Augmented Dickey-Fuller (ADF) test, the foreign exchange data series was determined to be integrated of order zero, or I(0). The model identified as the most appropriate, based on the Akaike Information Criterion (AIC), was the ARIMA(3,0,3) model, which indicated the optimal lag lengths for this analysis. The reaction of the foreign exchange market to the disturbance shock revealed a cyclical behavior and demonstrated a downward trajectory over the 30-period forecast horizon. Importantly, the impulse response function (IRF) stayed within the 95% confidence interval, signifying that the response to the shock was statistically significant and remained within a tolerable level of uncertainty. This observation implies that the predictions generated by the model can be regarded as trustworthy.

Keywords: Foreign exchange, ARIMA Model, ADF test, AIC, IRF.

Introduction

In Cambodia, the prevalent utilization of the U.S. dollar in conjunction with the Cambodian riel has resulted in a dollarized economy. This dual-currency framework developed in the aftermath of the Khmer Rouge regime's destruction, during which the riel depreciated significantly, leading to the U.S. dollar being perceived as a more reliable and stable medium for transactions. Currently, the dollar is predominantly employed for substantial transactions, savings, and international trade, whereas the riel is mainly utilized for minor everyday purchases. The National Bank of Cambodia closely regulates the exchange rate between the U.S. dollar and the riel. Although the riel remains legal tender, the U.S. dollar prevails in the economy, especially in urban regions. The limited application of the riel results in its value being primarily influenced by its exchange rate with the U.S. dollar. The NBC endeavors to stabilize the riel by managing foreign exchange rates and ensuring adequate dollar liquidity (Lim and Dash, 2021).

The stability of the exchange rate is vital for maintaining price stability, especially for a nation with a background of currency volatility. A stable exchange rate diminishes uncertainty in international trade and investment, facilitating better planning and pricing for businesses. This predictability is essential for controlling inflation, as it reduces abrupt changes in the costs of imported goods, which is particularly critical for countries dependent on imports for vital commodities such as fuel, food, and machinery (Gürkaynak et al., 2023). In an economy characterized by constrained domestic production, frequent fluctuations in exchange rates can create instability in import prices. This instability may lead to inflationary pressures, complicating the ability of consumers to preserve their purchasing power and hindering businesses in making long-term investment choices. By maintaining stable exchange rates, these risks are alleviated, allowing businesses to predict costs and prices with greater accuracy (Ha and So, 2023). Additionally, stable exchange rates enhance investor confidence, which in turn attracts foreign direct investment and promotes economic growth. The influx of foreign capital not only contributes to the stabilization of the local currency but also alleviates the burden on domestic monetary authorities, reducing the likelihood of adopting inflationary measures such as excessive money printing (Le et al., 2024).

In an economy that is significantly dollarized, the National Bank of Cambodia maintains that achieving price stability is contingent upon the stability of the exchange rate between the Khmer Riel and the US

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Dollar. One of the central bank's most effective strategies for managing exchange rate fluctuations involves the buying and selling of US Dollars in the domestic market through money exchangers. Consequently, forecasting the exchange rate movements between the Khmer Riel and the US Dollar is a valuable endeavor. This research primarily aims to employ an econometric model to analyze the behavior of exchange rate in Cambodia.

Literature Review

The determination of exchange rates through the Monetary Policy Theory (MPT) is associated with the international gold standard, as noted by Brown (2008). During the Bretton Woods System, which lasted from 1955 to 1970, exchange rates were fixed to gold, meaning that the currency in circulation was either composed of gold or could be converted into gold at a set rate. Consequently, the value of currency was directly linked to the weight of gold, and it was the responsibility of the central bank to be prepared to buy and sell gold at specified prices. The Quantity Theory of Money (QTM), regarded as the most straightforward model for establishing the long-term equilibrium exchange rate, is rooted in monetarist principles. According to Nyoni (2018), monetarists contend that any changes in the money supply exclusively influence the price level, leaving the real economy entirely unaffected. In the context of international economics, particularly regarding the international variant of the QTM, an increase in the money supply is reflected in a corresponding rise in the exchange rate. As illustrated by Oleka, Sabina, and Mgbodile (2014), the exchange rate is influenced by the demand for money, which is positively correlated with the growth rate of the real economy and negatively correlated with the inflation rate. Therefore, it is evident that real economic growth plays a crucial role in determining the value of a nation's currency. Ude (1999) contended that a limitation of the international QTM is its inability to account for fluctuations in the real exchange rate, as it is primarily focused on the nominal exchange rate.

As noted by Scott (2008), the purchasing power parity theory highlights inflation levels and trends as crucial factors influencing exchange rates in both emerging and developed economies. The theory posits that a currency's value will decline in response to high or anticipated rising inflation. This phenomenon occurs because inflation erodes purchasing power, subsequently diminishing demand for that particular currency. Furthermore, Obadan (2006) concludes that the equilibrium exchange rate between two convertible currencies is established through the equivalence of their purchasing power.

Numerous studies have been undertaken to predict the exchange rates of various currencies across different regions. Generally, these studies utilize time series data, which is inherently dynamic. Consequently, Dos (2018) and Dos & Diz (2019) proposed that forecasting models may need to adapt based on the behaviors, trends, or primary objectives of the research. For instance, certain factors influencing exchange rates are beyond control due to government interventions, as well as surpluses or deficits in the balance of payments or trade. This complexity has led to a sustained interest in the forecasting of exchange rates and other time series data among scholars. Various methodologies have been employed by researchers in their attempts to forecast exchange rates. For instance, Ishfaq (2018) utilized a time series approach to analyze the exchange rate of the Chinese Yuan (CNY) and found that the VIX index is effective in predicting the directional movement of the CNY exchange rate. In contrast, Prado et al. (2020) introduced a novel model that integrates several individual methodologies, including autoregressive integrated moving average, genetic algorithms, extreme machine learning, artificial neural networks, support vector regression techniques, adaptive neuro-fuzzy inference systems, and fuzzy inference systems. Their findings indicated that this integrated approach significantly improves the accuracy of the forecasting model.

Mance et al. (2015), conducted a causality test to explore the interconnections among exchange rate fluctuations, inflation, and various macroeconomic factors. Additionally, numerous studies have indicated the use of the ARMA/ARIMA methodology, proposing that it yields results that are more precise and closely aligned with actual data. For instance, Joshi et al. (2020) employed the ARIMA method to predict the time series of the Indian Rupee's exchange rate against the US dollar, utilizing the Box-Jenkins approach. Their findings indicated that the ARIMA(1,1,5) model produced results that were notably accurate, closely reflecting real observations. Al-Gounmein et al. (2020) similarly utilized the ARIMA methodology to

analyze the exchange rate of the Jordanian Dinar in relation to the US Dollar. Their findings indicated that the ARIMA(1,0,1) and SARIMA(1,0,1) models yielded superior forecasting outcomes. In a related study, Deka et al. (2019) applied the ARIMA approach to predict the consumer price index, the exchange rate of the Turkish Lira, and the Turkish inflation rate. Their research revealed that the ARIMA(3,1,3) and ARIMA(1,1,4) models were more effective in accurately forecasting the exchange rate and inflation rate, respectively. Furthermore, Abreu et al. (2019) evaluated the forecasting precision of both the ARIMA and Singular Spectrum Analysis (SSA) models for the exchange rate between the Euro and the US Dollar. The results demonstrated that the ARIMA model significantly outperformed the SSA model in terms of forecasting accuracy for this exchange rate.

Umar et al. (2019) demonstrated the significant impact of the ARIMA model in their research, concluding that the ARIMA(2,1,1) configuration is particularly effective for forecasting the exchange rate of the Naira against the UK Pound. Similarly, Farhan et al. (2019) utilized this method to analyze the exchange rate of the Iraqi Dinar against the US Dollar, finding that the ARIMA(1,1,1) model provided the most dependable forecasts when compared to alternative models. Furthermore, Dhankar (2019) applied the ARIMA approach to predict the exchange rates of the US Dollar, Sterling Pound, Euro, and Yen in relation to the Indian Rupee. The out-of-sample forecasting results indicated a slight appreciation in the exchange rates of the Pound, Dollar, and Euro over the following year, while the exchange rate of the Japanese Yen was expected to remain stable. Additionally, Tran (2016) forecasted the exchange rate between the Vietnamese Dong and the US Dollar using three years of data to project the subsequent year's exchange rate, concluding that the ARIMA model is more suitable for short-term forecasting than for long-term predictions.

Humphry et al. (2015) conducted a study on the exchange rate between the Zambian Kwacha and the US Dollar, utilizing an autoregressive-integrated model with data spanning from 1964 to 2014. In a separate investigation, Kadilar et al. (2009) identified the ARIMA model as the most suitable approach for analyzing weekly USDTRY exchange rates, focusing on a dataset that included 160 observations collected between January 3, 2005, and January 28, 2008. Similarly, Cenk et al. (2017) examined 3,069 observations of USDTRY from January 3, 2005, to March 8, 2017, developing both short-term and long-term forecasting models. Their findings indicated that the ARIMA(2,1,0) model was optimal for short-term predictions, while ARIMA(0,1,1) was more appropriate for long-term forecasts, concluding that short-term estimates were generally more reliable than those for the long term. Additionally, Bircan et al. (2003) analyzed the monthly average exchange rate of USD/TRY using 132 observations from 1991 to 2002, determining that the ARIMA(2,1,1) model was the best fit for their data. Overall, the ARIMA methodology has proven to be an effective tool for forecasting the USDTRY exchange rate. Other researchers have also applied the ARIMA model to various economic indicators; for example, Ahmed et al. (2017) assessed the KIBOR rate and found it to be a robust predictor, while Massarrat (2017) utilized the model to forecast gold prices, demonstrating its versatility in predicting macroeconomic trends.

Methodology

The ARIMA model proves to be exceptionally useful for analyzing exchange rate dynamics, primarily because of its capacity to identify temporal relationships within time series data. By integrating both autoregressive and moving average elements, it effectively accounts for historical values and their associated residuals, rendering it particularly adept at predicting exchange rates that frequently display trends and seasonal variations. Furthermore, the integration aspect of ARIMA facilitates the elimination of non-stationarity in exchange rate data, thereby enhancing the precision of its forecasts. The standard ARIMA(p, d, q) model utilized in foreign exchange (FX) analysis is expressed in the following manner.

$$\rho(L)(1-L)^d(FX_t - \mu_t) = \theta(L)\epsilon_t \quad (1)$$

$$\rho(L)u_t = \theta(L)\epsilon_t \quad (2)$$

$$u_t = (1-L)^d(FX_t - \mu_t) \quad (3)$$

$$= \nabla^d F X_t - \nabla^d X_t' \beta$$

And

$$\epsilon_t = u_t - \rho_1 u_{t-1} - \dots - \rho_p u_{t-p} + \theta_1 \epsilon_{t-1} + \theta_q \epsilon_{t-q} \quad (4)$$

In this context, L denotes the lag operator, u_t refers to the unconditional residuals, ϵ_t signifies the innovations, and X_t represents a vector of independent variables. The p and d indicate the optimal lengths of lags and the levels of integration for the dependent variable, whereas q illustrates the optimal lag lengths for the residual terms. The parameters that require estimation include ρ , θ , and β . This study employs the Maximum Likelihood (ML) method for estimation. The likelihood function, based on the assumption of Gaussian innovations within the ARIMA model, is presented as follows.

$$\begin{aligned} \log L(\beta, \rho, \theta, \sigma^2, d) &= -\frac{T}{2} \log(2\pi) - \frac{1}{2} \log|\Omega| - \frac{1}{2} u' \Omega^{-1} u \\ &= -\frac{T}{2} \log(2\pi) - \frac{1}{2} \log|\Omega| - S(\beta, \rho, \theta, d) \end{aligned} \quad (5)$$

The symmetric Toeplitz variance-covariance matrix, denoted as Ω , is derived from the unconditional residuals of the ARIMA model, as outlined by Doornik and Ooms (2003). The optimal lengths for the lags p and q are established using the Akaike Information Criterion (AIC), whereas the parameter d is determined through the Augmented Dickey-Fuller (ADF) test applied to the exchange rate data series. This study spans the period from December 2018 to September 2024, with data sourced from the International Financial Statistics provided by the International Monetary Fund.

Empirical Result

Before conducting the ARIMA regression analysis, it is essential to evaluate and describe the fundamental statistics and graphical representations pertinent to the time series data being examined, specifically the exchange rate. The subsequent step involves utilizing one of the most widely recognized unit root tests, the ADF test, to determine whether the exchange rate series is stationary or exhibits non-stationarity (indicating a unit root). If the null hypothesis of the ADF test is not rejected, this implies that the series possesses a unit root, necessitating a transformation of the series into its first difference, followed by a re-examination using the test. Following this, prior to employing the Maximum Likelihood Estimation (MLE) method for estimating the ARIMA model, it is crucial to ascertain the optimal lag lengths for both the autoregressive (AR) and moving average (MA) components of the model. Information criteria (IC) are utilized to evaluate the model's suitability, with a notable emphasis on the principle that a lower IC indicates a superior model. Although various ICs exist, this study specifically adopts the Akaike Information Criterion (AIC). Once the appropriateness of the ARIMA model is established and all estimated parameters—namely, the constant, autoregressive, and moving average components—are determined through the MLE method, the impulse response function (IRF) will be constructed. The final phase involves forecasting the exchange rate using the ARIMA model, followed by a comparison between the observed and predicted values.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
FX	70	4090.73	28.43	4013.58	4141.29

The analysis of exchange rate behavior is conducted using time series data spanning from December 2018 to September 2024, encompassing a total of 70 months of observations. Throughout this period, the average monthly exchange rate stands at KHR 4090.73 for each US dollar. The volatility of the exchange rate, as indicated by the standard deviation, is approximately KHR 28.43 on a monthly basis. The exchange

rates fluctuate within a minimum of KHR 4013.58 and a maximum of KHR 4141.29 per US dollar. As illustrated in Figure 1, the exchange rate demonstrates a cyclical trend, oscillating around the mean value. In the context of financial studies, this phenomenon is referred to as a mean-reverting process, which typically signifies a stationary process. To ascertain whether the exchange rate series is stationary or non-stationary, it is essential to conduct a unit root test.

Figure 1. Exchange rate between Khmer Riel (KHR) and US Dollar (USD)

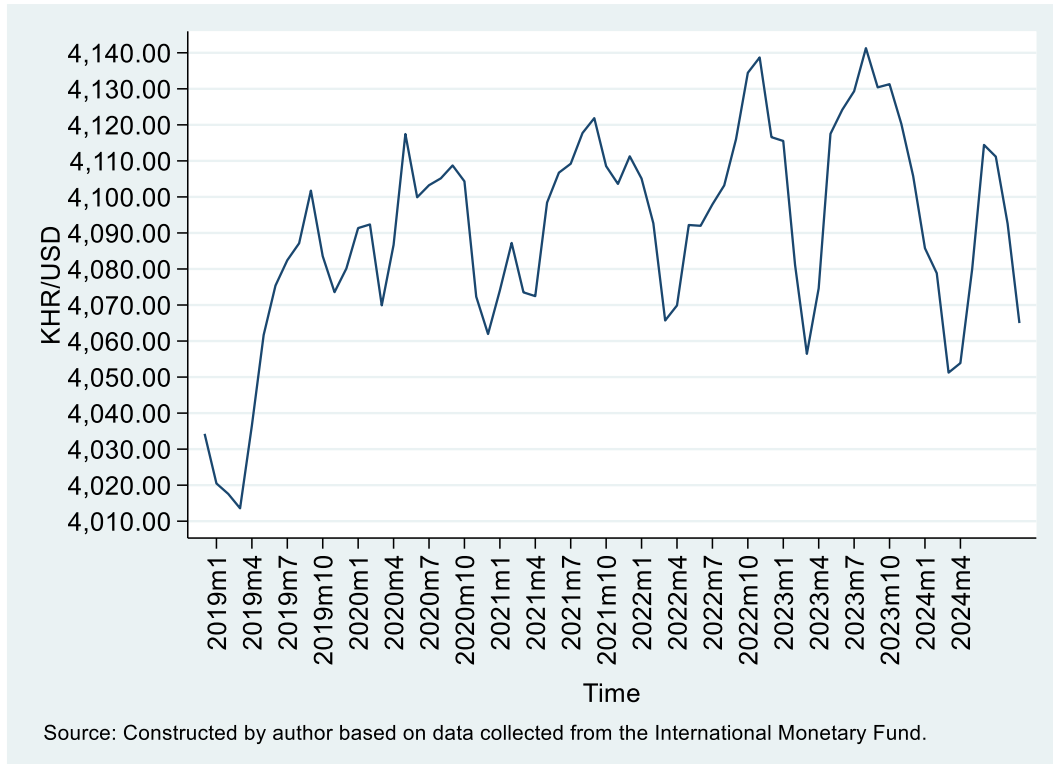


Table 2. Unit root test

Dickey–Fuller test for unit root	Number of obs = 69			
Variable: FX	Number of lags = 0			
	Test	Dickey-Fuller critical value		
H0: Random walk without drift, d = 0	statistic	1%	5%	10%
Z(t)	-2.867	-3.553	-2.915	-2.592

MacKinnon approximate p-value for Z(t) = 0.0493.

The results of the ADF test presented in Table 2 indicate that the Dickey-Fuller critical value at the 5% significance level is -2.915, which is greater than the computed Z(t) value of -2.867. Consequently, the null hypothesis of the ADF test, which posits that the data follows a random walk without or is non-stationary, is rejected at the 5% significance level. This analysis suggests that the exchange rate data series is stationary, implying the absence of a unit root, and can be classified as integrated of order zero, denoted as $I(0)$.

Table 3. ARIMA regression

Sample: 2018m12 thru 2024m9	Number of obs	70
	Wald chi2(5)	9203.95

Log pseudo likelihood = -282.015

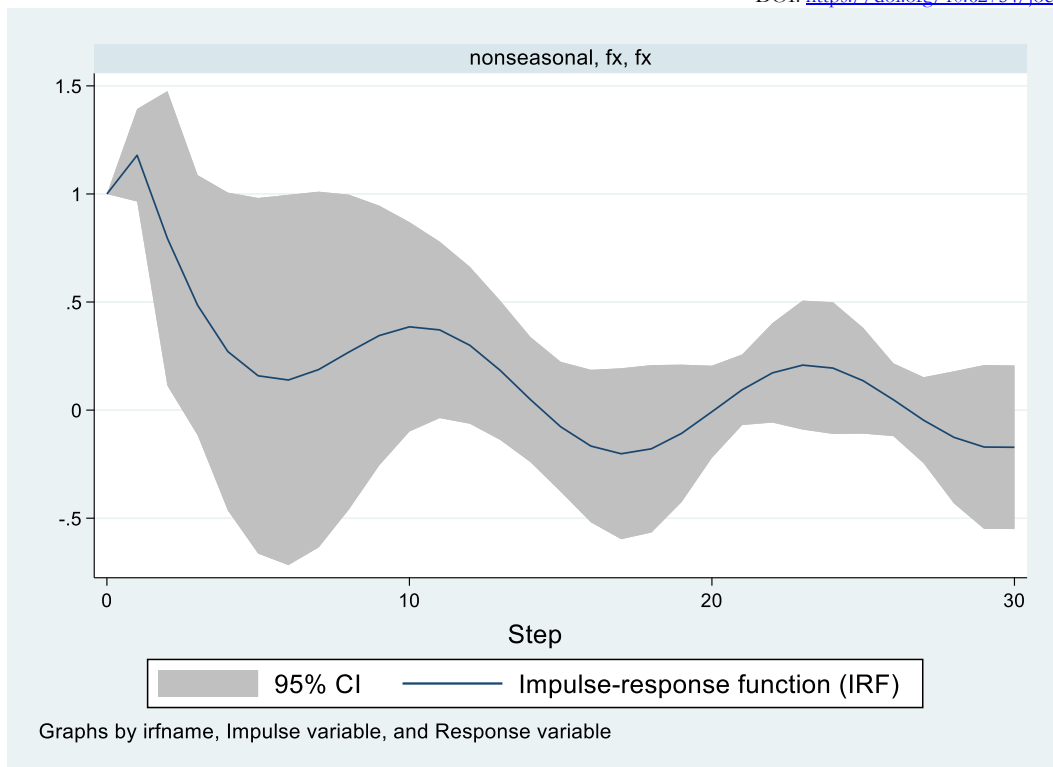
Prob > chi2

0.000

FX	Coefficient	Semi robust			P>z	[95% conf. interval]	
		std. err.	z				
<hr/>							
FX							
_cons	4086.11	10.57	386.47	0.000	4065.38	4106.83	
<hr/>							
ARMA							
AR							
L1.	2.5134	0.1109	22.66	0.000	2.2960	2.7309	
L2.	-2.3264	0.1830	-12.71	0.000	-2.6851	-1.9676	
L3.	0.7634	0.1063	7.18	0.000	0.5550	0.9718	
MA							
L1.	-1.3343	0.1179	-11.31	0.000	-1.5655	-1.1032	
L2.	0.1574	0.2078	0.76	0.449	-0.2500	0.5647	
L3.	0.4676	0.1139	4.1	0.000	0.2443	0.6910	
/sigma	13.0970	0.8758	14.95	0.000	11.3805	14.8135	

The analysis conducted using the AIC and ADF tests indicates that the most appropriate model for the duration of this study is ARIMA(3,0,3). The empirical findings, as shown in Table 3, demonstrate that the individual coefficients for AR(1), AR(2), and AR(3) are statistically significant in explaining the exchange rate at a 1% significance level. Additionally, the estimated parameters for MA(1) and MA(3) also significantly influence the exchange rate at the same level, whereas MA(2) does not show statistical significance. The estimated parameter for sigma is 13.097, which significantly accounts for fluctuations in the exchange rate. Furthermore, the calculated Wald chi-square statistic is 9203.95, a notably high value, and the corresponding p-value is less than 1%, indicating that all variables within the ARIMA model collectively exert a statistically significant effect on the exchange rate.

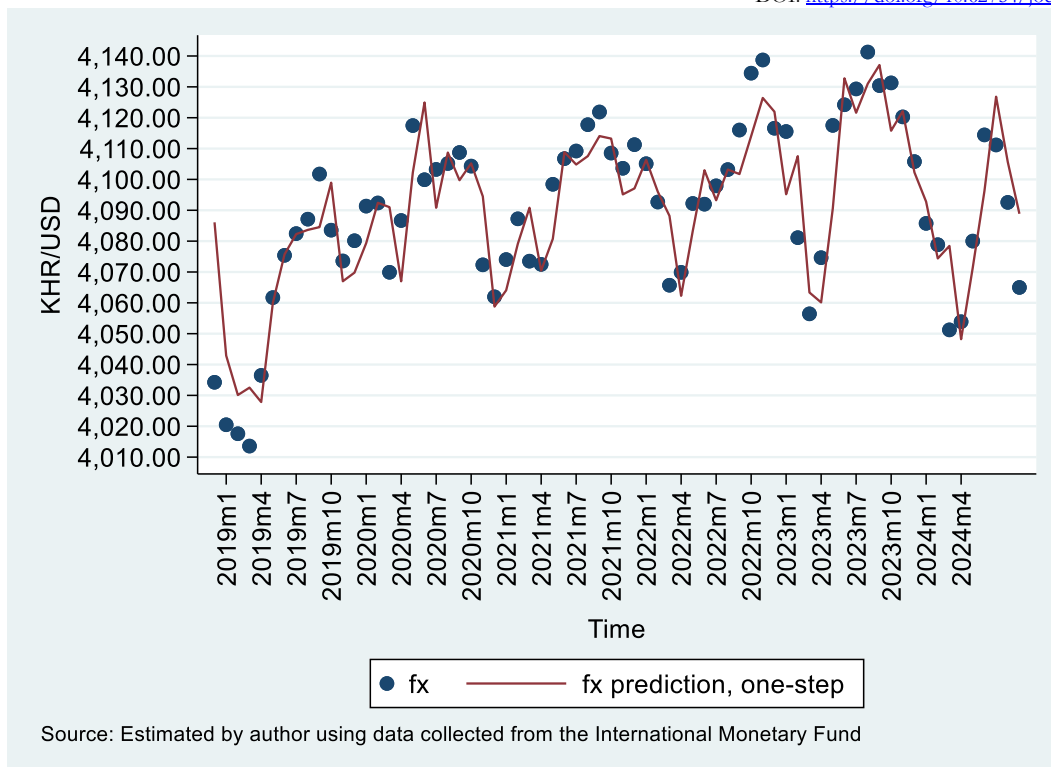
Figure 2. Impulse response function



The Impulse Response Function (IRF) is essential for comprehending the dynamics of time series data analyzed through ARIMA model. While ARIMA model utilize historical values and errors to forecast future outcomes, they do not inherently account for the effects of external shocks or disturbances. The IRF fills this void by demonstrating how a singular shock, or innovation, at a specific moment influences future values over time. Essentially, the impulse response function measures the dynamic repercussions of past errors and interventions, indicating the duration of a shock's impact and its effect on the system's trajectory. This capability enables analysts and forecasters to grasp how the system reacts to external alterations, such as policy changes or unforeseen events, which is particularly vital in the realms of economic, financial, and environmental modeling.

Furthermore, the IRF contributes to model validation, allowing practitioners to evaluate whether the model's behavior corresponds with real-world expectations. It illustrates whether the system adjusts rapidly or gradually and whether it returns to equilibrium following a disturbance. By offering insights into the persistence and intensity of effects, the impulse response function significantly enhances the interpretability, reliability, and practical application of ARIMA model in forecasting and decision-making. The IRF derived from the ARIMA(3,0,3) model, as illustrated in Figure 2, indicates that over a forecast horizon of 30 periods, the exchange rate's reaction to a shock or abrupt alteration in the system displays a cyclical pattern accompanied by a downward trend over time. In addition, the IRF lies within the 95% confident interval, which indicates that the response to the shock is statistically significant and within a reasonable range of uncertainty, meaning that the model's forecast is reliable. The confidence interval provides a boundary within which the true impact of the shock is expected to fall, accounting for sampling variability and model assumptions. If the IRF remains within this interval, it reflects robust statistical evidence.

Figure 3. Observed and predicted exchange rate



To evaluate the predictive capability of the chosen ARIMA(3,0,3) model, a one-step in-sample forecast is conducted. Throughout the forecast period, the predicted exchange rate, represented by a red solid line in Figure 3, closely aligns with the actual observed exchange rate at each data point. This close correspondence may imply a high level of accuracy in the model's predictive performance.

Conclusions

Comprehending exchange rate behavior is essential not only for investors but also for policymakers. Numerous econometric models exist to analyze the dynamics of exchange rate fluctuations; however, the ARIMA model stands out as the most widely utilized among single equation models. The results of the ADF unit root test indicate that the exchange rate data series is stationary at level, or integrated of order zero. Furthermore, the integration of the ADF test with the AIC criterion points to the ARIMA(3,0,3) model as the most appropriate choice for this analysis. The foreign exchange response to the disturbance shock clearly displays a cyclical pattern and exhibits a negative trend throughout the 30-period forecast horizon. Notably, the IRF remained within the 95% confidence interval, indicating that the response to the shock was statistically significant and fell within an acceptable range of uncertainty. This finding suggests that the model's predictions can be considered reliable. The confidence interval provided a framework for anticipating the actual impact of the shock, accounting for sampling variability and the underlying assumptions of the model. If the IRF continues to stay within this interval, it reflects robust statistical support for the results. The model's accuracy in predicting exchange rates is deemed reliable, as the forecasted values at each data point closely align with the observed values throughout the forecast period.

During the study period, the dynamic behavior of the exchange rate showed a cyclical pattern and a seasonal effect as it went up and down around the mean. Therefore, investors should be very careful when investing in foreign exchange between Khmer Riel and US Dollar and consider all available information before making an investment decision. In addition, investors should focus on understanding the factors that influence the strength of the dollar, such as interest rates, geopolitical events and global trade. Diversification is key to mitigating risk, as heavy reliance on the dollar can expose investments to volatility. Monitoring government policies and economic indicators in both the local economy and global markets helps investors make informed decisions and manage potential currency crises.

In an economy characterized by significant dollarization, it is essential to effectively manage fluctuations in exchange rates to ensure economic stability. The government must prioritize the accumulation of robust foreign exchange reserves to provide a safeguard against external economic shocks. Moreover, establishing a well-defined monetary policy framework can contribute to the stabilization of the domestic currency's value. In addition, enhancing fiscal discipline and fostering export growth can elevate the demand for the local currency, thereby alleviating exchange rate pressures. Clear and transparent communication with market participants, along with proactive strategies to mitigate excessive currency speculation, can further bolster confidence in the economy.

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