A Time Series Analysis of Overseas Filipino Workers' (OFW) Monthly Remittances in the Context of the COVID-19 Pandemic

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In partial fulfillment of the requirements for
Statistics 145: Introduction to Time Series

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Diliman, Quezon City

December 2024

ABSTRACT

The study investigates the behavior of Overseas Filipino Workers (OFW) remittances, which play a crucial role in the Philippine economy through their contributions to household income, investments, and foreign exchange reserves. Given the vulnerability of remittance trends to global economic fluctuations, exchange rate volatility, and unexpected events like the COVID-19 pandemic, this study aims to model and forecast remittance flows using a time series analysis on monthly OFW remittances, utilizing in-sample data from the Bangko Sentral ng Pilipinas from 2014-2019 to create out of sample forecasts from 2020-2024. The research analyzes the nature of OFW remittances which displayed both upward trends, seasonality, and non-stationarity. To achieve stationarity, a first difference and seasonal first difference was applied to the log-transformed data. A general multiplicative seasonality ARIMA (2,1,9) x (0,1,1) model was built and selected for its simplicity and strong predictive performance. Diagnostic tests confirmed the model's adequacy, as residuals were found to be uncorrelated, homoscedastic, and normally distributed. Out-of-sample forecasts from January 2020 to August 2024 closely matched actual values, except during COVID-19 disruptions, specifically for the months of April and May during the year 2020, emphasizing the influence of external shocks on remittances. Overall, the study's findings highlight the model's reliability in capturing seasonal and cyclical patterns, offering insights for policymakers and financial institutions.

Keywords: OFW Remittances, COVID-19 Pandemic, Time series analysis

I. Introduction

Background of the Study

Overseas Filipino Workers (OFWs) play a pivotal role in the Philippine economy—primarily through their remittances, which serve as a lifeline for millions of families and a significant source of national income (Bangko Sentral ng Pilipinas, 2022). OFW remittances contribute to household consumption, investment, and poverty alleviation for their families in the Philippines, while also contributing to foreign exchange reserves (Asian Development Bank, 2021). However, despite their importance, OFW remittances are susceptible to global economic fluctuations, geopolitical tensions, exchange rate volatility, and unforeseen events such as the COVID-19 pandemic (International Labour Organization, 2021). Thus, understanding and forecasting the trends in remittances is essential for financial institutions to guide important decisions on fiscal policies.

The COVID-19 pandemic, which began in the year 2020, had a profound impact on global economies, including the flow of remittances. Many OFWs faced job losses, wage reductions, and repatriations due to lockdowns and economic downturns in their respective host countries (World Bank, 2021). Consequently, remittance flows experienced significant disruptions during this period, emphasizing the need for accurate forecasting models to anticipate such shocks and mitigate their effects.

Statistical methods, such as time series analysis, offer opportunities to explore the dynamics of OFW remittances over time (Hyndman & Athanasopoulos, 2018). One such method, the Autoregressive Integrated Moving Average (ARIMA) model, has proven to be a robust tool for analyzing and predicting time series data. By utilizing historical data, ARIMA can provide insights into patterns, seasonal trends, and potential disruptions in remittance flows, enabling stakeholders to make data-driven decisions (Shumway & Stoffer, 2017).

This study focuses on analyzing a 10-year dataset of monthly OFW remittances to build a general multiplicative seasonal ARIMA model. The dataset, from the Bangko Sentral ng Pilipinas, spans from the years 2014 to 2024, with the period from 2014 to 2019 serving as the in-sample data for model training and the period from 2020 to 2024 serving as the out-of-sample data for forecasting.

Through this approach, the study aims to evaluate the predictive accuracy of the model. Moreover, it aims to contribute meaningfully to the discourse on OFW remittances and their role in the Philippine economy by bridging the gap between historical data analysis and forward-looking insights. The results are expected to provide practical and theoretical value, particularly in the context of global disruptions like the COVID-19 pandemic.

Statement of the Problem

The flow of OFW remittances is highly vulnerable to global economic conditions, such as exchange rate fluctuations and unprecedented crises such as the COVID-19 pandemic. The pandemic highlighted the susceptibility of remittance flows to disruptions, with many OFWs facing job losses, wage cuts, and forced repatriations. This creates a gap in understanding and planning for remittance trends, which are crucial for policymakers in formulating effective fiscal policies and economic strategies.

This study aims to address the issue of unpredictability in OFW remittance flows, which are influenced by seasonal, economic, and global factors. These disruptions highlight the need for a reliable and robust forecasting model to anticipate remittance flow fluctuations, mitigate adverse impacts, and optimize their economic benefits.

Objectives

Particularly, this study focuses on applying statistical procedures used in time series analysis to analyze OFW remittances. The following objectives will guide the researchers in this endeavor:

- To build a general multiplicative seasonal ARIMA model for analyzing OFW remittance trends using historical data from 2014 to 2024.
- To identify and analyze the seasonal, cyclical, and long-term patterns in OFW remittance flows.
- To assess the predictive accuracy of the model by using in-sample data from 2014-2019 to make comparisons of out-of-sample forecasts with actual data from 2020-2024.
- To evaluate the impact of global events, such as the COVID-19 pandemic, on OFW remittances using the developed model.
- To provide actionable insights and recommendations for policymakers to create data-driven strategies that address remittance variability and optimize the benefits of OFW remittance inflows.

II. Review of Related Literature

Examining Overseas Filipino Worker (OFW) remittances is vital due to their profound and multifaceted impact on individual households and the broader national economy. In the Philippines, remittances are integral in promoting social mobility, ensuring economic stability, and reducing poverty. As one of the world's largest recipients of remittances, understanding the dynamics of these financial flows enables financial institutions and policymakers to assess the macroeconomic implications better—which can help maximize the benefits of these remittances while addressing potential drawbacks. Analyzing both the opportunities and challenges posed by these financial flows can help strengthen the fact that remittances continue to contribute to inclusive, sustainable development that benefits Filipinos.

Remittances

Remittances are an unrequited transfer of income from individuals working abroad to their families in their home country (International Monetary Fund, 2019). These remittances serve as a vital source of foreign currency resources—alleviating pressure on the exchange rate, and reducing the need for foreign borrowing (Bangko Sentral ng Pilipinas, 2022). Sener (2023), highlights the significant macroeconomic effects of remittances, particularly on key development indicators in addition to the immediate financial benefits they provide to recipient households. Moreover, Deluna & Pedida (2014), described remittances as returns on migration, representing an investment in the human capital of migrants, often aimed at improving the present circumstances and securing a better future for their children or younger siblings. Reflecting this perspective, Wimaladharma et al. (2004), have even referred to remittances as a form of "new development finance," emphasizing its growing role in economic development during the early 2000s.

According to Light (2015), the Philippines is the leading labor exporter among its neighbors in East and Southeast Asia. This dynamic is largely driven by the redistribution of manpower to regions with higher labor demand and wage rates, as noted by Nijkamp (2017). The Philippine Statistics Authority (2018) estimates that there were approximately 2.3 million Overseas Filipino Workers (OFWs) in 2017. The top destination countries for OFWs included Saudi Arabia, the United Arab Emirates, Kuwait, Qatar, Hong Kong, and Singapore. Regionally, Calabarzon accounted for the largest proportion of OFWs at 20.7%, followed by Central Luzon with 12.9%, and Western Visayas and the National Capital Region, each contributing 9.5%. In contrast, the Cordillera Administrative Region (CAR) and Region XIII (Caraga) recorded the smallest proportion of OFWs. The data also reveal that more females (53.7%) work as OFWs compared to males (46.3%), with the largest age group being 30 to 34 years old (21.7%), followed by those aged 25 to 29 (20.4%). Among younger OFWs aged 25 to 29, females constitute a higher proportion (24.1%) than males (19.8%). However, for those aged 35 years and older, the proportion of male OFWs (19.8%) exceeds that of females. This demographic trend highlights the prominence of young females in the overseas workforce, particularly in the younger age brackets.

Impact of Remittances on Poverty

The significance of Overseas Filipino Worker (OFW) remittances in mitigating poverty has been a persistent area of research for decades, underscoring their essential contribution to the welfare of recipient families and communities. Research continuously demonstrates that remittances give households an ongoing source of income, enabling them to pay for basic necessities like housing, food, and medical care. Families are less vulnerable to economic shocks because of this safety net, which also helps them deal with unforeseen financial difficulties like medical emergencies or natural disasters (Sato, 2024).

According to studies, remittances assist recipient households in lowering the prevalence and severity of poverty. For instance, Yoshino et al. (2017) showed that in a number of Asian nations, a 1% rise in remittances in relation to GDP results in considerable decreases in the poverty gap and poverty severity. The ability of remittances to balance consumption and close disparities in local income distribution is associated with this decrease in poverty. This can be observed on how remittance flows has contributed to the decrease of poverty rate in the Philippines, falling from 22% in 2015 to 16% in 2018.

According to the Philippine Statistics Authority (2018), these remittances have been essential in helping families escape poverty by enhancing their living conditions. This has also provided more families with an avenue to access better healthcare and education, as well as empowering them to invest in small assets or properties. As a result, remittances not only offer short-term alleviation but also promote long-term economic mobility that leads to upward mobility—ending the generational cycle of poverty.

Nonetheless, some academics suggest that the effectiveness of remittances on long-term poverty alleviation may be limited, given their beneficial benefits on poverty reduction.

According to studies like those by Masron and Subramanian (2018), remittances lower immediate poverty levels, but they don't always promote local economic development or lasting economic growth. Rather, remittances may lead to a cycle of dependency in which households become overly dependent on outside money, which hinders them from looking for other sources of income or contributing to the local economy's growth (Masron & Subramanian, 2018).

Contribution to the Economy and Gross Domestic Product

Remittances from overseas Filipino workers (OFWs) are essential to the Philippines' economic growth and provide a substantial contribution to the GDP of the nation. Given that the Philippines is one of the biggest recipients of remittances worldwide, remittances have continuously contributed roughly 10% of the country's GDP in recent years. This money, according to the Bangko Sentral ng Pilipinas (BSP), is a significant source of foreign cash for the nation, increasing the value of the national currency, enhancing financial standing, and assisting the government manage its external debt (BSP, 2024).

In addition to aiding in economic stabilization, remittances also lessen the negative consequences of unexpected events. For instance, remittances operate as protection against the withdrawal of foreign investments and the contraction of the domestic economy during economic downturns or worldwide recessions. Moreover, according to Reside (2009), remittances have frequently increased during times of global financial crisis, supporting domestic consumption levels. Remittances' advantageous function has proven especially crucial in times of crisis, like the Asian financial crisis of 1997 and the global economic downturn of 2008.

Through raising household purchasing power, which in turn drives demand for goods and services, the remittance inflow also promotes economic growth. Local businesses observe an increase in sales as receivers spend their remittance cash on necessities like food, clothing, and medical treatment. This can result in the creation of employment and a boost to the economy. Additionally, remittances can promote local investment, especially in microenterprises and small businesses. These businesses support the expansion of the informal sector, which is essential in many developing nations, including the Philippines. Remittances have also contributed to the development of the nation's financial system. Through the expansion of the market for remittance services, the facilitation of money transfers through banks, and the encouragement of the development of mobile money systems, the consistent flow of remittances has helped the banking industry prosper. Families can easily and securely receive cash remittances through these financial services, which helps boost the economy by making financial resources for local development more accessible and available (Barkat et al., 2024).

Moreover, remittances support the stability of foreign exchange reserves, which helps the government reduce the impact of trade shortfalls and even out variations in the balance of payments. This financial cushion helps stabilize national currencies against volatility in global markets and is especially crucial for poor nations that mostly rely on remittances as a source of foreign exchange (Yoshino, Taghizadeh-Hesary, & Otsuka, 2017).

Effects on Household Income and Quality of Life

The most obvious advantage of remittances at the household level is the notable rise in financial flexibility, which immediately raises recipient families' standard of living. Remittances are utilized to cover a range of household expenses, including housing, healthcare, education, and food. The Bangko Sentral ng Pilipinas (2009) reports that 68.2% of families that receive remittances set aside the money for educational costs, while 96.2% utilize it to buy food. One of the main reasons remittances have been linked to lower poverty and better welfare outcomes is that they are widely used to raise living standards (Gupta, 2005).

Furthermore, remittances play a crucial role in fostering human capital development, beyond simply meeting immediate consumption needs. They provide the younger generation with opportunities to access education, equipping them with the knowledge and skills necessary to improve their future prospects. Families that receive remittances are more likely to support their children’s continued education, increasing the likelihood of school completion and paving the way for better employment opportunities and higher earnings in the future. Moreover, remittances enhance access to healthcare by enabling families to afford preventive care, medical treatments, and better nutrition. These improvements contribute to healthier, more productive individuals (Haseeb & Samsudin, 2016).

The enhancement of housing conditions serves as another testament to the positive impact of remittances on quality of life. Families often use remittances to build or renovate their homes, creating better living environments that improve the overall well-being of household members. These investments not only elevate individual living standards but also contribute to long-term community benefits (Yang, 2006).

It is important to recognize that the impact of remittances on household welfare largely depends on how they are utilized. While some households focus on consumption, which may not lead to long-term economic improvements, others allocate remittances to productive activities, such as starting a business or saving for future needs. Although remittances are often seen as a positive driver of economic growth, Deluna and Pedida (2014) highlight that, in certain cases, they can exacerbate income inequality. Wealthier households may benefit more significantly from remittances, further widening the gap between the rich and the poor.

OFW remittances during the pandemic

The COVID-19 pandemic posed significant challenges to Overseas Filipino Workers (OFWs) and their families, disrupting remittance flows and altering their socio-economic effects. Deinla et al. (2022) note that widespread job losses, reduced work hours, and health risks led to a slight decline in remittance inflows—the first in two decades.

In May 2020, the World Bank Group highlighted the heightened vulnerability of migrant workers to the COVID-19 pandemic, calling on governments to implement measures to limit the transmission of the virus, retain employment, and support distressed migrants (Moroz et al., 2020). In response, the Philippine government initiated programs under the Bayanihan to Heal as One Act, allocating PHP 2.5 billion (approximately USD 47 million) for one-time cash assistance and provisional aid through the Abot Kamay ang Pagtulong (AKAP) Program (Fernandez et al., 2020). Further support was extended under the Bayanihan to Recover as One Act, with PHP 820 million (around USD 15 million) designated for repatriation, medical aid, and the handling of OFWs' remains. Additional government efforts included emergency education, food, and livelihood assistance, with a particular focus on ensuring the prompt and safe repatriation of OFWs (Fernandez et al., 2020).

Despite the efforts mentioned earlier, they were insufficient to address the needs of the 1.1 million affected OFWs at the time. Reports emerged of delays in aid distribution, with some OFWs resorting to extreme measures, such as selling blood to survive, which gained widespread attention on social media (GMA News, 2020; DOLE, 2020). Repatriation efforts were also hindered by inadequate testing capacity, travel restrictions, and local governments refusing to allow returning migrants. These challenges, along with government mismanagement, led to significant criticism during the initial months of the pandemic (Fernandez et al., 2020).

Generally, the COVID-19 pandemic severely disrupted the lives of Overseas Filipino Workers (OFWs), affecting both their remittance flows and socio-economic stability. Despite the Philippine government's efforts to provide financial aid and repatriation assistance, these measures fell short of addressing the needs of the affected workforce. Challenges such as delayed aid, inadequate repatriation systems, and strained local resources highlighted the vulnerabilities faced by OFWs. This situation emphasizes the need for more effective support systems to protect and assist OFWs during crises.

III. Methodology

Method of Data Collection

The data used in this time series analysis is primary data collected by the Bangko Sentral ng Pilipinas (BSP). The dataset is characterized by the total monthly overseas cash remittances that Filipinos working abroad send back to the Philippines. These remittances are measured in million U.S. dollars, dating as far back as January 1989. However, for the purpose of this study, only monthly data over a span of the last 10 years was considered—starting from January 2014 to August 2024. As of writing, only preliminary values for 2024 are available, as the latest observation is from August 2024. The researchers manually inputted the data into a csv file with two columns, one for the time component and the other for the OFW cash remittances. The in-sample data for the time series has a total of 72 observations from 2014-2019, while 56 observations were used to compare out-of-sample forecasts with the actual values.

Analysis of data

Various statistical methods used in time series analysis were utilized to examine the dataset and meet the objectives set by the researchers. RStudio was the statistical software used for this analysis. All formal tests done tests were done at a level of significance $\alpha=0.05$.

The researchers built a non-structural general multiplicative seasonal model that captures autoregressive (AR), differencing (I), and moving average (MA) effects in both seasonal and non-seasonal dimensions. This multiplicative seasonal ARIMA (SARIMA) model is particularly suitable for the remittance data used, which exhibited seasonal fluctuations and autocorrelations across lags. A Kruskall-Wallis test was done to formally test the data for seasonality.

To build the general multiplicative seasonal model, the researchers analyzed the historical plot, Autocorrelation Function (ACF) plot, and Partial Autocorrelation (PACF) plot of the data to determine if transformations should be done to ensure stationarity—stationarity is a key component in building SARIMA models. This process involved visualizing trends and seasonality; and performing formal tests like the Augmented Dickey-Fuller (ADF) test and DF-GLS ERS test since the data exhibited increasing variance over time. Moreover, transformations were done to ensure that the mean was constant, and seasonal patterns were removed, making the process stationary. Log transformation, seasonal differencing, and regular differencing were performed on the data.

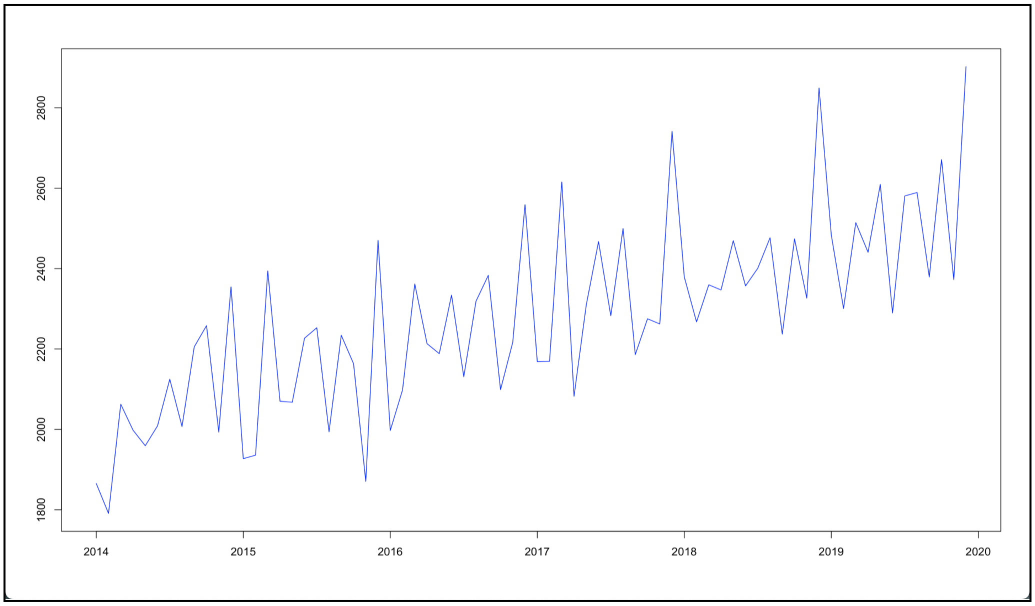
In selecting the appropriate order of seasonal and non-seasonal terms for the model. The ACF plot of the transformed series was used to determine the number of moving average (MA) terms, while the PACF plot helped determine the autoregressive (AR) terms to include. Different models were considered to evaluate the most appropriate model for the data. The response variable in this model is the cash remittances from OFWs, denoted as OFW_t, while the past observations of the series, random error terms, and lagged random error terms will serve as the explanatory variables, which are specified in the final model.

Diagnostics play a crucial role in validating the model. Analysis of the residuals is done to verify the assumption that a_t is a white noise process. Thus, the Ljung-Box test was performed to check the uncorrelatedness of the error terms, the ARCH LM test was used to check for the constancy of variance of the error terms, and the Jarque-Bera test was used to check for the normality of the error terms. Moreover, goodness-of-fit measures like the Akaike Information Criterion (AIC) help assess the model's performance where lower AIC values indicate a better fit. Forecast accuracy is measured using metrics such as the Mean Absolute Percentage Error (MAPE). The final model was selected based on its ability to minimize error metrics and provide robust and reliable diagnostics. After validation, the final model was used to generate monthly forecasts for 2020-2024. These forecasts are compared against actual values to evaluate the model's predictive power.

IV. Results

Preliminary Stage

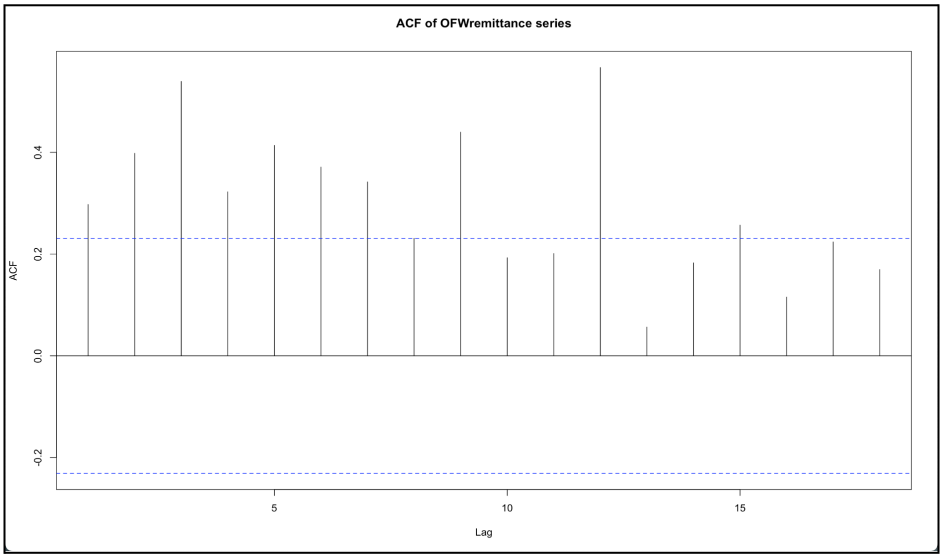
***Figure 1**. Time Series Plot of OFW Remittances Series, Jan 2014 - Dec 2019*



The time-series plot of the OFW remittances series for January 2014 to December 2019 illustrates an upward trend in OFW remittances, characterized by a peak at the end of the year, followed by a notable decline during the first month of the year. Remittances gradually increase, reaching a significant surge toward the end of each year, which contributes to the overall upward trend and visual evidence of seasonality.

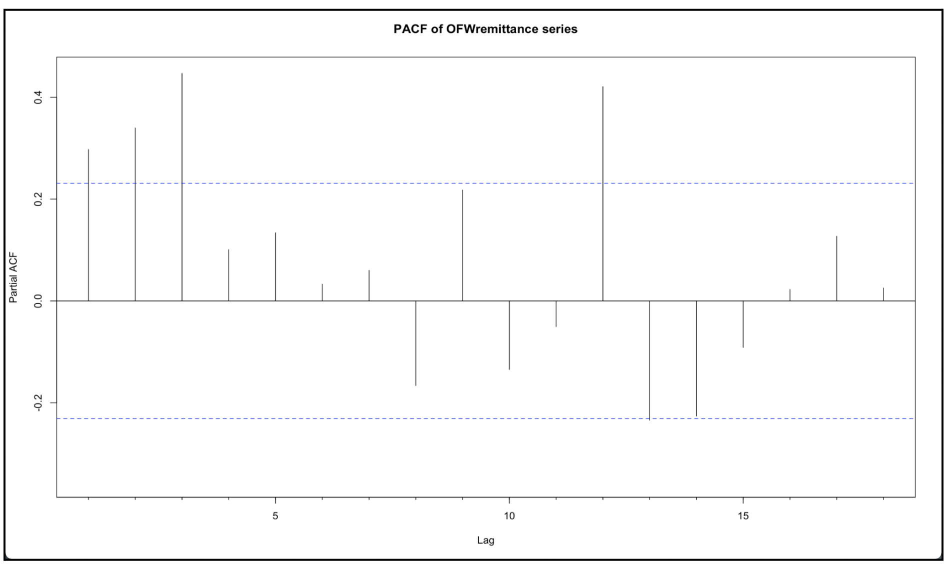
Notably, the year 2014 exhibits irregularities, as its initial remittance values are significantly lower compared to other years. This deviation makes 2014 stand out, as it does not follow the trend from other years; subsequent years do not exhibit comparable dramatic increases in the plot. On the other hand, the plot reveals varying magnitudes of fluctuations, indicating that the variance is not constant. Consequently, it can be hypothesized that the OFW remittances series is non-stationary given the presence of an upward trend and unequal fluctuation sizes.

***Figure 2**. ACF of OFW Remittances Series, Jan 2014 - Dec 2019*



The Autocorrelation Function plot of the OFW remittances series for January 2014 until December 2019 correlogram exhibits a slow decay toward zero. A stationary series should have correlograms that have a fast decay to zero. However, the ACF of the OFW remittance series does not decay fast to zero, indicating that the OFW remittances series is non-stationary.

***Figure 3**. PACF of OFW Remittances Series, Jan 2014 - Dec 2019*



Similar to the ACF plot, the Partial Autocorrelation Function plot of the OFW remittances series for January 2014 until December 2019 correlogram exhibits a slow decay to zero, further suggesting that the OFW remittances series is not stationary. However, formal tests must be performed to confirm these visual assumptions.

Table 1. *Test for Seasonality of OFW Remittances Series, Jan 2014 - Dec 2019 using the Kruskall-Wallis Test*

Test	Test Statistic	Critical Value	p-value
Kruskall-Wallis Test	H = 61.9973	19.6751	4e-9

A formal test, the Kruskall-Wallis test, was performed to check if the data exhibited seasonality. From the very low p-value, it can be concluded that at a significance level of 0.05, the null hypothesis of the test, that the time series is not seasonal, is rejected. Thus, the time series has seasonality.

Table 2*. Test for Stationarity of OFW Remittances Series, Jan 2014 - Dec 2019 using the Augmented Dickey-Fuller Test*

Test	Test Statistic	Lag order	p-value
Augmented Dickey-Fuller Test	-4.9128	4	0.01

Next, the stationarity of the OFW remittances series from January 2014 to December 2019 was formally tested using the Augmented Dickey-Fuller (ADF) test. The p-value obtained was 0.01, leading to the rejection of the null hypothesis, which asserts that the series is non-stationary. At a significance level of 0.05, we have sufficient evidence to conclude that the OFW remittances series is stationary.

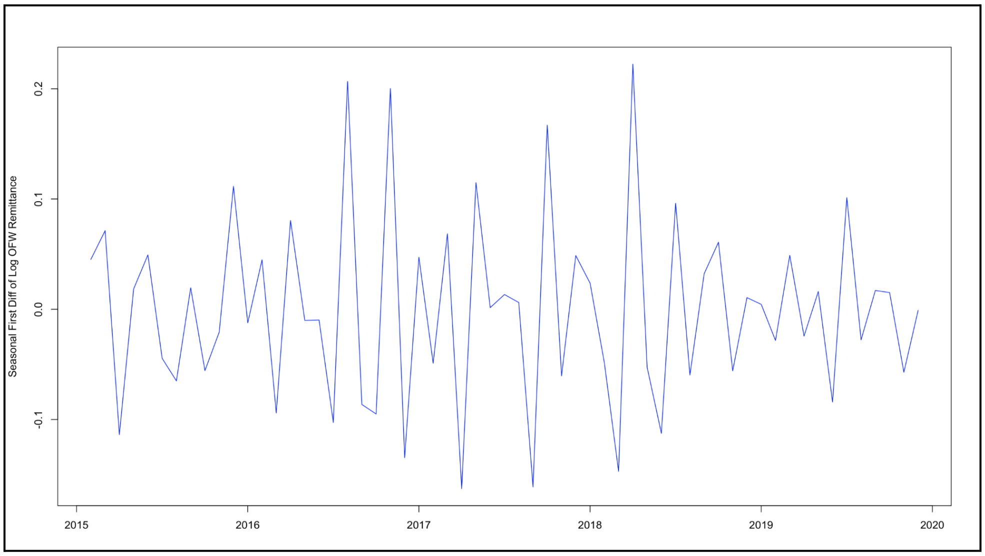
Table 3*. Test for Stationarity of OFW Remittances Series, Jan 2014 - Dec 2019 using the DF-GLS Test Elliot, Rothenberg, and Stock (ERS)*

		Critical Values		
Test	Test Statistic	1%	5%	10%
DF-GLS Test Elliot, Rothenberg, and Stock (ERS)	0.9878	-2.59	-1.94	-1.62

Furthermore, the stationarity of the OFW remittances series from January 2014 to December 2019 was also tested using the Elliot, Rothenberg, and Stock (ERS) test. The test statistic obtained was 0.9878, which is greater than -1.94, leading to the failure to reject the null hypothesis. Therefore, the series is non-stationary. At a significance level of 0.05, we do not have sufficient evidence to conclude that the OFW remittances series is stationary.

Generally, given the conflicting results of the ADF test and the ERS test, we consider the findings of the ERS test of non-stationarity, as it is the more powerful test. This implies that the series requires transformation/s to achieve stationarity. Specifically, we apply a seasonal first difference to the log-transformed OFW Remittances to remove both the trend and seasonality of the series.

Figure 4. *Time Series Plot of First Difference of First Seasonal Difference of Log Transformed OFW Remittances, Feb 2015 - Dec 2019*



The time series plot of the transformed OFW remittances for January 2014 to December 2019 presents a time series with no discernible trend. However, the plot possibly indicates that the fluctuation sizes remain unequal, as evidenced by the spikes observed during the last months of 2016 and the first few months of 2018. To verify whether the series still exhibits non-stationarity, formal tests must be performed.

Table 4. *Test for Stationarity of the Transformed OFW Remittances Series using the Augmented Dickey-Fuller Test*

Test	Test Statistic	Lag order	p-value
Augmented Dickey-Fuller Test	-5.8655	3	0.01

The stationarity of the transformed OFW remittances series was tested using the Augmented Dickey-Fuller (ADF) test. The p-value obtained was 0.01, which is less than the 0.05 significance level, suggesting the rejection of the null hypothesis. Since the null hypothesis asserts that the series is non-stationary, we conclude that, at a 0.05 significance level, there is sufficient evidence to assert that the OFW remittances series is stationary.

Table 5. *Test for Stationarity of the Transformed OFW Remittances Series*

using the DF-GLS Test Elliot, Rothenberg, and Stock (ERS)

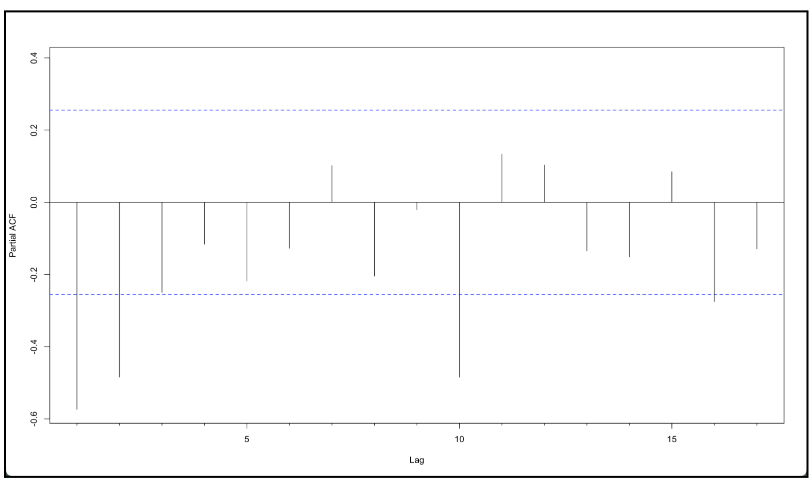
		Critical Values		
Test	Test Statistic	1%	5%	10%
DF-GLS Test Elliot, Rothenberg, and Stock (ERS)	-2.0142	-2.6	-1.95	-1.62

Additionally, the stationarity of the transformed OFW remittances series was also tested using the Elliot, Rothenberg, and Stock test. A test statistic value of -2.0142 was obtained, which is less than -1.95. Therefore, we reject the null hypothesis, which states that the series is non-stationary. At the 0.05 significance level, we have sufficient evidence to conclude that the OFW remittances series is stationary.

Identification and Estimation of the Model

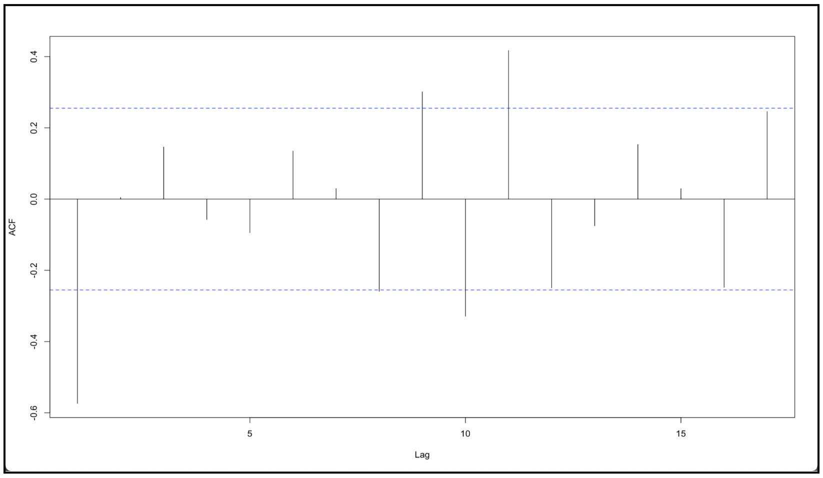
Based on the formal tests performed in the preliminary stage, the transformed OFW remittances series is now stationary, which allows for identifying an appropriate model for the data.

Figure 5. *PACF of Transformed OFW Remittance Series*



The Partial Autocorrelation Function (PACF) plot of the transformed OFW remittances series reveals significant spikes at lags 1, 2, and 10. These spikes suggest the inclusion of Autoregressive (AR) terms at these lags in the ARIMA model. These significant spikes indicate a strong correlation between the current value of the series and its past values at these specific lags.

Figure 6. *ACF of Transformed OFW Remittance Series*



The Autocorrelation Function (ACF) plot of seasonal first difference log transformed OFW remittances reveals significant spikes at lag 1, 8, 9, 10, and 11 correspond to the Moving Averages (MA) terms to be included in the ARIMA model. Moreover, it seems like lag 12 is close to being significant, which may be an indication to include a seasonal MA (SMA) term. Based on the principle of parsimony, which maintains that all other things being equal, simple models are preferable over complicated models. Thus, only MA terms at lags 1, 8, and 9 are considered to be included, along with one SMA term.

Table 6. *Comparison of Performance Metrics for ARIMA Models Considered*

Criteria for Evaluation:	**Model 1: ARIMA (10,1,9) x (0,1,1)**	**Model 2: ARIMA (2,1,9) x (0,1,1)**
Dependent Variable	$Y_t = \Delta\Delta_{12} ln(OFW_t)$	$Y_t = \Delta\Delta_{12} ln(OFW_t)$
Terms in the Equation	$(1 - B)(1 - B^{12})(1 - \phi_1 B + \phi_2 B^2 + \phi_{10}$ $= (1 - \theta_1 B + \theta_8 B^8 + \theta_9 B^9)(1 - \Theta_1 B^{12})a_t$	$(1 - B)(1 - B^{12})(1 - \phi_1 B + \phi_2 B^2)Yt$ $= (1 - \theta_1 B + \theta_8 B^8 + \theta_9 B^9)(1 - \Theta_1 B^{12})a_t$
AIC	-174.97	-171.69
RMSE	0.04089095	0.04315542
MAPE	0.3659864	0.3906103
Normality Test OK?	Yes	Yes
ARCH Test OK?	Yes	Yes
Ljung Box Test OK?	Yes	Yes

Comparing the AIC, RMSE, and MAPE of the two models, ARIMA (10, 1, 9) x (0, 1, 1) (Model 1) appears to be the better model to fit the data, as it has the lower values for all performance metrics. However, the differences in these metrics between the two models are relatively small. For instance, the difference in AIC, RMSE, and MAPE is only 3.28, 0.0023, and 0.0246, respectively. Such differences are unlikely to significantly impact the accuracy of the forecasts. Another point to consider is that ARIMA (2, 1, 9) x (0, 1, 1) (Model 2) is simpler, with fewer autoregressive terms (p = 2) compared to Model 1 (p = 10), which makes it more parsimonious. This simplicity reduces the risk of overfitting and improves the interpretability of the model. Moreover, both models pass the necessary diagnostic tests. Balancing goodness-of-fit with model complexity, the researchers chose Model 2 for the analysis.

Table 10. *Results from the ARIMA (2,1,9) x (0,1,1) model*

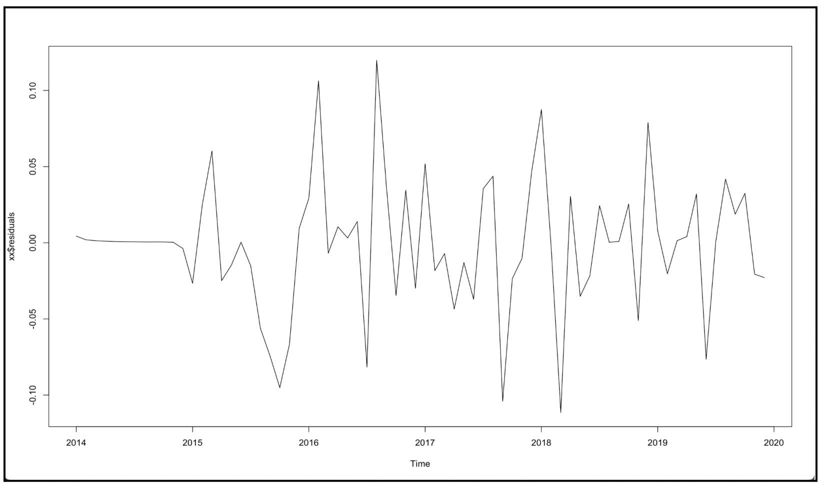
Variable	Coefficient	Standard Error	$\left\lvert \frac{Coefficient}{Standard\ Error} \right\rvert$
AR(1)	-0.5053	0.1773	2.8499
AR(2)	-0.3962	0.1438	2.7552
MA(1)	-0.4646	0.2092	2.2208
MA(8)	-0.4560	0.1351	3.3752
MA(9)	0.5427	0.1564	3.4699
SMA(1)	-0.3305	0.1628	2.0301
Log Likelihood	92.84		
AIC	-171.69		
RMSE	0.04315542		
MAPE	0.3906103		

The estimates of coefficients of the model were estimated using the non-linear least squares method via the statistical software, R Studio. All parameters in the chosen model are found to be significant as all values of the absolute value of the coefficient divided by the standard error all exceed 2, which is a common basis for determining if the coefficient is significant. With this, the ARIMA (2,1,9) x (0,1,1) model is chosen.

Diagnostic Checking

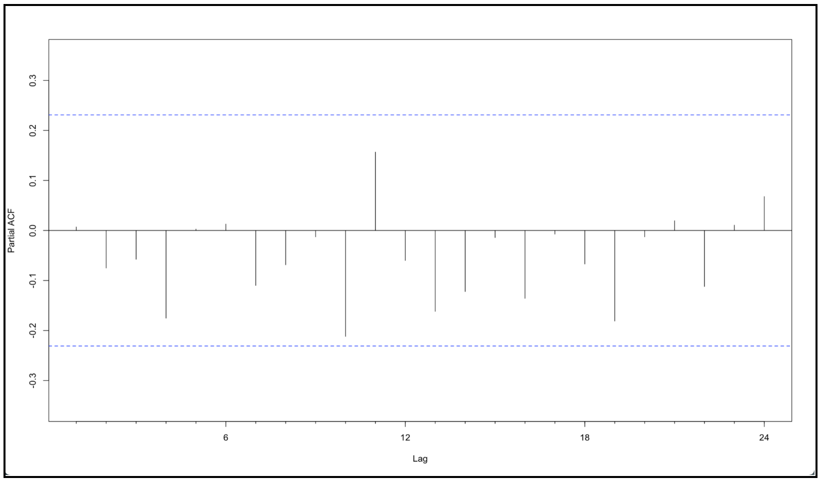
To help determine if chosen model is statistically adequate, diagnostic checks on the residuals, or the error terms, will be performed. The error terms must satisfy the three diagnostic checks, it must constitute a white noise process, the variances of the error terms must be constant, and the distribution of the error terms is normal.

Figure 7. *Plot of the Residuals of the Model for OFW Remittances*



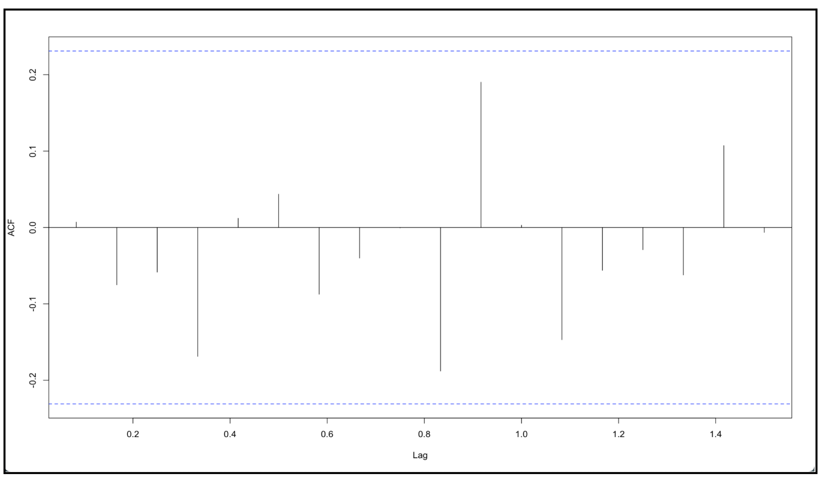
The residual plot of the model of the model for OFW remittances has no apparent pattern. Upon visual inspection, it can be analyzed that there is no underlying trend that has been captured. Moreover, some spikes are evident at some point in time. Thus, further inspection is needed to determine if there is any issue with the model.

Figure 8. *PACF of the Residuals of the Model for OFW Remittances*



The Partial Autocorrelation Function (PACF) plot of the residuals indicates minimal to no serial correlation, suggesting that partial autocorrelation issues have been effectively addressed. Furthermore, the absence of any discernible structure in the residuals supports the model's adequacy in capturing the underlying time series dynamics.

Figure 9. *ACF of the Residuals of the Model for OFW Remittances, Jan 2014 - Dec 2019*



The Autocorrelation Function (ACF) plot of the residuals of the final model reveals no significant correlation in the residuals. The absence of significant spikes across all lags, suggests that any issues with autocorrelation have been effectively resolved.

Table 7. *Test for Stationarity of the Residuals of the Model using the Augmented Dickey-Fuller Test*

Test	Test Statistic	Lag order	p-value
Augmented Dickey-Fuller Test	-4.2154	4	0.01

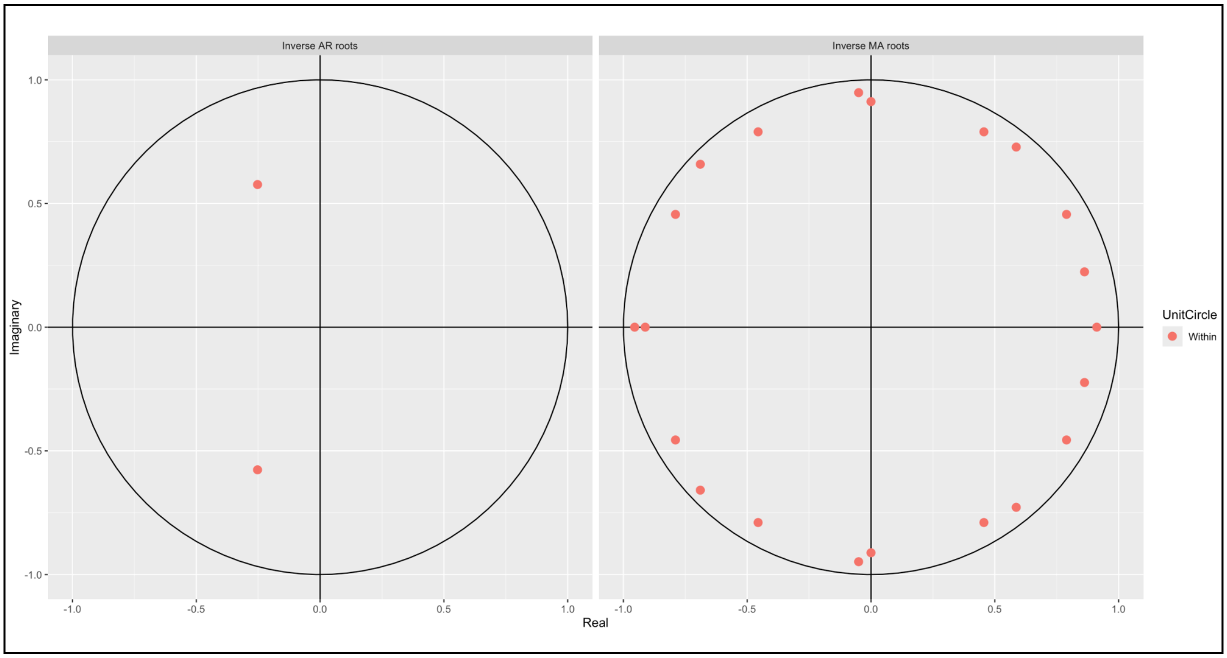
The stationarity of the residuals of the model was assessed using the Augmented Dickey-Fuller (ADF) test. The test yielded a p-value of 0.01, leading to the rejection of the null hypothesis. Notably, the null hypothesis of the ADF test states that the series is not stationary. Therefore, at a significance level of 0.05, there is sufficient evidence to conclude that the OFW remittances time series is stationary.

Table 8. *Test for Stationarity of the Residuals of the Model using the DF-GLS Test, Elliot, Rothenberg, and Stock (ERS)*

		Critical Values		
Test	Test Statistic	1%	5%	10%
DF-GLS Test Elliot, Rothenberg, and Stock (ERS)	-4.1978	-2.59	-1.94	-1.62

The stationarity of the residuals of the model was also evaluated using the Elliott, Rothenberg, and Stock (ERS) test. The test produced a test statistic value of -4.1978, which is less than the critical value of -1.94. Consequently, the null hypothesis is rejected. Therefore, at a significance level of 0.05, there is sufficient evidence to conclude that the series is stationary.

Figure 10. *Plot of the inverse AR and MA roots of the Model.*



The plot of the inverse Autoregressive and Moving Average roots of the model in Figure 10 shows that it is both invertible and stationary. According to R documentation, since the inverse of the roots are plotted, then a process would be stationary or invertible if the roots lie inside the unit circle, as opposed to outside the unit circle, which is what is commonly the point of reference.

Table 9. *Diagnostic Checking of the Residuals of the Model using the Ljung-Box Test, ARCH LM Test, and Jarque-Bera Test*

Test	Test Statistic	Degrees of freedom	p-value
Ljung-Box Test	18.686	24	0.7685
ARCH LM Test	12.686	12	0.3923
Jarque-Bera Test	2.6493	2	0.2659

The Ljung-Box test was conducted to assess the uncorrelatedness of the error terms. The test yielded a p-value of 0.7685, which is greater than the significance level of 0.05. Consequently, the null hypothesis is not rejected. The null hypothesis of the Ljung-Box test states that the error terms are uncorrelated. Therefore, at a significance level of 0.05, there is sufficient evidence to conclude that the error terms are uncorrelated.

The ARCH LM test was performed to evaluate the constancy of variance. The test produced a p-value of 0.3923, which is greater than the significance level of 0.05. As a result, the null hypothesis is not rejected. The null hypothesis of the ARCH LM test asserts that the variance is constant. Therefore, at a significance level of 0.05, there is sufficient evidence to conclude that the variance is constant.

The Jarque-Bera test was conducted to assess the normality of the time series, with the null hypothesis stating that the model is normally distributed. The test yielded a p-value of 0.2659, which is greater than the significance level of 0.05. Consequently, the null hypothesis is not rejected. Therefore, at a significance level of 0.05, there is sufficient evidence to conclude that the residuals are normally distributed.

Final Model:

The researchers decided on the final model based on the adequacy of the diagnostic checks on the residuals and the significance of all parameters.

$$Y_t = \Delta\Delta_{12} ln(OFW_t) \sim ARIMA\,(2, 1, 9) \times (0, 1, 1)_{12}$$

Estimated Model Equation:

$$\widehat{OFW}_t = (1 - B)(1 - B^{12})(1 + 0.5053B + 0.3962B^2)OFW_t =$$
$$(1 + 0.4646B + 0.4560B^8 - 0.5427B^9)(1 + 0.3305B^{12})a_t \;, where\; a_t \sim WN(0, \sigma^2)$$

Forecasts:

Table 11. *Out-of-sample Forecasts and 95% Prediction Intervals of OFW Remittances for Jan 2020 to Aug 2024 based on the Final Model*

Time Period	Actual Value	Forecasts	Lower Bound	Upper Bound
Jan 2020	2648.019	2582.184	2352.328	2834.501
Feb 2020	2357.902	2522.707	2298.071	2769.301
Mar 2020	2396.624	2562.99	2333.103	2815.529
Apr 2020	2045.913	2467.591	2225.387	2736.155
May 2020	2105.65	2738.597	2463.19	3044.796
Jun 2020	2465.333	2435.814	2186.411	2713.666

Jul 2020	2782.536	2694.04	2408.365	3013.601
Aug 2020	2482.665	2732.012	2434.815	3065.484
Sep 2020	2601.263	2453.07	2183.23	2756.262
Oct 2020	2747.464	2740.989	2408.047	3119.963
Nov-2020	2379.474	2501.561	2186.655	2861.818
Dec-2020	2890.413	3038.792	2653.366	3480.204
Jan 2021	2602.547	2685.678	2272.842	3173.502
Feb 2021	2475.782	2594.905	2187.887	3077.64
Mar 2021	2514.297	2695.25	2264.459	3207.995
Apr 2021	2305.151	2593.142	2157.132	3117.279
May 2021	2382.115	2840.573	2348.808	3435.297
Jun 2021	2637.942	2547.82	2096.298	3096.594
Jul 2021	2853.023	2795.488	2285.342	3419.513
Aug 2021	2608.916	2837.657	2306.505	3491.126
Sep 2021	2736.862	2565.23	2083.366	3158.545
Oct 2021	2812.044	2855.425	2293.894	3554.415
Nov 2021	2501.82	2604.025	2077.758	3263.589
Dec 2021	2987.115	3169.249	2518.999	3987.353
Jan 2022	2668.184	2799.142	2163.978	3620.737
Feb 2022	2508.601	2703.402	2077.937	3517.134
Mar 2022	2594.398	2809.266	2146.423	3676.802
Apr 2022	2395.493	2702.643	2041.111	3578.58
May 2022	2425.326	2960.078	2217.735	3950.905
Jun 2022	2754.674	2655.286	1975.319	3569.318
Jul 2022	2917.314	2913.421	2149.263	3949.271
Aug 2022	2721.458	2957.236	2164.887	4039.585
Sep 2022	2840.042	2673.382	1952.368	3660.669
Oct 2022	2910.946	2975.835	2146.747	4125.121
Nov 2022	2643.861	2713.802	1940.983	3794.325
Dec 2022	3159.134	3302.863	2348.745	4644.569
Jan 2023	2761.93	2917.162	2020.494	4211.758
Feb 2023	2569.345	2817.378	1936.564	4098.813
Mar 2023	2670.972	2927.705	1996.772	4292.656
Apr 2023	2484.793	2816.59	1896.303	4183.496

May 2023	2493.803	3084.877	2057.001	4626.378
Jun 2023	2812.471	2767.234	1829.071	4186.598
Jul 2023	2991.816	3036.253	1987.011	4639.546
Aug 2023	2795.825	3081.915	1998.256	4753.247
Sep 2023	2912.882	2786.094	1799.17	4314.388
Oct 2023	2997.925	3101.298	1976.062	4867.281
Nov 2023	2718.835	2828.218	1784.016	4483.602
Dec 2023	3280.333	3442.114	2155.301	5497.214
Jan 2024	2835.905	3040.151	1855.426	4981.346
Feb 2024	2645.557	2936.16	1775.597	4855.289
Mar 2024	2737.834	3051.139	1828.016	5092.651
Apr 2024	2562.307	2935.339	1734.125	4968.625
May 2024	2583.469	3214.937	1878.481	5502.223
Jun 2024	2881.751	2883.903	1667.952	4986.291
Jul 2024	3084.757	3164.263	1809.568	5533.124
Aug 2024	2885.405	3211.851	1817.323	5676.475

Table 11 shows the forecasted values of OFW remittances for January 2020 to December 2024 and their respective 95% prediction intervals. It also includes the actual values of OFW remittances for the same period for comparison. Notably, all forecasted values are within the lower and upper limits. However, April and May 2020 of the actual values fall outside the prediction intervals, likely due to the global lockdowns caused by the COVID- 19 pandemic.

Figure 11. *Plot of Actual Values, Forecasts, and 95% Prediction Intervals for OFW Remittances based on the Final Model*

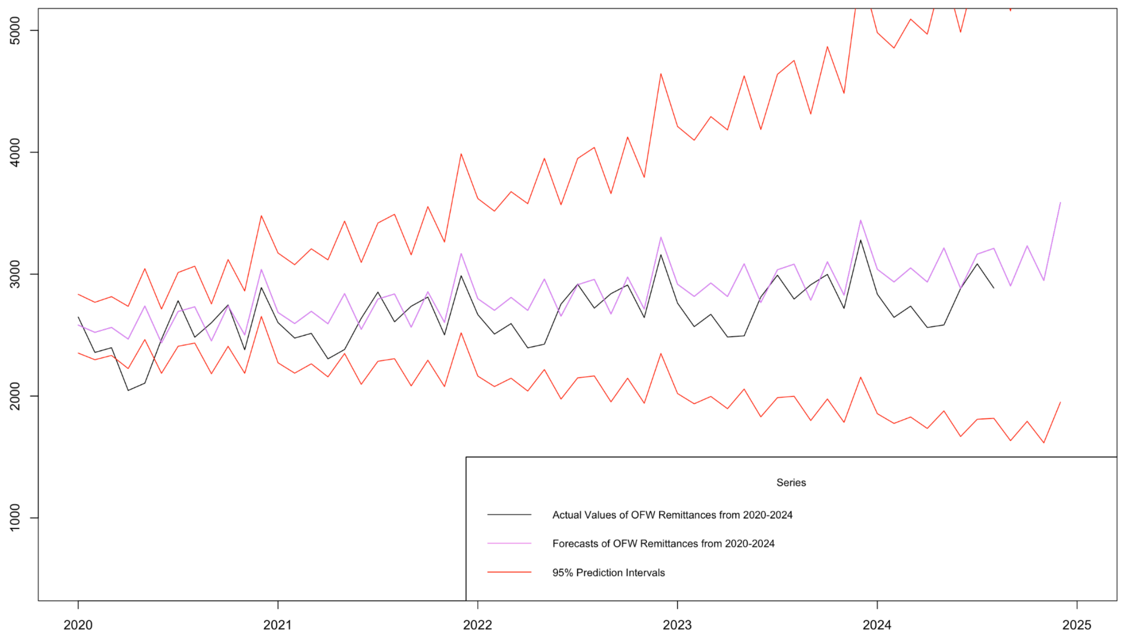


Figure 11 demonstrates the short-term accuracy of the model, with forecast values closely matching the actual remittances in the earlier periods. However, as the forecast horizon extends further into the future, the prediction intervals widen significantly. Furthermore, it also highlights periods of underprediction and overprediction by the model. Despite these deviations, the model aligns well with the observed trends and captures the seasonal dynamics of OFW remittances. Overall, the researchers consider the final model to be an appropriate fit for the OFW remittances.

V. Conclusions and Recommendations

Conclusions

The study aimed to analyze the behavior of OFW remittances and develop a forecasting model that captures its seasonal and cyclical patterns. The results of the analysis confirmed that the original OFW remittances series exhibited an upward trend and seasonality, making it non-stationary. To address this, a seasonal first difference was applied to the log-transformed series, resulting in a stationary time series suitable for model development.

Using the transformed series, two ARIMA models were considered: ARIMA (10,1,9) x (0,1,1) and ARIMA (2,1,9) x (0,1,1). While ARIMA (10,1,9) x (0,1,1) showed slightly better performance metrics, ARIMA (2,1,9) x (0,1,1) was selected due to its simplicity and reduced risk of overfitting. This model demonstrated strong predictive capabilities, as supported by low AIC, RMSE, and MAPE values. Residual diagnostic tests, including the Ljung-Box Test, ARCH Test, and Jarque-Bera Test, confirmed the adequacy of the model, indicating that the residuals were uncorrelated, homoscedastic, and normally distributed.

The out-of-sample forecasts for January 2020 to August 2024 closely aligned with the actual values, particularly in the earlier periods. All the actual values and forecasted values fell within the 95% prediction intervals, except for the actual values of April and May 2020, since these were affected by disruptions caused by the COVID-19 pandemic. This deviation highlights the impact of external factors on remittance trends.

Moreover, the ARIMA (2,1,9) x (0,1,1) model successfully captured the seasonal and cyclical patterns of OFW remittances, providing reliable short-term forecasts. The findings of the study are expected to aid policymakers and financial institutions in understanding remittance trends and preparing for potential disruptions. However, as prediction intervals widen in later years, continuous updates to the model and incorporation of real-time data are recommended to maintain accuracy in long-term forecasts.

Overall, the findings from the final general multiplicative seasonality model provide actionable insights into OFW remittance patterns. For instance, identifying peak remittance months can help stakeholders prepare for seasonal inflows while assessing long-term growth or decline trends can inform economic strategies.

Recommendations

Future researchers could explore alternative time series methods, such as structural models and panel data analysis, to examine OFW remittances. A structural model can help identify the underlying factors and dynamics that influence remittance flows, exploring other explanatory variables such as exchange rates, economic indicators, and global economic conditions may provide additional insights. In contrast, panel data analysis provides the advantage of capturing both time series and cross-sectional variations, enabling a comprehensive understanding of remittance patterns. This data structure integrates information from multiple time periods and entities (e.g., regions, countries, or households), offering valuable insights into the factors driving remittance flows.

Additionally, future researchers could examine how changes in remittance-related policies (e.g., remittance fees, foreign exchange regulations, or financial incentives) influence the volume and behavior of remittances. Understanding these policies is crucial, as it can significantly inform the design of interventions aimed at enhancing the economic benefits of remittances. Moreover, investigating external factors such as global economic crises, natural disasters, or political changes in host countries would offer valuable insights into the resilience of remittance flows. This could provide a foundation for exploring adaptive strategies for OFWs and their families.

These recommendations can assist future researchers in refining their data analysis of OFW remittances, which in turn can help policymakers develop adaptive strategies for OFWs, ultimately contributing to the enhancement of the economy.

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VII. Appendices

R codes used:

```
library(zoo)
library(forecast) #Needed for forecasting
library(tseries) #Needed for Jarque-Bera Test, ADF Test, Acf
library(FinTS) #For the ARCH LM Test
library(urca)
OFWremittancedata <- read.csv('/Users/jbvictorio/Documents/145 dataset
copy.csv',h=T)$remmittance
OFWremittancedata
OFWremittance <- ts(OFWremittancedata,start=c(2000,1),end=c(2024,8),frequency=12)
#creating a time series
OFWremittance
OFWremittance1 <-ts(OFWremittancedata,start=c(2000,1),end=c(2013,12),frequency=12)
OFWremittance2 <-
ts(OFWremittancedata[-c(1:length(OFWremittance1))],start=c(2014,1),end=c(2019,12),frequenc
y=12)

#PRELIMINARY STAGE
plot(OFWremittance2,col='blue',main='',ylab='', xlab='')
adf.test(OFWremittance2) #Stationary according to the ADF Test
summary(ur.ers(OFWremittance2)) #Not Stationary according to the DF-GLS ERS Test
Acf(as.numeric(OFWremittance2),main='ACF of OFWremittance series') #Does not decay to
zero fast, implying non-stationarity
Pacf(as.numeric(OFWremittance2),main='PACF of OFWremittance series')

#Transformations for Stationarity
yt<-log(OFWremittance2)
#Seasonal Differencig + 1st Differencing of Logarithm Transformed Series
dlog.OFWremittance <- ts(diff(diff(yt,12)),start=c(2015,2),end=c(2019,12),frequency=12)
plot(dlog.OFWremittance^2,col='blue',main='',ylab='Seasonal First Diff of Log OFW Remittance',
xlab='')
#Plot Shows no more evidece of trend nor seasonality
adf.test(dlog.OFWremittance)
summary(ur.ers(dlog.OFWremittance))
#Series is now stationary according to the ADF and ERS Test

#IDENTIFICATION AND ESTIMATION
#AR Terms (1,2,10)
Pacf(as.numeric(dlog.OFWremittance),main='')
#MA Terms(1,8,9,10,11) include SMA Term
Acf(as.numeric(dlog.OFWremittance),main='')

xx <-
arima(yt,order=c(10,1,9),seasonal=list(order=c(0,1,1)),fixed=c(NA,NA,0,0,0,0,0,0,0,NA,NA,0,0,0
,0,0,0,NA,NA,NA))
#AR 1 is not significant, significant spike in PACF
summary(xx)

xx <-
arima(yt,order=c(2,1,9),seasonal=list(order=c(0,1,1)),fixed=c(NA,NA,NA,0,0,0,0,0,0,NA,NA,NA))
summary(xx)
#All coefficients are significant
```

```
#RESIDUAL DIAGNOSTICS
plot(xx$residuals)
#No significant lags for both ACF and PACF
Acf(xx$residuals,main='')
Pacf(xx$residuals,main='')
#Process is both stationary and invertible
autoplot(xx)
#Residuals are Stationary
adf.test(xx$residuals)
summary(ur.ers(xx$residuals))
#Diagnostic Checking
#Do not Reject
Box.test(xx$residuals, lag = 24, type = "Ljung-Box", fitdf = 0) #Ljung-Box Test
#Do not Reject
ArchTest (xx$residuals)  #Testing constancy of variance
#Do not Reject
jarque.bera.test(xx$residuals) #Testing normality

#POINT FORECASTS
#Forecasts for the series
expforecast <- exp(forecast(xx,60)$mean)
cbind(expforecast,exp(forecast(xx,60)$lower[,2]),exp(forecast(xx,60)$upper[,2]))
#Plotting Forecasts against actual values
OFWremittance3 <-
ts(OFWremittancedata[-c(1:(length(OFWremittance1)+length(OFWremittance2)))],start=c(2020,
1),end=c(2024,8),frequency=12)
plot(OFWremittance3,col='black',main='',ylab='', xlab="",xlim=c(2020,2025),ylim=c(500,5000))
lines(expforecast, col='violet')
lines(exp(forecast(xx,60)$lower[,2]),col='red') #lower 95%
lines(exp(forecast(xx,60)$upper[,2]),col='red') #upper 95%
legend('bottomright',title='Series',pt.cex=2,cex=0.8, c("Actual Values of OFW Remittances from
2020-2024", "Forecasts of OFW Remittances from 2020-2024"
                                        ,"95% Prediction Intervals"), col=c("black", "violet","red"),
lty=c(1,1),y.intersp=1 )
```