

Research Project Report V2.pdf

by Ooi Hian Gee

Submission date: 20-Jan-2025 10:52AM (UTC-0800)

Submission ID: 2566900648

File name: Research_Project_Report_V2.pdf (2.83M)

Word count: 24315

Character count: 138757

**ECONOMETRIC MODELLING OF USD/MYR
EXCHANGE RATE DYNAMICS AND KEY
MACROECONOMIC FACTORS**

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2024

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Field of Study: Economics

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ABSTRACT

Stability in a country's currency exchange rates is extremely crucial as fluctuations in the exchange rates significantly impact the international trade, investment, debt and a country's overall economic health. The exchanges rates are always linked to a variety of internal and external factors, among them are what we call macroeconomic factors which include money supply, inflation rates, Industrial Production Index (IPI) and others. The motivation behind this research lies in the recognition that a thorough understanding of the relationships between macroeconomic variables and currency exchange rates can be beneficial for informed policymaking and budgeting. In view of Malaysia as a developing country where its economy is evolving by leap and bounds at the present, a comprehensive analysis becomes necessary. Six models, namely ARDL, SVM, Random Forest, XGBoost, LightGBM and LSTM were implemented to build predictive models for the currency exchange rate of USD/MYR by utilising the latest macroeconomic data up to July 2024. Performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and R-squared were used to evaluate the effectiveness of the models in out-of-time generalisation. LightGBM emerged as the best model achieving lowest RMSE of 0.0566 and highest R-squared value of 0.91759. For practical application, the system is deployed using Streamlit, allowing users to input macroeconomic indicators and forecast exchange rate movement. Future efforts will focus on expanding dataset diversity, improving model interpretability and enhancing model generalisations for more robust predictions.

Keywords: monetary economics; bilateral analysis; predictive model; machine learning

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ACKNOWLEDGEMENTS

I would like to take this chance to express my sincere gratitude to all those who have made this research possible.

First and foremost, I wish to thank my supervisor, Dr. Riyaz Ahamed Ariyaluran
28 Habeeb Mohamed for his invaluable guidance, support and encouragement throughout the course of this research. His insights and constructive feedback have been crucial in determining the direction and ensuring the quality of this research.

Special thanks to Dr. Maizatul Akmar Ismail who acts as my panel for her kind advice and assistance. Her knowledge and expertise have greatly enriched my exposure on how to write a comprehensive research paper.

129 I would like to also extend my appreciation to my friends and colleagues who have shared their thoughts and opinions to make the research more meaningful and impactful. Their support, whether in discussions, collaborations or any other forms, has been greatly
79 appreciated.

I am particularly thankful to my family for their dedicated love, patience and understanding. Their emotional support has been a source of strength for me during challenging times.

9 Finally, I would like to acknowledge Faculty Of Computer Science & Information Technology, University of Malaya for their approval and support which have enabled me to pursue this research.

To all of you, I extend my heartfelt thanks.

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LIST OF SYMBOLS AND ABBREVIATIONS

ARDL : Auto Regressive Distributed Lag 222

BNM : Bank Negara Malaysia

CPI : Consumer Price Index

EDA : Exploratory Data Analysis

FFER : Federal Funds Effective Rate

IPI : Industrial Production Index

LGBM : Light Gradient-Boosting Machine 18

LSTM : Long Short-Term Memory

MAE : Mean Absolute Error

MAPE	:	True Positive
ML	:	Machine Learning
OOT	:	Out-of-Time
OPR	:	Overnight Policy Rate
PCA	:	Principle Component Analysis
RF	:	Random Forest
RMSE	:	True Negative
SHAP	:	SHapley Additive exPlanations
STD	:	Standard Deviation
SVM	:	Support Vector Machine
WHO	:	World Health Organisation
XGB	:	eXtreme Gradient Boosting

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Appendix A: ACF and PACF Plots

CHAPTER 1: INTRODUCTION

This chapter provides a brief overview of the research. The background and problem statement of the study are discussed in Section 1.1 and Section 1.2 respectively, followed by the research questions in Section 1.3 and research objectives in Section 1.4. Section 1.5 presents the scope of the study while Section 1.6 is about the significance of the study. Lastly, the outline of the whole report is laid out in Section 1.7.

1.1 Introduction

As pinpointed by (Biswas et al., 2023), ever since the global economy is highly reliant on international trade, buying goods and services from a country requires an individual or an organisation to purchase them in the accepted local currency of that country. From that moment, the currency exchange rate plays its part and parcel in the transactions across national borders. The currency exchange rate reflects the price of one currency against the other and it facilitates the international trade of goods and services and the capital transfer. It indicates the external competitiveness of a country's economy (Dahal & Raju, 2022).

The currency exchange rate, as a key indicator of a nation's economic well-being, influences various aspects of its economy. The fluctuations in exchange rates potentially induce either symmetric or asymmetric effects on the trade flows. A simple proportionate link between trade volume and exchange rate volatility is implied by symmetric effects. On the other side, since various traders can have different expectations, asymmetric effects involve varying responses to changes in exchange rates. It is worth noting that these effects may differ in different industries and change over time, as discussed by (Lal et al., 2023). Within an open economy, exchange rates and the Consumer Price Index (CPI) can be intercorrelated. When the domestic currency depreciates, the import costs will certainly surge. This will consequently lead to increased CPI within the home country.

Simultaneously, as the home currency weakens against foreign counterparts, it will make local products comparatively more affordable. The expenditure switching effect comes into play where it will lead to an increase in the relative demand for domestic products and home country CPI, as highlighted by (Kim et al., 2021).

Regardless of whether the exchange rate strengthens or weakens, there are always winners and losers within the domestic economy. A depreciation of the currency adversely impacts consumers of imported goods and services. It potentially leads to an overall increase in the cost of living. However, a weakened currency may boost earnings for exporters. Conversely, an appreciation benefits those involved in importing goods, services and international travel yet it can be detrimental to exporters and the domestic tourism industry. It is crucial for these exchange rate adjustments to occur in an orderly manner to facilitate continued economic activity. The primary focus of a country's exchange rate regime should not be on favouring specific sectors over others but rather on ensuring long term benefits for the overall economy, as emphasised by (BNM, 2022). (Ribeiro et al., 2020) argued that exchange rate undervaluation or depreciation can enhance the growth of nations by stimulating technological progress and knowledge spillovers. They suggest that, to promote economic growth, it is essential to avoid overvaluing the currency since this can impede the growth.

Examining the sensitivity of exchange rate volatility is valuable to identify direction of movements in exchange rates and the economic consequences. A concise understanding along with effective modelling of exchange rate movements is essential for policymakers to formulate appropriate monetary and fiscal policies tailored to a specific country's needs. It helps to guide informed policy decisions and lead the country on the right track. Gauging the sensitivity the currency exchange rates reacting to changes

assists to predict their future direction and understand the potential impacts brought to the country's economy (Thevakumar & Jayathilaka, 2022).

Article presented by (Boyoukliy et al., 2022) depicted that several main macro factors, commonly called key macroeconomic indicators such as inflation, unemployment, gross domestic product, main interest rate, foreign exchange rate, etc. determine the strength of a certain economy. These important economic indicators are often connected to each other, when one variable changes, the others change as well. Significant changes can lead to imbalances that are hard to predict and fix which in turns produce both positive and negative outcomes. Currency strength is directly dependent on the changes in the minimum of the above key macroeconomic indicators.

(Pasionek, 2023) reflected that in the globalised world, the exchange rates are mainly impacted by economic factors. In foreign exchange (FOREX) transactions, the exchange rate of the given currency pair is expressed as one figure, indicating a relation of the quoted currency to the notional amount. The demand and supply for the given currency pair depends on many factors. The primary economic factors that influence the short-term exchange rate volatility are macroeconomic data from the American economy. Thus, he implemented the linear regression model to assess the impact of selected macroeconomic data from the American economy on the performance of USD/PLN currency pair.

As also highlighted in the paper presented by (Munir & Iftikhar, 2023), maintaining an equilibrium level of the real exchange rate is critical in which the underlying factors shall be assessed. This study used a general-to-specific method to investigate the macroeconomic drivers of the real exchange rate in Pakistan. The study adopted an ARDL technique to analyse both long-run and short-run correlations using quarterly data from Quarter 1 of 1980 to Quarter 4 of 2020. Money supply, productivity, trade openness, worker remittances, government consumption spending, terms of trade and foreign direct

²¹⁵
investment (FDI) were all possible contributions to the real effective exchange rate in the model.

The global economic landscape is always evolving and filled with constant fluctuations and uncertainties. Malaysia with its vibrant economy is not an exception. Shifts in global trade patterns, changes in commodity prices, monetary policy adjustments and geopolitical events can all have profound effects on the values of the Malaysian Ringgit. A systematic exploration of these relationships ¹⁹¹ will provide invaluable insights into the factors contributing to the MYR exchange rate movements.

¹⁰³
This research aims to bridge existing knowledge gaps by looking into the relationship between macroeconomic variables and the USD/MYR exchange rates. By examining data up to the year 2024, a contemporary and insightful work is to be performed ²²⁰ as a guide for the policymakers, businesses and investors in making informed decisions in an ever-evolving economic landscape. Through the empirical analysis, this study seeks to contribute not only to the academic discourse but also to the practical understanding of the core factors shaping Malaysia's currency exchange rate dynamics.

1.2 Problem Statements

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The exchange rate plays a crucial role in a country's international trade and economic position. ¹⁴² Fluctuations in exchange rates can have significant consequences for policymakers, investors, businesses and consumers in making their decisions. Even though many of the researchers came up with different approaches such as VAR model (Antwi et al., 2020), ARDL model (Munir & Iftikhar, 2023; Thevakumar & Jayathilaka, 2022) and deep learning models (Biswas et al., 2023) to examine the effect of ¹²³ macroeconomic factors on the currency exchange rates., they were focusing the studies on their own countries. Several studies had been conducted in Malaysia (Mohamed et al., 2021; Shukri et al., 2021) to investigate the impact of economic factors on Malaysia's ³⁵

exchange rate volatility. However, these studies had utilised annual data which may not effectively capture the fast-paced fluctuations in currency exchange rates.

Many of the recent research undertook a variety of novel methods and models to draw relationships between macroeconomic features and the currency pairs. Nevertheless, the data they used were mostly not up to date. For instance, (Biswas et al., 2023) used data until 2019 and (Ohaegbulam & Iheaka, 2024) used data until 2021 only in their studies. This limits the relevance of their findings in the context of current economic conditions. Aside from that, most studies focus solely on the macroeconomic factors of only one country.¹ Since currency pairs represent the relative values between two countries' currencies, we may overlook the potential mutual influence from the other country on the strength of currency pairs.

In conclusion, the existing literature furnishes substantial relationship established between the macroeconomic variables and the overall currency exchange rate of a country.

Notably, this study will fill the research gap by focusing the context mainly to Malaysia instead of other countries. In addition, this study aims to also utilise the most contemporary dataset from a set of both Malaysia and US macroeconomic factors to discern the determinants of both long-run and short-run dynamics of the Malaysia currency exchange rates over the time.⁶¹

1.3 Research Questions

The research questions of this study are stated as follows:

- i. How do macroeconomic factors in the United States and Malaysia exhibit influence on their paired exchange rates?
- ii. Can we map macroeconomic factors and currency exchange rates of US Dollars against Malaysian Ringgits to forecast future rates?

- iii. How do the predictive performances of different econometric models differ in forecasting the USD/MYR exchange rate?

1.4 Research Objectives

This study wishes to achieve three main objectives which are:

- i. To investigate the influence that each identified macroeconomic factor has on the paired exchange rates between United States and Malaysia.
- ii. To develop an econometric model that can predict the USD/MYR exchange rates using macroeconomic indicators.
- 13 iii. To evaluate the performance of different econometric models in forecasting the USD/MYR exchange rates.

1.5 Research Scope

The principal of this research will be mainly focusing in building different models to trace the impacts of key macroeconomic factors such as crude oil prices, Industrial Production Index, money supplies, etc. on the currency exchange rates in Malaysia. By utilising monthly data spanning from January 2015 to July 2024, this study seeks to provide insights which can reflect the current economic conditions and align with the 205 contemporary financial landscape. The data will be gathered from a range of reliable and reputable sources, namely Yahoo Finance, Department of Statistics Malaysia (DOSM), Central Bank of Malaysia and Federal Reserve Economic Data (FRED).

1.6 Research Significance

The outcome of the research is anticipated to provide more in-depth economical insights into the impacts of various macroeconomic factors on the economic growth in Malaysia which can be crucial for Malaysia to attain sustainable and steady long-term economic growth. The findings may contribute to a more informed and sound decision-making by the policy makers and government in formulating new economic policies,

developing stimulus packages as well as allocating the budget for different industrial sectors. The results may also serve as a reference for the investors to foresee the future growth in Malaysia's economy and perform decisions on whether to invest in Malaysia.

1.7 Report Outline

Chapter 1 introduces the overall project, which focuses on gauging the relationship between the macroeconomic variables and USD/MYR currency exchange rates. This chapter outlines the problem statements, research objectives, research questions, scope of the research and significance of the research.¹⁹

Chapter 2 provides a literature review related to this study. It includes the critical review of the related works, discussions on the performance of different algorithms implemented by the previous researchers along with their benefits and limitations.

Chapter 3 details the research's methodology. This chapter describes the proposed design and interface, including a research flowchart, model specifications as well as explanation of each step taken along with the software and tools used.

Chapter 4 presents the results and discussion based on the methodology outlined in Chapter 3. Key quantitative data is summarised with experimental outcomes, statistical analyses and evaluation metrics performance of every model used. The results are displayed in tables and graphs with discussions interpreting them.¹⁹⁷

Lastly, Chapter 5 synthesises the entire research project by providing a comprehensive summary of the key findings, implications, contributions and future direction of the study.²²⁵¹⁴⁹

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter mainly explains about how each macroeconomic factor influence currency exchange rates theoretically and the literature study of the previous research related to this study.

2.2 History of Foreign Currency Exchange Rate Systems

Prior to the establishment of formal systems, foreign currency exchange rates were determined by the relative weight and purity of the metals used in coinage. The adoption ⁵⁰ ₁₂₈ of the Gold Standard in the late 19th and early 20th centuries marked a significant shift towards a more structured system. Under the Gold Standard, each currency's value was directly linked to a fixed quantity of gold. At that time, we can observe explicitly the stability and predictability in foreign currency exchange rates. This system prevailed until the outbreak of World War I which had disrupted international trade and led countries to abandon the gold (Dahal & Raju, 2022). The interwar period between World War I and ¹⁴⁸ World War II caused instability and experimentation in exchange rate arrangements. Several countries including Iceland had resorted to currency controls and devaluations to address the economic challenges (Edwards & Cabezas, 2021).

In 1944, the Bretton Woods Agreement introduced a new era of fixed exchange rates, ⁵⁴ with the currencies pegged to the US dollar, which in turn was pegged to gold. This system was aimed to foster the international trade and economic stability after World War II. However, primarily due to inflationary pressures in the United States and the growing divergence in economic performance among participating countries, the Bretton Woods system ultimately collapsed in 1971 (Subacchi & Vines, 2023).

Afterwards, the Bretton Woods system gradually made transition to a floating exchange rate regime. Under the floating exchange rate system, currency values were determined by market forces of supply and demand which offers greater flexibility depending on the market conditions (Shukri et al., 2021). In the meantime, it also introduced volatility in exchange rates as currencies were now subject to market speculation, geopolitical events and economic policies (Elgahry, 2022). The great volatility became a key driver of the growth and importance of the Foreign Exchange (FOREX) market, one of the world's largest and dynamically evolving financial markets.

FOREX market basically allows virtually anyone to participate as an investor without going through any entry or exit barriers. It is known for its exceptional liquidity, dynamism and rapid turnover (Pasionek, 2023). According to BIS Triennial Central Bank Survey from the Bank for International Settlements, trading in over-the-counter FOREX market had reached average daily transaction volume of \$7.5 trillion in April 2022 (a 14% rise from \$6.6 trillion in 2019). Being the largest and most liquid financial market globally, the pricing of currencies is also related significantly with the relative value of domestic and foreign goods. It presents both opportunities and challenges for investors and businesses engaged in international trade (Flores-Sosa et al., 2022).

Looking back to Malaysia, the country had adjusted its fixed exchange-rate system to a regulated floating-exchange rate regime at the late July 2005 to build an open capital market and autonomy of monetary policy. The system of regulated exchange rates is a regime of international exchange rates where the exchange rate is permitted to travel freely but only on a regular basis, according to the market powers. This is believed to help the country respond to currency valuation adjustments where rates and demand can be changed if the exchange rate does not adjust (Ng & Geetha, 2020).

2.3 Development of Malaysia's Economy

Starting from the pre-colonial era, Malaysia's economic development has been significantly influenced by the globalisation. Initially, the economy was heavily reliant on primary commodities such as tin and rubber (Lee, 2021). Following independence in 1957, Malaysia's economy was primarily led by agricultural industry. However, by 1980s,

the focus shifted towards industrialisation, particularly in gas and petroleum production.

²⁴⁵ This transition marked a significant change in economic policies and contributed to the modernisation of the trade economy (Ibrahim, 2022). Over time, Malaysia harnessed trade, foreign capital and labour to transit into an economy driven by manufactured exports. The establishment of industrial hubs and export processing zones (EPZs) during this period which aimed to attract investment and create jobs had successfully reduced unemployment and poverty rates (Rasiah & Krishnan, 2020). As a result, according to

¹³⁰ statistics from World Bank national accounts data and OECD National Accounts data files, the manufacturing sector as a share of Malaysia's GDP had risen from 10% in 1960 to 22% in 1980 which can be clearly seen in Figure 2.1. The GDP per capita of Malaysia had also increased more than threefold from \$1,266.3 thousands in 1960 to \$4,184.8 thousands in 1990 as depicted in Figure 2.2.

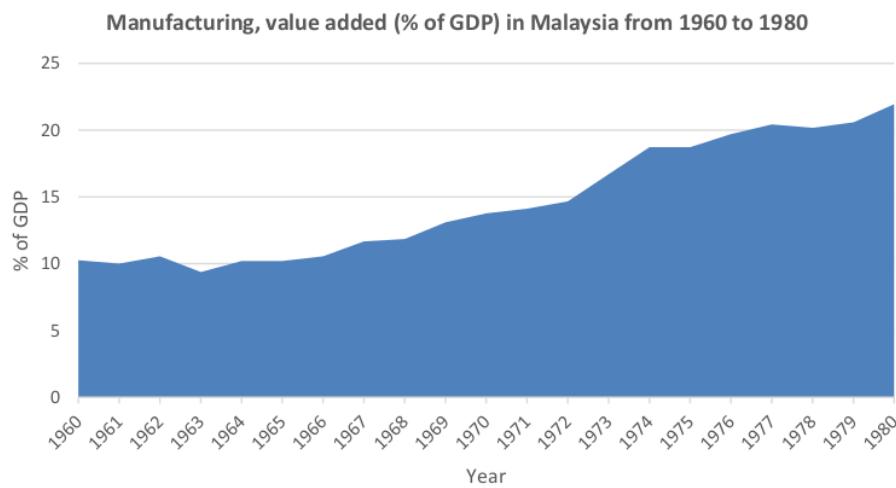


Figure 1.1 Manufacturing, value added (% of GDP) in Malaysia from 1960 to 1980

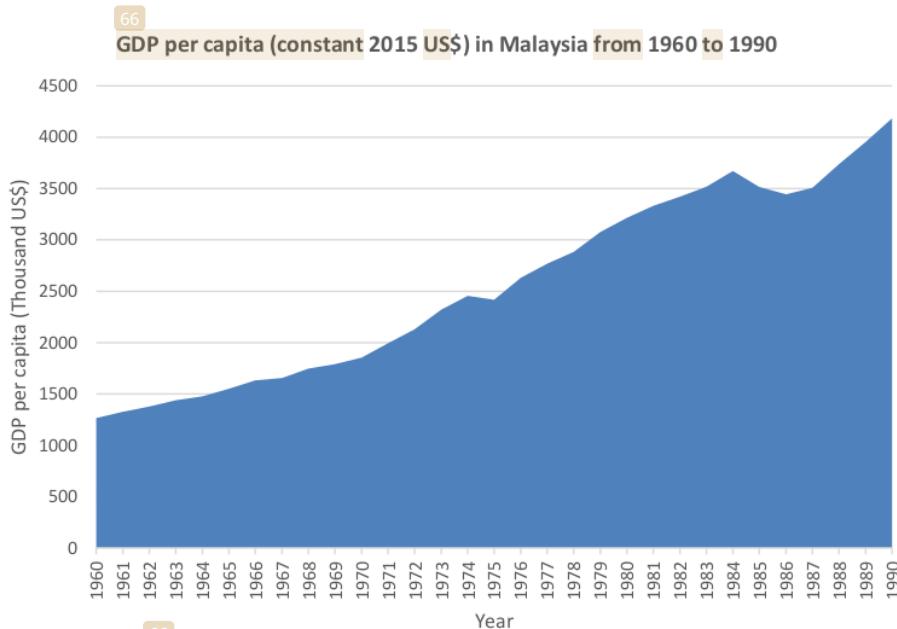


Figure 2.2 GDP per capita (constant 2015 US\$) in Malaysia from 1960 to 1990

In the early 1990s, Malaysia experienced spectacularly high growth rates. In the Sixth Malaysia Plan, the government led by Malaysia's fourth Prime Minister, Tun Dr Mahathir had introduced the New Development Plan (NDP) for ten years and launched Vision 2020 to aspire the nation to achieve a self-sufficient industrialised nation by the year of 2020. Vision 2020 covers all aspects of life including economic prosperity, social well-being, educational world-class, political stability and psychological balance (Edrak et al., 2022). During that great time, Malaysia had the potential to position itself to be an 'Asian Tiger.' However, the Asian Financial Crisis of 1997 - 1998 severely impacted the economy and it triggered the need for structural reforms (Abidin, 2020).

Stepping into the 21st century, Malaysia aimed to transform to a knowledge-based economy which focuses more on the innovation and human capital development (Kamyshnikova, 2023). Again, the global financial crisis of 2008 further tested the economy. At this time, it prompted the government to launch the Government Transformation Programme (GTP) and subsequently the Economic Transformation

Programme (ETP), both aimed to develop a more sustainable future and improve Malaysians' quality of life. There are six pillars or National Key Result Areas (NKRAs) in the GTP which are Reducing Crime, Fighting Corruption, Improving Student Outcomes, Raising Living Standards of Low-Income Households, Improving Rural Basic Infrastructure and Improving Urban Public Transport (PMO, 2011).

In recent years, advancements in information and communication technology (ICT) have led to the era of the Industrial Revolution 4.0 and the digital economy. Digital transformation has revolutionised the business processes, economic activities and societal interactions. People are now meeting their daily needs via smartphones where purchases of goods and services can just simply be done at the fingertips within seconds. The Covid-19 pandemic further accelerated the digital economy as face-to-face interactions were discouraged. In Malaysia, digitalisation and technological investment have now been prioritised as the key drivers of economic growth. (Puspaningtyas, 2022).

Malaysia's economic development has been a complex journey marked by significant transitions. It continues to face challenges such as economic diversification, technological advancements and alleviating the impacts of globalisation.

2.4 Macroeconomic Factors

Macroeconomic factors are believed to have large impacts on economy which might comprise of factors related to economic, social and political activities. In the previous literature, researchers have identified several fundamental and technical factors that cause exchange rate volatility. Each of them will be discussed in the next sub-sections.

2.4.1 Crude Oil Prices

Crude oil is making up about one-third of global energy use and considered the world's core energy source. Aside from fuel, its byproducts such as gasoline, plastics and even some medicines are widely used in our everyday lives and in modern economies (Shahnazi et al., 2023). In commodity-exporting economies, the price of crude oil is a significant factor influencing exchange rates. This was proven true for countries like Canada where crude oil constitutes a considerable share of exports. Canada's crude oil exports have grown substantially in which it had reached 14.1% of total exports in 2019²⁰ and made Canada the largest supplier of crude oil to the U.S. (Pirayesh Neghab et al., 2023). As crude oil prices increase, the value of the Canadian dollars tends to rise as well since more buyers seek to purchase Canadian oil. Conversely, when crude oil prices decline, the CAD tends to weaken (Davood Pirayesh et al., 2024).

As crude oil is a major export and import commodity for many countries, changes in its price can significantly affect their trade balances. A rise in crude oil prices can lead to a trade surplus for oil-exporting countries and further strengthen their currencies. A decline in crude oil prices can weaken their currencies due to a decrease in export revenue and a potential trade deficit. On the flip side, increase in crude oil prices can negatively impact oil-importing countries by increasing their import costs (Moshiri & Kheirandish, 2024). Indirectly, this can contribute to inflation as the increased cost of oil affects transportation costs and the prices of goods and services. Eventually, it can lead to a depreciation of their currencies as they need more of their domestic currency to purchase the same amount of oil.

For oil-exporting countries like Saudi Arabia, Russia and Iraq, higher oil prices would induce the economic growth and the vice versa for oil-importing countries like Bangladesh (Nandi et al., 2024). Oil price shocks can cause long-lasting volatility in

exchange rates with negative shocks resulting in greater volatility than positive ones (Nandi et al., 2024).

2.4.2 Stock Index

A stock index measures the performance of an entire stock market or a group of related stocks, bonds or other securities which is often associated with specific stock exchanges or industries. It serves as an indicator of market fluctuations and trends to guide investors in decision-making (Lv et al., 2022). The relationship between stock index and currency exchange rates is complex and varies across different contexts. Stock indices impact national economies by affecting the value of securities and financial instruments which in turn influence currency rates (Horbanevych & Ivanyuta, 2021).

Studies indicate that fluctuations in exchange rates and stock market performance can influence each other, particularly in emerging economies. According to (Suri et al., 2024), a stable positive relationship exists between stock markets and exchange rates in the long run as evidenced in G20 nations. The study by (Rao et al., 2024) which examined the correlation between the SENSEX 30 returns and INR/USD exchange rate movements from 2014 to 2024 did also achieve a strong positive correlation. A 1% increase in the exchange rate corresponded to a 0.90% increase in SENSEX 30 returns. It was also discovered by (Tabash et al., 2022) that stock market indexes significantly transmit economic shocks to currency valuation during both pre and post-financial recession periods.

2.4.3 Exports and Imports

Exports significantly influence currency exchange rates through various mechanisms, primarily by affecting the demand for a country's currency. Theoretically, when exports increase, foreign buyers need to purchase the exporting country's currency to pay for goods which can lead to appreciation of the currency of the exporting country. Conversely, a

decline in exports can result in depreciation. The study by (A Rebello, 2018) had found a positive correlation between exports and each of the exchange rates. Regression analysis showed that a 1% increase in Indian exports led to a 0.016% increase in the euro, a 0.0164% increase in the US dollar, a 0.0155% increase in the British pound and a 0.0001% increase in the Japanese yen.

A country will conduct the import activities whenever they want to obtain certain goods and services that cannot be produced locally or more advanced technologies. The imports can accelerate the national development, yet it needs more foreign currency to pay for these goods when a country imports more. As a result, it can lead to a depreciation of its own currency. This is because the demand for foreign currency increases while the demand for the domestic currency decreases (Nurjanah & Mustika, 2021). Countries that rely heavily on imports like Nigeria were experiencing increased demand for foreign currency to settle trade obligations. This demand often exceeds the available supply and led to fluctuations in exchange rates (Dada et al., 2023).

In a nutshell, the balance of payments which includes imports and exports is a crucial factor in determining exchange rates.

2.4.4 Industrial Production Index (IPI)

The Industrial Production Index (IPI) is an economic indicator that measures the real output of various industries within a country's economy. It is often used to gauge the level of industrial activity and production performance over time. The index is expressed as a percentage relative to a base year with the base year's production level set to 100. The Industrial Production Index (IPI) can influence currency exchange rates through its impact on economic growth, inflation and trade balances.

An increase in the IPI often signals economic growth, which can lead to higher inflation. For instance, in Turkey, a 1% increase in the IPI leads to a 1.04% increase in the Wholesale Price Index (WPI). It indirectly indicates that industrial growth can drive inflation which in turn affects exchange rates (Sanli, 2022). Similarly, in Malaysia, changes in the real effective exchange rate are linked to changes in economic growth. It suggests that industrial production influences currency value through economic performance (Cheng et al., 2024).

26 2.4.5 Consumer Price Index (CPI)

The Consumer Price Index measures the overall change in consumer prices based on a representative basket of goods and services over time. The CPI is a widely used measure of inflation closely followed by policymakers, financial markets, businesses and consumers.

One of the key concepts linking CPI to exchange rates is the theory of purchasing power parity (PPP). PPP suggests that in the long run, exchange rates should adjust to equalise the price of a basket of goods and services in different countries (Ali et al., 2022). If a country experiences a higher inflation rate as reflected in a rising CPI compared to another country, its currency is expected to depreciate against the currency of the country with lower inflation. This depreciation occurs because the higher inflation erodes the purchasing power of the currency in the high-inflation country (Davood Pirayesh et al., 2024; Hasan & Islam, 2023).

Changes in CPI can influence investor confidence and consequently, currency exchange rates. Investors may perceive a rising CPI (high inflation) environment as risky and may move their investments out of the country. Consequently, this is going to put a downward pressure on the currency (Bawuah et al., 2023). As discovered in the study by Anuar & Abu Bakar, 2022), they discovered a causality relationship between exchange

rate and CPI for Vietnam, that is, the exchange rate is affected by CPI. While higher inflation can lead to currency depreciation, exchange rate changes can also significantly impact CPI, especially in economies with high import ratios. Implementing inflation targeting is crucial to reduce inflation inertia and make monetary policy more effective in stabilising CPI as well as exchange rates (Kolpashnikov, 2024).

73 2.4.6 Money Supply

The money supply refers to the total amount of money available in an economy at a specific time including various forms of currency and liquid assets. It is a critical indicator of economic health and impacts the overall economic growth of a country. The money supply can be categorised into different measures, primarily M1 and M2. M1 includes currency held by the public and demand deposits which represent the most liquid forms of money (Bujung et al., 2024). M2 provides a broader view of money supply by including M1 and quasi-money that are less liquid such as savings accounts, time deposits and certain securities (Alif & Kurniawan, 2024).

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The money supply significantly influences currency exchange rates both short-term and long-term. In the short run, especially under quantitative easing policies, an increase in the monetary base can lead to currency depreciation. This effect is more pronounced than that of the money stock which has a limited role in short-term exchange rate dynamics (Funashima, 2020). In some regions, such as Indonesia, the short-term effects of money supply changes can lead to exchange rate overshooting, where a 1% change in money supply results in more than a 1% change in exchange rates (Syamad & Handoyo, 2023). This phenomenon was also observed in Malaysia and Thailand within the ASEAN-5 countries (Maghfiroh & Jayadi, 2024).

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Over the long term, an increase in the money supply often results in currency depreciation. This is because a larger money supply can lead to higher inflation and

reduction in the currency's purchasing power as well as its value relative to other currencies (Sangadji et al., 2024). However, the money supply can positively impact economic growth which may also stabilise or strengthen the currency in the long run (Daoud & Al-Ezzi, 2023).

Overall, the money supply is a critical determinant of exchange rate fluctuations, with its effects varying between short and long-term scenarios. In the short term, changes in the monetary base can lead to rapid currency depreciation. Whereas, in the long term, the monetary base remains a stable predictor of exchange rate trends. Inflation and interest rates further modulate these effects which highlights the complex interplay between monetary policy and exchange rate dynamics.

2.4.8 U.S. Federal Funds Effective Rate

The Federal Funds Effective Rate (FFER) is a crucial interest rate that reflects the cost of banks borrowing funds from each other overnight and it is a significant indicator of the financial system's health and stability in the United States (H et al., 2023). Fed rate hikes can reduce inflation and pressure domestic economies. Nevertheless, it does also pressure the foreign countries to use expansionary fiscal policy to stimulate consumption and investment (Ni, 2023). The studies from (Chen, 2023; Kang, 2023) suggested that increases in the U.S. federal funds effective rate generally lead to an appreciation of the U.S. dollar and a depreciation of other currencies such as the Chinese Yuan and Indonesian Rupiah.

The U.S. federal funds effective rate significantly influences currency exchange rates against other countries, primarily through its impact on capital flows and investor sentiment. Higher interest rates offer better returns on investments denominated in dollars. As a result, it attracts foreign capital and increases demand for US dollar which can typically lead to a stronger U.S. dollar. Conversely, this can lead to capital outflows from

other countries which potentially weakens their currencies (Wu, 2024). The federal fund rate, the primary instrument of U.S. monetary policy, influences currency exchange rates by increasing or decreasing the money in circulation, which can affect the U.S. dollar's position as an international reserve currency and trade share (Davydov, 2020).

Overall, the federal funds effective rate is a critical tool in U.S. monetary policy that influences currency exchange rates by affecting capital flows, investor sentiment and the relative attractiveness of dollar-denominated assets. The anticipation of rate hikes can influence investor behaviour and lead to fluctuations in exchange rates even before the actual changes occur. This sentiment-driven movement can cause the dollar to appreciate as investors adjust their portfolios in anticipation of higher returns (Mohammed et al., 2023).

2.4.9 Overnight Policy Rate (OPR)

According to (Bank Negara, 2024), overnight policy rate (OPR) is BNM's sole indicator used to signal the stance of monetary policy. It is BNM's policy interest rate that can affect banks' lending and financing rates as well as deposit rates which will be decided and revised bi-monthly. These rates tell you how much the cost of loan is or how much the returns are for deposits. They are applicable for both conventional and Islamic finance products.

The overnight policy rate can influence currency exchange rates, primarily through its impact on interest rates and investor behaviour. An increase in the overnight policy rate generally leads to a short-term appreciation of the national currency as higher interest rates attract foreign capital and increase demand for the domestic currency (Hashchysyn et al., 2020). This happens because the investors are seeking higher returns on their investments. When a country raises its overnight policy rate, it makes its currency more attractive to foreign investors who want to take advantage of the higher interest rates. This

increased demand for the domestic currency pushes up its value relative to other currencies.

On the other side, lowering the overnight policy rates can lead to depreciation of the domestic currency. When a central bank lowers the overnight policy rate, it can make domestic investments less attractive compared to those in other countries. This can lead to capital outflows and a decrease in demand for the domestic currency which result in depreciation.¹⁴¹

2.5 Modelling of Macroeconomic Variables and Currency Exchange Rates

A few research had been conducted in the past to study on how the macroeconomic factors such as unemployment rates, economic indicators by industrial sectors, gross domestic product (GDP), etc can be related to the currency exchange rate.¹²

One of the studies was presented by (Antwi et al., 2020) focusing on applying a multivariate modelling technique of the Vector Autoregression (VAR) to assess the impact of macroeconomic variables such as broad money supply (M2), lending rate, inflation and real GDP on the exchange rate in Ghana. The empirical results depicted that real GDP, inflation and money supply significantly influence the exchange rate in Ghana while historical values of lending rate are insignificant to make the predictions. Even though the outcome seems reasonable, yet the research utilises only limited set of macroeconomic variables in its modelling. The model has limitations as it is lack of any external variables, for instance, other exogenous factors like Foreign Direct Investment (FDI), unproductive government spending and balance of payments for a more comprehensive analysis.¹⁸²

(Kim & Park, 2020) utilised a factor-augmented predictive regression technique to examine the correlation between macroeconomic variables and nominal exchange rates.¹⁴⁴

They used principal component analysis (PCA) to estimate eight components from a large panel of US macroeconomic time series data to forecast both the short-term and long-term variations in nominal exchange rates. The study's findings demonstrated that variables obtained from US macroeconomic data have a strong ability to predict changes in the bilateral US exchange rate and can significantly increase the Purchasing Power Parity's (PPP) ability to predict changes through both in-sample and out-of-sample analyses. Nevertheless, the data ingested by the model was limited only up to year 2011 and the landscape may have changed since then.

(Pozzi & Sadaba, 2020) on the other hand focused on assessing if there are scapegoats in determining the currency exchange rate. Bayesian Gibbs sampling approach was implemented to evaluate if the macroeconomic factors, i.e., real GDP growth, the inflation rate, the long-run nominal interest rate and the current account to GDP ratio of eight selected countries contribute significantly to their currency exchange rate versus US dollar over the past years from 2002 Quarter 1 to 2014 Quarter 4. The paper asserted that nominal exchange rates are not isolated from the macroeconomic variables and their relationship fluctuates based on the time horizon and the nature of the factors involved instead. Despite a novel and rigorous testing method for the scapegoat model was introduced, the model may come to its limitation as the data used was only up to the year 2014 and this may result in not up-to-date analysis.

Another paper discussed by (Boyukliev et al., 2022) implemented ART Ensembles and Bagging method to build predictive models to forecast the EUR/USD exchange rate based on key macroeconomic indicators such as inflation, unemployment, GDP and interest rates. The outcome of the paper concluded that achievement of accurate forecast of the future values of the foreign exchange rate cannot be made without considering the other key macroeconomic indicators. Although the models proposed can explain up to

98.8% of the data variation and have only MAPE of 1%, the paper only uses four macroeconomic indicators which may not account for other factors that influence the exchange rate, such as government debt.

(Dahal & Raju, 2022) presented the Multiple regression using OLS, Engle-Granger cointegration and Standard Vector Autoregressive models with impulse response analysis to analyse the multivariate relationship between the USD-NPR exchange rate and major macroeconomic variables as well as the long-run relationship between Nepal and India's exchange rate. The findings inferred that the exchange rate of India which is Nepal's main trading partner as well as other macroeconomic factors not limited to inflation, interest rates, trade balances, foreign reserves and state debt influenced Nepal's exchange rate. While the research studied on the inter-dynamic relationship among major macroeconomic variables and apply impulse analysis to generate some policy recommendations, it was limited to make comparisons only between the currency exchange rates of India and Nepal against USD.

(Thevakumar & Jayathilaka, 2022) had proposed a combination of ARIMA and GARCH models to examine the short-run and long-run relationships between the macroeconomic variables and the exchange rate volatility of the USD/LKR currency pair. The findings of the work indicated that there is no long-run relationship between any of the macroeconomic variables and the exchange rate, however there is a short-run relationship between exchange rate lags, inflation and merchandising trade balance. Even though the models were proved statistically reliable, however solely USD/LKR currency pair was focused, which may not reflect the exchange rate movements of other major currencies that Sri Lanka trades with, such as the Euro, the British Pound and the Indian Rupee.

Article presented by (Biswas et al., 2023) studied on developing various types of models, such as MLP, LSTM, GRU, ANN, etc. in modelling macroeconomic factors to predict and forecast the USD/BDT exchange rate. After comparisons of all models, Time Distributed MLP provided the best results with an RMSE of 0.1984. The article deduced that the inclusion of macroeconomic factors improves the accuracy and reliability of the exchange rate forecasts. Despite usage of diverse models consolidated the research, it lacked explanations on how the models linked together the macroeconomic factors and exchange rates since deep learning models are often complex and hard to interpret.

(Hillebrand et al., 2023) conducted research in investigating how US macroeconomic factors affect US dollar exchange versus 14 currencies between May 1990 and September 2021 using a two-step maximum likelihood estimator. The paper extracted factors from the dataset using principal component analysis and then estimated time-varying factor loadings using a Kalman filter approach. The paper concluded that exchange rates are related to macroeconomic factors but that the relationship is unstable and nonlinear due to some external factors. Even though it was discovered that the time-varying loadings model performed in this paper exhibited significantly better forecast accuracy, it may not capture the full diversity and complexity of the global currency market.

To assess the long-term and short-term correlations between the real exchange rate and a variety of macroeconomic variables, including the money supply, trade openness, worker remittances and productivity in Pakistan, (Munir & Iftikhar, 2023) took Autoregressive distributed lag (ARDL) approach. The article concluded that money supply, trade openness and workers' remittances have significant short-run effects on the real exchange rate, while productivity does not. Over an extended period, the real exchange rate was positively connected with worker remittances and productivity but adversely correlated with trade openness and money supply. Although the model's results

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were noteworthy, other macroeconomic factors including inflation and interest rates, which could have an impact on the actual exchange rate were not considered.

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(Pasionek, 2023) had assessed the impact of US macroeconomic data on the short-term volatility of the USD/PLN exchange rate by applying linear regression model with GARCH process for the random parameter. The studies implied that the exchange rate volatility was higher after the publication of the macroeconomic data, especially the data on inflation, manufacturing PMI and retail sales during the COVID pandemic and the war in Ukraine. Even though the research was quite up to date, the author did not compare the results with other currency pairs or other time periods to test the robustness of the findings.

Table 2.1 summarises some of the previous key studies related by highlighting the factors considered, techniques used, focuses and limitations.

Table 2.0.1: Previous Works

Reference	Factors	Techniques	Study's Focus	Limitations
(Antwi et al., 2020)	227 Foreign exchange rates, GDP, broad money supply, inflation rates and interest rates.	Vector Autoregression (VAR)	12 Examined the effects of macroeconomic variables on exchange rate in Ghana.	<ul style="list-style-type: none"> Quarter data was used which maybe not that comprehensive. Only consider factors of own country and exclude the economic conditions of the paired country.
(Biswas et al., 2023)	USD/BDT exchange rate, GDP, inflation rates, reserves, trade, money supply, exports, imports, interest rates.	5 Encoder-Decoder, Time Distributed MLP, SVM, XGBM, LSTM, GRU, ANN, CNN	5 Integrated macroeconomic theory with deep learning and machine learning models to enhance the accuracy and reliability of USD/BDT exchange rate forecasting.	<ul style="list-style-type: none"> Quarter data was used which maybe not that comprehensive.
(Kim & Park, 2020)	83 Korea-US bilateral exchange rate, US & Korean macroeconomic data.	Factor-augmented predictive regression	Applied US macroeconomic time series data to forecast both the short-term and long-term variations in nominal exchange rates.	<ul style="list-style-type: none"> The data ingested by the model was limited only up to year 2011 and the landscape may have changed since then.

Table 0.2.1 continued: Previous Works

Reference	Factors	Techniques	Study's Focus	Limitations
(Ohaegbulem & Iheaka, 2024)	Nigerian-Naira exchange rate external reserve, inflation rates, Gross Domestic Product Growth (GDPGR), public debt, unemployment rates and export.	Multiple Linear Regression	243 Examined the relationship between NGN exchange rates and macroeconomic factors to analyse their contributions and long-term effects on exchange rate variations from 1981 to 2021.	<ul style="list-style-type: none"> Annual data was used which maybe not that comprehensive. Only linear model was used in the study which may not be fit for time series data.
(Shukri et al., 2021)	113 Nominal exchange rates, domestic inflation rate, domestic real interest rate, domestic national income growth rate.	Autoregressive Distributed Lag (ARDL)	199 Explored the role of macroeconomic factors in determining the Malaysia's equilibrium exchange rate to analyse long-term relations and short-term dynamics among variables.	<ul style="list-style-type: none"> Annual data was used which maybe not that comprehensive.
Suhana et al. (2021)	Foreign exchange rate, gross domestic product, unemployment rate, inflation rate.	Multiple regression analysis	35 Examined the impact of economic factors on foreign exchange rate volatility in Malaysia.	<ul style="list-style-type: none"> Annual data was used which maybe not that comprehensive. Only linear model was used in the study which may not be fit for time series data.
(Thevakumar & Jayathilaka, 2022)	Inflation, interest rate, remittances, gross official reserve, money supply growth, merchandise trade balance	ARIMA, ARDL, ARCH, GARCH family models	35 Examined the impact of macroeconomic factors on Sri Lanka's exchange rate volatility to provide insights for policymakers and international trade firms.	<ul style="list-style-type: none"> Only consider factors of own country and exclude the economic condition of the paired country.

2.6 Summary

While existing research has examined in how the macroeconomic variables can potentially influence the currency exchange rates in short and long run, a notable gap remains. Many recent studies continue to use outdated data in perform their modelling and primarily concentrate on the authors' own countries other than Malaysia. This gap emphasises the need for an updated study that not only considers the latest data but also the unique economic dynamics of Malaysia. Addressing this research gap is crucial to understand the factors influencing currency exchange rates of Malaysia and for the development of robust forecasting models.

9 CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the methodology for modelling the macroeconomic factors with currency exchange rates fluctuations is explained and illustrated using flowchart. The data pre-processing steps and the models adopted for training are also discussed in this chapter. Additionally, the methods and evaluation metrics are explained in detail.

3.2 Variables and Data Sources

There are a total of 18 variables utilised in this study to map the relationship between the macroeconomic factors and USD/MYR currency exchange rates. All the data is secondary data obtained from a range of reliable source, namely Yahoo Finance at <https://finance.yahoo.com/>, Malaysia's official open data portal at <https://data.gov.my/>, Central Bank of Malaysia (BNM) at <https://www.bnm.gov.my/>, United States Census Bureau at <https://www.census.gov/> and Federal Reserve Economic Data (FRED) at <https://fred.stlouisfed.org/>. The data obtained is of monthly time series data which spans the period from January 2015 until July 2024. Table 3.1 below provides the summary and short description of each of the variable.

Table 3.0.1: Data Variables Descriptions

No.	Variables	Abbreviations	Unit	Descriptions	Sources
1	USD/MYR Currency Exchange Rates	ER	USD/RM	Price of Ringgit Malaysia for every 1 United States Dollar	Yahoo Finance
2	Crude Oil Prices	CRUDE	USD/barrel	Price of every barrel of crude oil from Brent, Dubai and West Texas Intermediate (WTI)	Yahoo Finance
3	¹⁷ Dow Jones Industrial Average	DJ	USD	Price-weighted index that tracks 30 large, publicly owned U.S. companies trading on NYSE and NASDAQ	Yahoo Finance

Table 3.0.2 continued: Data Variables Descriptions

No.	Variables	Abbreviations	Unit	Descriptions	Sources
4	Kuala Lumpur Composite Index	KLCI	RM	Market-valued-weighted stock market index made up of the thirty largest companies on the Bursa Malaysia	Yahoo Finance
5	Malaysia Exports	EXPMY	RM (million)	The value of goods and services exported from Malaysia	Malaysia Open Data
6	Malaysia Imports	IMPMY	RM (million)	The value of goods and services imported into Malaysia	Malaysia Open Data
7	Malaysia Industrial Production Index	IPIMY	Index	Measurement of production of industrial commodities in the mining, manufacturing and electricity sectors in real terms	Malaysia Open Data
8	Malaysia Consumer Price Index	CPIMY	Index	Measurement of the cost of purchasing a constant, representative 'basket' of goods and services	Malaysia Open Data
9	Malaysia Money Supply M1	M1MY	RM (billion)	Currency in Circulation + Demand Deposits	Malaysia Open Data
10	Malaysia Money Supply M2	M2MY	RM (billion)	M1 + Narrow Quasi-Money ¹¹	Malaysia Open Data
11	Malaysia Overnight Policy Rates	OPR	Percentages	BNM's policy interest rate that influences, among others, banks' lending and financing rates, as well as deposit rates.	BNM
12	U.S. Exports	EXPUS	USD (million)	The value of goods and services exported from the United States ⁸⁸	U.S. Census Bureau
13	U.S. Imports	IMPUS	USD (million)	The value of goods and services imported into the United States	U.S. Census Bureau

Table 3.0.3 continued: Data Variables Descriptions

No.	Variables	Abbreviations	Unit	Descriptions	Sources
14	U.S. Industrial Production Index	IPIUS	Index	Measurement of the real output of industrial commodities in the mining, manufacturing and electricity sectors	FRED
15	³⁰ U.S. Consumer Price Index	CPIUS	Index	Measurement of the cost of purchasing a constant, representative 'basket' of goods and services	FRED
16	U.S. Money Supply M1	M1US	USD (billion)	most liquid forms of money, such as cash, checking deposits and other highly liquid accounts.	FRED
17	U.S. Money Supply M2	M2US	USD (billion)	M1 plus savings accounts, small time deposits and retail money market funds	FRED
18	U.S. Federal Fund Effective Rates	FFER	Percentages	Interest rate at which depository institutions (banks and credit unions) lend reserve balances to each other overnight.	FRED

Based on Table 3.1, while Variable 1, i.e., USD/MYR currency exchange rates will be selected as our dependent variable, macroeconomic factors from Variable 2 until 18 namely crude oil prices, stock indexes, exports, imports, consumer price indexes, industrial production indexes, money supplies, overnight policy rates and federal fund effective rates are acting as independent variables in this study. The stock market indexes of Malaysia and the United States, namely the FBMKLCI and the DJ, are incorporated as new variables in this study. FBMKLCI is made up of largest 30 companies from various industries on Bursa Malaysia's Main Board while DJ tracks the performance of 30 large, publicly owned companies listed on stock exchanges in the United States. Hence, both stock indexes can serve as indicators of economic conditions and reflect investor

confidence in their respective countries. In the meanwhile, the other macroeconomic variables are selected based on the previous research (Biswas et al., 2023; Dahal & Raju, 2022; Hasan & Islam, 2023; Nor et al., 2020; Pasonek, 2023).

3.3 Tools Used

This research was conducted using Visual Studio Code (VS Code), a versatile and feature-rich integrated development environment (IDE). VS Code supports Python development with tools like debugging, syntax highlighting and a wide range of extensions. These features made it easy to manage data exploration, modelling and result interpretation. The IDE also allowed seamless transitions between data manipulation, modelling and visualisations for the study.

195 Python was the primary programming language for this research due to its powerful ecosystem of data science and econometric libraries. Pandas and NumPy were used for data preprocessing, transformation and exploratory analysis. These libraries ensured the data was well-prepared for modelling. Predictive modelling was performed using machine learning models such as Support Vector Machine (SVM), Random Forest (RF),
111 XGBoost, LightGBM and Long Short-Term Memory (LSTM). The ARDL model was used for econometric analysis to study dynamic relationships in time series data. Scikit-learn, XGBoost, LightGBM and Statsmodels were the key libraries supporting these implementations. Trained models were saved as .pkl files using joblib for deployments.

To present the results interactively, Streamlit was used to build dynamic dashboards. This open-source Python framework allowed the creation of web-based interfaces to display key findings, model predictions and visualisations. Streamlit's simplicity and Python compatibility made it ideal for deploying the saved models in pkl format and presenting insights to both technical and non-technical audiences.

The complete programming codes and reference materials for this research are available on GitHub at <https://github.com/ooihianggee/Econometric-Modelling-of-USD-MYR>. The Streamlit deployment app can be accessed at <https://usd-myr-modelling.streamlit.app/>.

3.4 Research Design

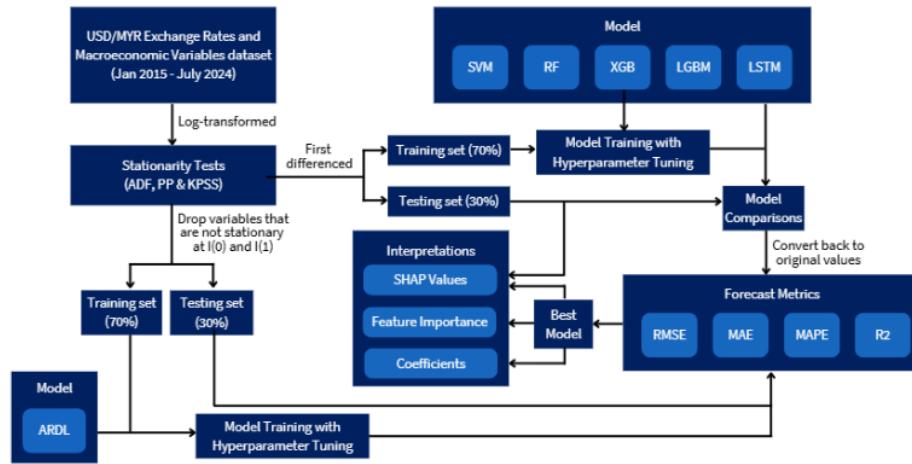


Figure 3.1 Research Design Flow

Figure 3.1 above illustrates the flow of analysis of this study. First, the whole dataset was log-transformed and then subjected to ADF, PP and KPSS stationarity tests. For ARDL model, variables that were not stationary at both I(0) and I(1) were excluded to fit its assumption. For machine learning models i.e., SVM, RF, XGB, LGBM and LSTM which can often handle trends and seasonality without explicitly requiring stationarity, all variables were included in the training and were first differenced prior to train-test split.
 The dataset was then divided into 70% training set (Jan 2015 – Sep 2021) and 30% testing sets (Oct 2021 – Jul 2024) for all models. After that, with introduction of lagged values, ARDL and the machine learning models were trained with hyperparameter tuning. Best models were selected based on lowest value of RMSE achieved. All the best models were evaluated based on forecast metrics i.e., RMSE, MAE, MAPE and R² after the predictions were converted back to their original scale. Model interpretations were performed using

SHAP values, feature importance and coefficients. The workflow was designed to ensure careful data pre-processing, model training and evaluation to identify the best approach for drawing relationship among the macroeconomic factors and USD/MYR exchange rates.

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3.5 Exploratory Data Analysis

Exploratory Data Analysis (EDA) for time series data focuses on understanding the temporal structure and characteristics of the dataset to inform model development. The process begins with visualising the time series to identify overall trends, seasonality and potential outliers. Line plots are commonly used to observe the progression of the series over time while seasonal decomposition can help isolate trend, seasonal and residual components. For instance, trends may indicate long-term changes while seasonality highlights recurring patterns at regular intervals.

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Statistical analysis is another crucial aspect of time series EDA. Descriptive statistics, such as mean, standard deviation and skewness provide insights into the data's central tendency and variability over time. Autocorrelation and partial autocorrelation plots (ACF and PACF) are used to explore the relationships between observations at different lags to help identify temporal dependencies. These plots guide the selection of appropriate lag values for models. Lastly, domain knowledge plays a significant role in interpreting findings and aligning them with real-world phenomena. By thoroughly exploring the data, EDA ensures a solid foundation for effective time series modelling and forecasting.

3.6 Data Preprocessing

Once the data was gathered, data quality assurance (DQA) is crucial to avoid producing misleading, inaccurate and biased insights. DQA involved tasks such as checking for duplicates, missing values, etc.

Since different data from different sources with different time spans were integrated, the time span to be studied in this research was trimmed to be from January 2015 to June 2024. In addition, to standardise all data in monthly format, daily USD/MYR currency exchange rates for each month will be aggregated to compute the average. Next, various datasets were combined into a unified and cohesive structure. This involves aligning common data fields and handling discrepancies in naming conventions to ease us in feeding the data into the models more conveniently.

3.6.1 Log-Transformation and First Differencing

Once the data is ready from the previous steps, the data was then log-transformed as a measure to stabilise the variance of a time series and address issues of skewness and heteroscedasticity as what similar previous studies by (Dahal & Raju, 2022; Munir & Iftikhar, 2023; Ohaegbulem & Iheaka, 2024) had suggested. With log transformation, it can lead to a better fit of the econometric model.¹

After the data was log transformed, it was differenced. Differencing is a statistical transformation used to make a time series stationary by removing trends and seasonality.⁵¹ It involves subtracting the value of a variable at a previous time step from its current value. Log differencing, which involves taking the first difference of the log-transformed data, is often used to approximate percentage change. It had been used in the study by (Thevakumar & Jayathilaka, 2022). This technique is particularly useful in time series analysis and econometrics to ensure that models like ARDL meet the stationarity requirement for valid results.

3.6.2 Introduction of Lagged Features

Currency exchange rates often exhibit autocorrelation, meaning their current values are influenced by past values. In addition, the rates may follow trends or recurring patterns influenced by economic cycles, policy changes or seasonal effects. Lagging variables

allow the model to account for this dependency. Lagging variables do also provide additional explanatory power as they bring in historical information that might explain current and future movements in the exchange rates.

In this study, we are lagging all the features up to three months. This derives the values of the variables from the previous one, two and three months. In mathematical forms,

Lag 1 Month: $X_{(t-1)}$

Lag 2 Months: $X_{(t-2)}$

Lag 3 Months: $X_{(t-3)}$

41 where X_t = Value of the time series variable at time t (current month),

$X_{(t-1)}$ = Value of the time series variable one month ago,

$X_{(t-2)}$ = Value of the time series variable two months ago,

$X_{(t-3)}$ = Value of the time series variable three months ago.

3.6.3 Unit Root and Stationarity Tests

69 Unit root test is used to assess whether a time series data possess stationarity. It is an
143 important step in most studies (Ali et al., 2022; Bawuah et al., 2023; Boyoukliiev et al.,
2022; Ghauri et al., 2024; Munir & Iftikhar, 2023) since estimators that are not stationary
may yield false and inaccurate results. The data is considered as non-stationary and
having unit root if the mean and variance are not constant. Before proceeding to any
49 analysis related to time series data, the first step is to test for the presence of unit root and
stationarity. Hence, Augmented Dickey-Fuller (ADF) test developed by David Dickey
and Wayne Fuller in 1979 was conducted. To examine the robustness of ADF test result,
185 alternative methods, Phillips-Perron (PP) test proposed by Peter Phillips and Pierre Perron
7 in 1988 as well as Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test proposed by Denis
Kwiatkowski, Peter Phillips, Peter Schmidt and Yongcheol Shin in 1992 were used.

(Afriyie et al., 2020) pointed that KPSS test as the most robust performer among the three due to its consistent accuracy across various sample size and model specifications.

The test estimation formulae by three tests are stated in Equation (3.1), (3.2) and (3.3).

ADF test:

$$\Delta y_t = \alpha_0 + \alpha_1 t + \delta_1 y_{t-1} + \alpha_i \sum_{i=1}^m \Delta y_{t-i} + \varepsilon_t \quad (3.1)$$

PP test:

$$y_t = \beta_0 + \beta_1 t + \delta_2 y_{t-1} + \varepsilon_t \quad (3.2)$$

KPSS test:

$$y_t = r_t + \beta_t + \varepsilon_t \quad (3.3)$$

where Δ = first difference operation,

y = all time series variables including dependent and independent variables,

t = time trend variable,

m = number of lags,

α = coefficient on time trend for ADF test,

δ_1 = parameter on time trend for ADF test,

β = coefficient on time trend for PP test,

δ_2 = parameter on time trend for PP test,

T = number of observations,

r_t = random walk,

β_t = deterministic trend,

ε_t = error term.

Three tests are interested in the estimate of the parameter and the p-values for the hypothesis test to determine the presence of unit root for each time series. The hypothesis tests are stated as follow:

³⁷ ADF test: H_0 : Presence of unit root which indicates non-stationary

H_A : Absence of unit root which indicates stationary

³⁷ PP test: H_0 : Presence of unit root which indicates non-stationary

H_A : Absence of unit root which indicates stationary

KPSS test: H_0 : Absence of unit root which indicates stationary

²⁰¹ H_A : Presence of unit root which indicates non-stationary

¹ For both the ADF and PP tests, if the p-value is less than the chosen significance

²¹⁶ level (α), such as 0.05, the null hypothesis is rejected at the 5% significance level. This

³⁷ implies there is only a 5% risk of incorrectly concluding that the time series is stationary

⁷ when it is not. In this case, the series is deemed stationary and integrated of order zero,

⁴¹ I(0). Conversely, if the p-value is greater than the significance level, the null hypothesis

is not rejected and it indicates that the time series is non-stationary. To achieve stationarity

²²³ in such cases, differencing the series is necessary.

²⁵ For the KPSS test, the logic is reversed. If the p-value is greater than the chosen

significance level, the null hypothesis is not rejected and it indicates the series is

stationary. However, if the p-value is less than the significance level, the null hypothesis

is rejected and it implies that the time series is non-stationary.

3.6.4 Train-Test Split

¹⁰⁶ Prior modelling, data will be split into 7:3 for the training and testing data. The training data will span period from January 2015 to September 2021 while the testing data will cover period from October 2021 to July 2024. The train data used by the models to learn the relationships between the independent variables (macroeconomic factors) and the dependent variable (USD/MYR exchange rates). The test data is to evaluate how well the trained models generalise to unseen data. This phase simulates real-world forecasting by

testing the model on future (out-of-time) data points. It helps us in assessing the model accuracy and robustness.

3.7 Models

The econometric and machine learning models selected for this research included Autoregressive Distributed Lag (ARDL), Support Vector Machines (SVM), Random Forest (RF), XGBoost (XGB), LightGBM (LGBM) and Long Short-Term Memory (LSTM) models. These models were chosen for their demonstrated efficacy in capturing relationships and dependencies in time series and macroeconomic datasets.

The training methodology incorporated a rolling-window cross-validation strategy to evaluate model performance. The dataset was split into training and testing subsets, with the training data spanning January 2015 to September 2021 and the testing data covering October 2021 to July 2024. This approach allows out-of-time validation and provides a robust evaluation of each model's predictive capability. Hyperparameter tuning was performed for the machine learning models. It was a significant measure to control the model's ability to generalise and avoid overfitting or underfitting.

3.7.1 Autoregressive Distributed Lag (ARDL)

The Autoregressive Distributed Lag (ARDL) model is a powerful econometric approach used to investigate the relationship between the USD/MYR currency exchange rates and macroeconomic factors from both the United States and Malaysia by including lags of both the dependent and independent variables. This model is particularly suitable for time series data which can accommodate time series variables that are either stationary at level I(0), first difference I(1) or a combination of both. Its flexibility in handling mixed integration orders makes it ideal for studying complex economic relationships and more robust compared to traditional cointegration techniques like the Engle-Granger method.

For a dependent variable y_t (USD/MYR currency exchange rates) and independent variables $x_{(1,t)}, x_{(2,t)}, \dots, x_{(k,t)}$ (macroeconomic factors from both U.S. and Malaysia),³ the ARDL model can be expressed as follows:

$$y_t = \alpha + \sum_{j=1}^n \gamma_j y_{t-j} + \sum_{i=0}^m \sum_{k=1}^K \beta_{ik} x_{(k,t-i)} + \epsilon_t^{211}$$

where y_t = dependent variable (USD/MYR exchange rates) at time t ,

α = intercept term,

γ = coefficients of the lagged dependent variable y_{t-j} ,

i = number of months lagged,

$x_{(k,t-i)}$ = independent variables (macroeconomic factors) at time $t - i$,

β_{ik} = coefficients of the each macroeconomic factor k at lag i ,

K = total number of macroeconomic factors included in the model,

m = maximum lag order for the independent variables,

n = maximum lag order for the dependent variable,

ϵ_t = error term to account for random variations.

The terms $\sum_{j=1}^n \gamma_j y_{t-j}$ capture the influence of past exchange rates on the current rate while the terms $\sum_{i=0}^m \sum_{k=1}^K \beta_{ik} x_{(k,t-i)}$ represent the short-term effects of U.S. and Malaysian macroeconomic factors on the exchange rate.¹³⁵ The error term, ϵ_t accounts for any unexplained variations in the exchange rate.¹³⁵ If the variables are cointegrated, the ARDL model identifies the relationship between the exchange rate and macroeconomic factors.³

198 To avoid excessively large models, the optimal lag order in an ARDL model can be determined by minimising either the Bayesian Information Criterion (BIC) or the Akaike Information Criterion (AIC). 169

$$\text{BIC}(p) = \log\left(\frac{\text{SSR}(p)}{T}\right) + \frac{(p+1) \cdot \log(T)}{T}$$

$$\text{AIC}(p) = \log\left(\frac{\text{SSR}(p)}{T}\right) + \frac{(p+1) \cdot 2}{T}$$

Here, $\text{SSR}(p)$ represents the sum of squared residuals for lag order p and T is the sample size. These criteria aim to strike a balance between model fit (minimising SSR) and model simplicity (penalising larger lag orders). The lag order \hat{p} that minimises the criterion is considered optimal.

204 From the model results, the optimum lag length chosen by the lowest values of AIC and BIC were 1. The selection of lag length should prefer to the lowest BIC values if ARDL estimation is used to determine the cointegration to avoid spurious regression and can define more constrained requirements. Thus, lag order of 1 was used to develop the ARDL model. Different combinations of variables were used to fit the ARDL model to minimise the RMSE as much as possible.

The ARDL model is particularly valuable in economic analysis because it accounts for both immediate impacts of sudden economic shocks and the gradual adjustment process towards long-term equilibrium. It is interpretable in examining the relationships between variables.

60 3.7.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a powerful supervised learning algorithm primarily used for classification and regression tasks. In the context of modelling USD/MYR

exchange rates and macroeconomic factors, SVM was acting as **Support Vector Regression (SVR)**.⁵⁸

In the SVR approach, the objective is to predict the USD/MYR exchange rate by learning ³ the relationship between the exchange rate and the macroeconomic factors ⁶⁸ influencing it. SVM works by mapping the input data (macroeconomic factors) into a higher-dimensional feature space using a kernel function. This transformation enables the ¹²² model to create a hyperplane that best fits the data points while ensuring that the margin between the hyperplane and the data points is as large as possible. The goal is to minimise the prediction error while keeping this margin wide which helps to improve the generalisation capability of the model and prevent overfitting.

¹⁷¹ The core idea behind SVR is to find a function $f(\mathbf{x})$ that approximates the target variable \mathbf{y} within a margin of tolerance ϵ , while also minimising the model's complexity. Mathematically, the SVR optimisation problem seeks to minimise both the error (the ¹ deviation between predicted and actual values) and the complexity ¹²¹ of the model. This is achieved through minimisation of the following objective function:

$$\frac{1}{2} |\mathbf{w}|^2 + C \sum_{i=1}^N \xi_i$$

where w = weight vector,

¹³ C = regularisation parameter,

ξ_i = slack variables that allow for some error in the model.

The hyperparameter tuning specifications used for SVR in this study were as follows.

Table 3.0.4 Hyperparameter Tuning for SVR

Hyperparameters	Search space
Kernel type	['sigmoid', 'linear', 'rbf', 'poly']
Regularisation parameter, C	[0.01, 0.1, 1, 10, 100]
Margin of tolerance, ϵ	[0.01, 0.1, 0.5, 1]

From Table 3.2, the kernel type defines the type of transformation applied to the input data. It determines how the data is mapped into a higher-dimensional feature space. The regularisation parameter, C controls the trade-off between achieving a low error on the training data and maintaining a large margin. A higher value of C gives more importance to minimising the error on the training set while a smaller value allows for more error tolerance. Margin of tolerance, ϵ defines the margin within which no penalty is given for errors. Smaller values lead to a stricter model while larger values allow for more tolerance.

3.7.3 Random Forest (RF)

Random Forest (RF) is an ensemble learning method that works by training multiple decision trees on random subsets of the data. Each tree is built using a random selection of features and samples which helps to reduce overfitting and increase the generalisation ability of the model. When it comes to predicting the USD/MYR exchange rate, the macroeconomic factors of both U.S. and Malaysia served as the input features. The Random Forest model used these factors to learn complex, non-linear relationships between the predictors and the target variable, which is the USD/MYR exchange rate.

In brief, Random Forest provides an aggregation of multiple decision trees to make predictions. Each individual tree is built based on a random subset of data and the final prediction is obtained by averaging the predictions of all trees. This helps in reducing the variance and improving the accuracy of the model. The model is robust to overfitting, particularly when there are plenty of trees built which is advantageous when dealing with noisy data.

The hyperparameter tuning specifications used for RF in this study were as follows.

Table 3.0.5 Hyperparameter Tuning for RF

Hyperparameters	Search space
75 n_estimators	[50, 100, 200]
max_depth	[50, 100, 200]
min_samples_split	[50, 100, 200]
min_samples_leaf	[1, 2, 4]
max_features	['sqrt', 'log2']

From Table 3.3, the parameter ‘n_estimators’ 34 determines the number of decision trees to include in the forest. More trees generally result in a more stable and accurate model as the variance is reduced by averaging predictions from multiple trees. The parameter 15 ‘max_depth’ controls how deep each individual decision tree can grow. A deeper tree can model more complex relationships but may also lead to overfitting by capturing noise in the data and vice versa. The parameter ‘min_samples_split’ controls how many samples must be present in a node before it can be split. Larger values result in more conservative trees while smaller values allow the tree to grow more freely. The parameter 80 ‘min_samples_leaf’ determines the minimum number of samples required to be at a leaf node. Increasing this value can help reduce overfitting by ensuring that leaves contain sufficient data points. The parameter ‘max_features’ defines how many features to consider when looking for the best split. ‘sqrt’ (the square root of the number of features) and ‘log2’ (the logarithm base 2 of the number of features) are common choices for controlling model complexity.

3.7.4 XGBoost (XGB)

36 Extreme Gradient Boosting which is also known as XGBoost or XGB is a highly efficient and scalable machine learning algorithm. It operates by building an ensemble of 108 decision trees sequentially. In each step, it tries to correct the errors made by the previous

trees by giving more weight to the misclassified or poorly predicted data points. This results in an iterative process that improves the model's accuracy as more trees are added.

The core principle behind XGBoost is to minimise the objective function which consists of a loss function that measures the error between the predicted and actual values, along with a regularisation term to control the model's complexity and prevent overfitting.

The mathematical form of objective function, $L(\theta)$ can be written as follow.

$$L(\theta) = \sum_{i=1}^n \mathcal{L}(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k)$$

where n = number of data points,

y_i = true value,

\hat{y}_i = predicted value,

$\mathcal{L}(y_i, \hat{y}_i)$ = loss function for each data point,

$\Omega(f_k)$ = regularisation term to control the complexity of the model,

K = number of trees in the ensemble.

The hyperparameter tuning specifications used for XGB in this study were as follows:

Table 3.0.6 Hyperparameter Tuning for XGB

Hyperparameters	Search space
n_estimators	[50, 100, 200]
learning_rate	[0.01, 0.1, 0.2]
max_depth	[3, 5, 7]
subsample	[0.8, 1.0]
colsample_bytree	[0.8, 1.0]

From Table 3.4, the parameter 'n_estimators' specifies the number of boosting rounds (trees) in the model. More trees generally improve model performance. However, they can also lead to overfitting. The parameter 'learning_rate' controls the contribution of each tree to the overall model prediction. A smaller learning rate results in more

conservative updates while a higher learning rate speeds up the learning process but may risk overfitting. The parameter ‘max_depth’ controls the maximum depth of the individual decision trees. A higher ‘max_depth’ allows the model to capture more complex relationships but may also increase the risk of overfitting. The parameter ‘subsample’ determines the fraction of training data used for each boosting round. Testing values like 0.8 and 1.0 allows for tuning the trade-off between bias and variance. The parameter ‘colsample_bytree’ controls the fraction of features used for building each tree. Lower values can prevent the model from relying too heavily on only a few variables.

3.7.5 LightGBM (LGBM)

LightGBM (Light Gradient Boosting Machine) is a powerful gradient boosting framework widely used for classification and regression tasks. It builds an ensemble of decision trees in a sequential manner where each tree aims to correct the errors of the previous ones. Its efficiency, speed and accuracy have made it a suitable choice for modelling the time series data with macroeconomic variables.

Almost like what XGB does, the fundamental objective of LightGBM is to minimise an objective function that consists of a loss function measuring the error between predicted and actual values and a regularisation term that controls model complexity. The mathematical form of objective function, $\mathcal{L}(\theta)$ can be written as follow.

$$L(\theta) = \sum_{i=1}^n \mathcal{L}(y_i, \hat{y}_i) + \Omega(f)$$

where n = number of data points,

y_i = true value,

\hat{y}_i = predicted value,

$\mathcal{L}(y_i, \hat{y}_i)$ = loss function for each data point,

$\Omega(f)$ = regularisation term to control the complexity of the model.

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One key difference between XGBoost and LightGBM is that LightGBM uses a leaf-wise tree growth strategy as opposed to level-wise in XGBoost. This allows it to grow trees with deeper and more imbalanced structures which leads to improved accuracy. In addition, LightGBM uses histogram-based binning for feature values which does speed up the computation works and reduce the memory usage.

The hyperparameter tuning specifications used for LGBM in this study were as follows:

Table 3.0.7 Hyperparameter Tuning for LGBM

Hyperparameters	Search space
n_estimators	[50, 100, 200]
learning_rate	[0.01, 0.1, 0.2]
max_depth	[-1, 5, 7]
subsample	[0.8, 1.0]
colsample_bytree	[0.8, 1.0]

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From Table 3.5, the parameter ‘n_estimators’ controls the number of trees in the model. Higher values improve accuracy but increase the risk of overfitting. The parameter ‘learning_rate’ determines the contribution of each tree. Smaller values improve generalisation but require more iterations. The parameter ‘max_depth’ limits the depth of each tree, controls complexity and prevents overfitting. The parameter ‘subsample’ specifies the fraction of data used for each iteration, improving robustness and reducing overfitting. The parameter ‘colsample_bytree’ controls the fraction of features used for each tree to reduce feature dependency and improve generalisation.

3.7.6 LSTM

5

Long Short-Term Memory which is also known as LSTM is a widely used model for time series forecasting due to its ability to process entire sequences of data and capture both short-term and long-term dependencies. Generally, a LSTM network cell is made up

³⁸ of three main components which are the cell state, the hidden state and three gates (input gate, forget gate and output gate).

The cell state acts as a memory which passes relevant information through the network ¹ and maintains the context over time. The input gate determines which values should be ⁴⁰ added to the cell state using a sigmoid function, σ as a filter. It processes inputs H_{t-1} (the hidden state from the previous time step) and x_t (the current input). The hidden layer ⁵ helps to generate a vector of potential values using the tanh function. The values will then ⁶⁴ be scaled by the regulated input and added to the cell state. The forget gate is responsible for removing unnecessary information from the cell state to reduce redundancy. The overall process can be described as follows:

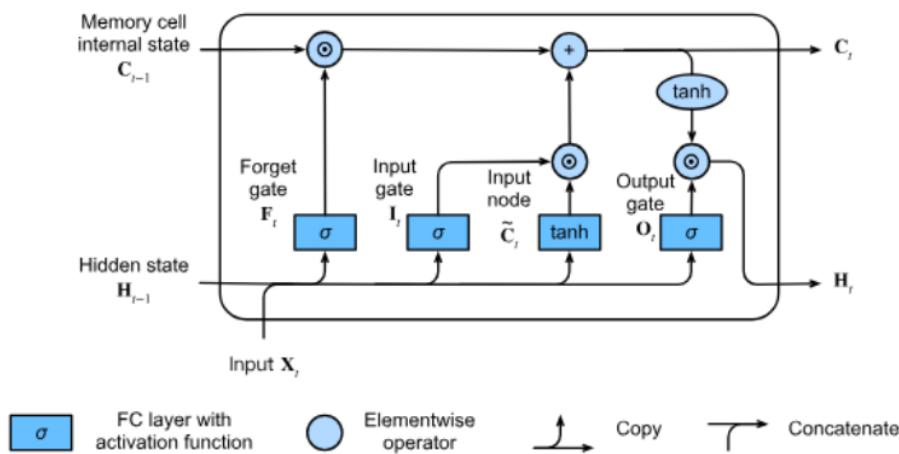


Figure 4 Hyperparameter Tuning for SVR

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

$$\tilde{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t$$

$$h_t = o_t \cdot \tanh(c_t)$$

21 Here, i_t , f_t and o_t represent the input, forget and output gates, respectively. c_t and
 44 h_t denote the cell state and hidden state, while W and b are the weight matrices and
 230 biases.

The hyperparameter tuning specifications used for LSTM in this study were as follows:

Table 3.0.8 Hyperparameter Tuning for LSTM

Hyperparameters	Search space
units	[50, 100]
dropout	[0.2, 0.3]
batch size	[16, 32]
epochs	[50, 100]
learning rate	[0.001, 0.01]

24 From Table 3.6, the ‘units’ parameter specifies the number of memory cells or neurons in the LSTM layer. Increasing the number of units allows the model to capture more complex patterns yet larger numbers of units can lead to overfitting. The ‘dropout’ 3 parameter is a regularisation technique used to prevent overfitting by randomly deactivating a fraction of neurons during training. Lower dropout rates retain more information while higher dropout rates increase regularisation and help the model generalise better but may hinder learning.

87 The parameter ‘batch size’ defines the number of samples the model processes before 160 updating its weights. Smaller batch sizes allow for more frequent weight updates while larger batch sizes provide more stable gradient updates. The parameter ‘epochs’ 24 represents the number of complete passes through the training dataset. A higher number of epochs gives the model more opportunities to learn patterns but increases the risk of overfitting if not paired with early stopping. A lower number\ may result in underfitting.

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The parameter ‘learning rate’ controls the step size for weight updates during training. A lower learning rate allows the model to converge more steadily, reducing the risk of overshooting the optimal weights. A higher rate speeds up convergence but might lead to instability or divergence if too aggressive.

3.8 Evaluation Metrics

We have mapped the macroeconomic variables with the USD/MYR exchange rates using various models. To determine each model’s predictive performance, we will analyse the resulted accuracy in predicting the USD/MYR exchange rates on the testing (also known as Out-Of-Time) data. To evaluate that, we have opted for the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) which are widely used in the fields of regression research and forecasting. We will also calculate the R-square value (R^2) to gauge how effectively our models align with the unseen OOT data. The evaluation metrics are discussed in the section below.

3.8.1 RMSE

³⁴ Root Mean Squared Error (RMSE) measures the average magnitude of error between predicted and observed USD/MYR exchange rate values. This metric is sensitive to large errors due to the squaring of differences and best in capturing extreme fluctuations in the exchange rate. A lower RMSE will indicate a better model performance. The formula to compute RMSE is as follow.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$$

⁴ where y_i = actual value of the USD/MYR exchange rates,

\hat{y}_i = predicted value of the USD/MYR exchange rates,

N = total number of predictions or actual values.

3.8.2 MAE

Mean Absolute Error (MAE) measures the average magnitude of errors between predicted and actual USD/MYR exchange rate values without considering their direction.

Unlike RMSE, it treats all errors equally instead of squaring the errors. This makes it less sensitive to large outliers. ¹ The lower the MAE, the better the model's predictions. The formula to compute MAE is as follow.

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

⁴ where y_i = actual value of the USD/MYR exchange rates,

\hat{y}_i = predicted value of the USD/MYR exchange rates,

N = total number of predictions or actual values.

3.8.3 MAPE

¹⁸ Mean Absolute Percentage Error (MAPE) expresses the prediction error as a percentage of actual values. It is useful for understanding the scale of the errors relative to the magnitude of the actual values. A lower MAPE is indicating a better accuracy. The formula to compute MAPE is as follow.

$$MAPE = \frac{1}{N} \sum_{i=1}^N \frac{|y_i - \hat{y}_i|}{y_i}$$

⁴ where y_i = actual value of the USD/MYR exchange rates,

\hat{y}_i = predicted value of the USD/MYR exchange rates,

N = total number of predictions or actual values.

3.8.4 R-Squared

R-squared (R^2) measures the proportion of the variance in the dependent variable (USD/MYR exchange rates) that can be explained by the independent variables (macroeconomic variables fitted) in the model. It offers a valuable indicator of goodness

of fit of the models to the data. The value of R^2 ranges from 0 to 1 and we can say that the model is fitted better when the value of R^2 is closer to 1. Sometimes, negative values can occur if the model fits very poorly to the data. The formula to compute R^2 is as follow.

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}$$

where y_i = actual value of the USD/MYR exchange rates,

\hat{y}_i = predicted value of the USD/MYR exchange rates,

\bar{y} = mean of actual values of the USD/MYR exchange rates,

N = total number of predictions or actual values.

3.9 Summary

The chapter began with a discussion of the dataset, the variables included and the timeframe covered. This was followed by an overview of the tools and software utilised for analysis and the rationales behind the usage. The research design was then elaborated to explain how the study was structured to address the key research questions effectively.

Exploratory data analysis (EDA) and data preprocessing steps were described in detail ensure the dataset was ready and fit enough for modelling. The theoretical foundations and specification of the models used in this study were also discussed. Hyperparameter tuning strategies explained how model parameters were optimised to enhance performance and avoid overfitting. Lastly, the details of each evaluation metrics applied to assess the models' accuracy and robustness were highlighted.

In summary, this chapter has laid a solid foundation for understanding the methodology behind the study.

CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter describes the exploratory data analysis of the time series data as well as the comparison of using six pre-trained models, namely ARDL, SVM, RF, XGB, LGBM and LSTM, on modelling of USD/MYR currency exchange rates with macroeconomic factors followed by benchmarking the results against the previous research. Results were expressed in table and visual forms followed by respective interpretations.

4.2 Exploratory Data Analysis

Exploratory Data Analysis (EDA) summarises the main characteristics of a dataset using statistical methods to gain insights and understand its underlying structure.

4.2.1 Descriptive Statistics

The descriptive statistics for the variables provide insights into their central tendencies, dispersion and distribution characteristics.

Table 4.0.1 Descriptive Statistics of Each Variable (Jan 2015 – Jul 2024)

Variable	Mean	Std	Min	Median	Max	Skewness	Kurtosis
ER	4.23	0.26	3.58	4.18	4.76	-0.01	0.18
CRUDE	61.58	18.23	16.70	58.17	114.34	0.47	0.11
DJ	27058.12	6776.11	16299.90	26232.67	40050.00	0.05	-1.19
KLCI	1615.24	122.59	1363.54	1607.52	1863.15	0	-0.77
EXPMY	91836.43	23562.21	52473.78	84721.27	144275.50	0.51	-0.88
IMPMY	78274.77	19052.11	48643.97	73156.94	124231.30	0.67	-0.62
IPIMY	114.56	10.90	77.05	114.77	134.30	-0.28	0.13
CPIMY	121.85	5.76	109.90	121.10	133.10	0.2	-0.64
M1MY	478185.40	100236.10	346300.40	435747.00	645343.90	0.25	-1.48
M2MY	1944426.00	271682.70	1545766.00	1922423.00	2423484.00	0.14	-1.25
OPR	2.75	0.56	1.75	3.00	3.25	-0.96	-0.71
EXPUS	141575.40	21127.75	91026.76	135977.00	183432.80	0.33	-0.68
IMPUS	218598.00	34006.91	162949.70	207985.50	295671.00	0.47	-0.89
IPIUS	100.70	3.29	82.68	101.53	106.09	-2.51	10.4
CPIUS	264.87	24.92	233.71	256.57	314.54	0.7	-0.92
M1US	10321.28	7707.93	2941.10	3924.90	20826.80	0.26	-1.88
M2US	16714.31	3632.22	11759.00	15112.20	21859.70	0.17	-1.69
FFER	1.65	1.79	0.05	1.15	5.33	1.05	-0.23

From Table 4.1, we can observe that USD/MYR exchange rates and price indices (ER, CPIMY, CPIUS) showed low variability with minimal skewness. This suggests their consistent trends throughout the years. On the other side, trade-related variables (EXPMY, IMPMY, EXPUS, IMPUS) and monetary aggregates (M1MY, M2MY, M1US, M2US) showed significant variability as indicated from large values of standard deviations and wide ranges. They were having positive skewness which suggests steady upward trend. In terms of stock market indicators, broader range of DJ suggested it was having more fluctuations and volatility as compared to KLCI).

Energy and production variables (CRUDE, IPIMY, IPIUS) showed moderate to high variability. Industrial production in the US (IPIUS) was suspected to have extreme outliers as indicated by its high kurtosis and negative skewness. Interest rates (OPR, FFER) were more stable. OPR was negatively skewed while FFER was positively skewed.

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4.2.2 Time Series Plots



Figure 4.1 USD/MYR Currency Exchange Rates (Jan 2015 – Jul 2024)

Figure 4.1 observed a general upward trend in the USD/MYR currency exchange rate over the last eight years with numerous times of fluctuations and periods of volatility. Starting from the lowest point, around 3.5 MYR per USD in early 2015, the rate experienced a sharp increase that year and nearly surpassed 4.0 MYR per USD. Over the subsequent years, the USD/MYR exchange rate oscillated between approximately 3.9 and

4.5. A significant spike occurred in 2022 where it briefly exceeded 4.5. The exchange rate had recorded its highest value at 4.79 MYR per USD in February 2024.



Figure 4.2 Time Series Plot of Each Variable (Jan 2015 – Jul 2024)

Figure 4.2 shows a series of time series line plots for the USD/MYR exchange rates and the macroeconomic variables of both US and Malaysia from Jan 2015 to Jul 2024.

USD/MYR exchange rates (ER) showed an overall upward trend from 2020 to 2024 and indicated the depreciation of the local currency. Crude oil prices (CRUDE) exhibited significant variability with peaks and troughs that align with global market disruptions. The prices experienced a sharp drop in 2020 due to the COVID-19 pandemic and a sharp rise in 2022 due to ²⁰⁹ Russia's full-scale invasion of Ukraine threatened the supplies. Similar with ER, the Dow Jones Index (DJ) showed a strong upward trend and indicated sustained growth in the U.S. stock market. On the other side, KLCI displayed moderate fluctuations with a slight decline followed by recovery post-2020.

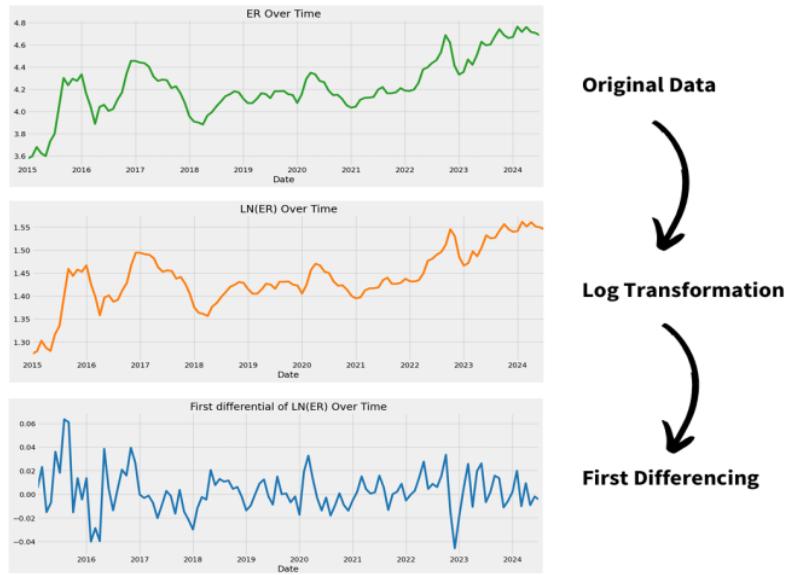
Trade-related variables including exports (EXPMY, EXPUS) and imports (IMPMY, IMPUS) were showing consistent upward trends. The values declined in the beginning of 2020 particularly impacted by the COVID-19 pandemic. Price indices (CPIMY, CPIUS) were also experiencing steady growth which reflect inflations in both countries. Meanwhile, industrial production indices (IPIMY, IPIUS) measuring the performance of manufacturing sectors were on a roller coaster ride. They also made significant drops during 2020 due to the pandemic. Soon after that, Malaysia's index recovered steadily while the U.S. index showed sharper short-term variability.

Monetary aggregates, M1 and M2 for both countries, highlighted strong upward trends, particularly after 2020 as consequences of the expansionary monetary policies during the COVID-19 pandemic. From the aspects of interest rates, both Malaysia's ²³⁶ Overnight Policy Rate (OPR) and the U.S. Federal Funds Effective Rate (FFER) experienced sharp drop since beginning of year 2020 due to outbreak of Covid-19 pandemic. The rates only rose post-2022 which signalled a shift to a tighter monetary policy.

4.3 Data Preprocessing

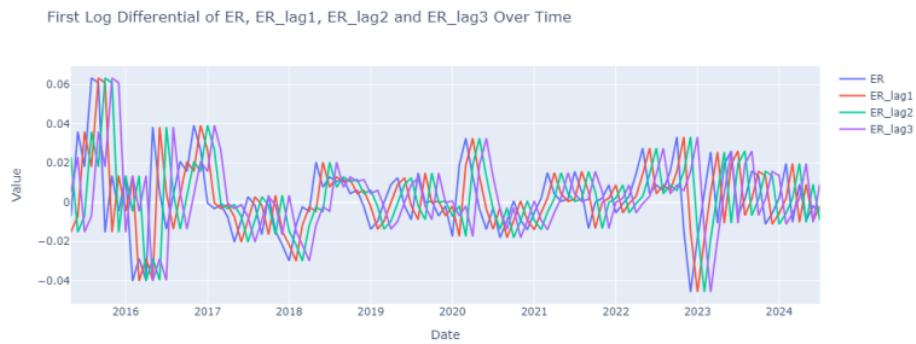
Data preprocessing was conducted to ensure the data is fit prior modelling.

4.3.1 Log-Transformation and First Differencing



The time series variables were log-transformed and first differenced to reduce the variance and to achieve stationarity.

4.3.2 Introduction of Lagged Features



Three months of lagged values were introduced to account for the time it takes for changes in the macroeconomic factors to impact USD/MYR currency exchange rates.

4.3.3 Unit Root and Stationary Tests

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Table 4.0.2 Unit Root Test Results from ADF, PP and KPSS Tests

131 Variable	ADF		PP		KPSS	
	At Level	At 1 st Diff	At Level	At 1 st Diff	At Level	At 1 st Diff
LER	-2.6196*	-	-2.147	-7.1948***	0.9866	0.0713***
LCRUDE	-2.0822	-7.7400***	-7.7146	-8.1041***	0.9621	0.0505***
LDJ	-0.202	-9.8518***	-0.0587	-9.8575***	1.6626	0.0649***
LKLCI	-1.954	-9.2435***	-1.9437	-8.1795***	1.2123	0.0966***
LEXPY	-0.61	-3.2946**	-1.5746	-23.2177***	1.5333	0.1020***
LIMPY	-0.7734	-3.8305***	-1.68	-21.5964***	1.4229	0.0477***
LIPIMY	-0.2698	-3.9792***	-3.3342**	-	1.76	0.0711***
LCPIMY	-0.5209	-7.6479***	-0.5438	-7.8745***	1.5721	0.0967***
LM1MY	0.2538	-2.037	0.171	-11.1549***	1.7007	0.1898***
LM2MY	0.8213	-10.2125***	1.1374	-10.2699***	1.7376	0.1718***
LOPR	-1.6533	-4.0755***	-1.5633	-12.0824***	0.6646	0.2332***
LEXPUS	-0.9158	-3.3616**	-2.2262	-17.6903***	1.2178	0.0763***
LIMPUS	-0.8656	-2.6257*	-1.5698	-20.0113***	1.4123	0.0639***
LIPIUS	-2.0401	-2.6743*	-3.9888***	-	0.2100***	-
LCPIUS	-0.1506	-1.7177	1.5908	-6.0002***	1.6134	0.5974
LM1US	-0.7074	-9.7408***	-0.8492	-9.8346***	1.4584	0.1347***
LM2US	-0.947	-1.7511	-0.7548	-6.0674***	1.6417	0.2474***
LFFER	-1.8173	-2.9061**	-0.5488	-5.5451***	0.7736	0.2413***

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For ADF and PP estimates, ***, ** and * represents rejection at 1%, 5% and 10% level of significance. For KPSS estimates, *** represents no rejection.

Table 4.0.3 Order of Integration Results from ADF, PP and KPSS Tests

Variable	Order of Integration		
	ADF	PP	KPSS
LER	I(0)	I(1)	I(1)
LCRUDE	I(1)	I(1)	I(1)
LDJ	I(1)	I(1)	I(1)
LKLCI	I(1)	I(1)	I(1)
LEXPY	I(1)	I(1)	I(1)
LIMPY	I(1)	I(1)	I(1)
LIPIMY	I(1)	I(0)	I(1)
LCPIMY	I(1)	I(1)	I(1)
LM1MY	Not Stationary at both I(0) and I(1)	I(1)	I(1)
LM2MY	I(1)	I(1)	I(1)
LOPR	I(1)	I(1)	I(1)
LEXPUS	I(1)	I(1)	I(1)
LIMPUS	I(1)	I(1)	I(1)
LIPIUS	I(1)	I(0)	I(0)
LCPIUS	Not Stationary at both I(0) and I(1)	I(1)	Not Stationary at both I(0) and I(1)
LM1US	I(1)	I(1)	I(1)
LM2US	Not Stationary at both I(0) and I(1)	I(1)	I(1)
LFFER	I(1)	I(1)	I(1)

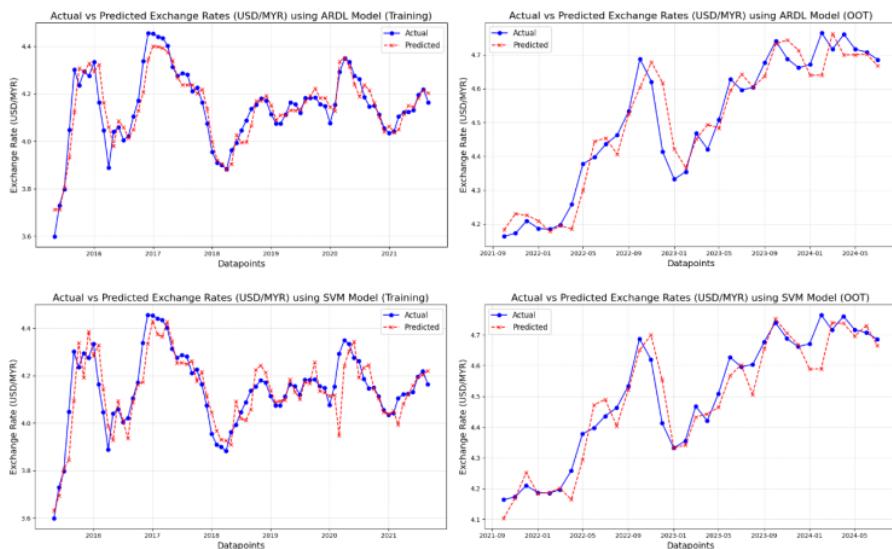
Based on the results from Table 4.2 and Table 4.3, we observed that most of the variables were stationary at I(1), in other words, stationary after first differenced. However, the ADF test had concluded that LM1MY, LCPIUS and LM2US were not stationary at both I(0) and I(1). To meet the assumptions of the ARDL model, we have decided to exclude these three variables. On the other hand, for the other five models—SVM, RF, XGB, LGBM and LSTM, all variables will be included in the modelling.

4.4 Model Evaluation

The selection of the best-performing models was guided by the principle of minimising prediction error. In this study, we were using RMSE as our main criteria.

Models	Best Hyperparameter Tuning
SVM	{'kernel': 'sigmoid', 'C': 0.01, 'epsilon': 0.01}
RF	{'n_estimators': 50, 'max_depth': 10, 'min_samples_split': 2, 'min_samples_leaf': 2, 'max_features': 'sqrt'}
XGB	{'n_estimators': 200, 'learning_rate': 0.01, 'max_depth': 5, 'subsample': 1.0, 'colsample_bytree': 1.0}
LGBM	{'n_estimators': 200, 'learning_rate': 0.01, 'max_depth': -1, 'subsample': 0.8, 'colsample_bytree': 1.0}
LSTM	{'units': 100, 'dropout': 0.3, 'batch_size': 16, 'epochs': 50, 'learning_rate': 0.01}

Table XX shows the best hyperparameter specifications that had been applied for the machine learning models to yield the lowest RMSE.



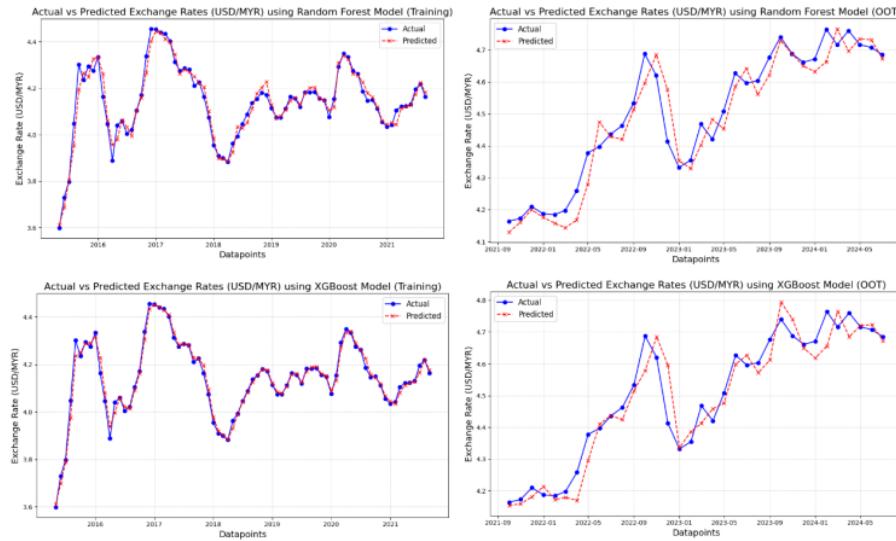


Figure 5 Actual vs Predicted USD/MYR Exchange Rates

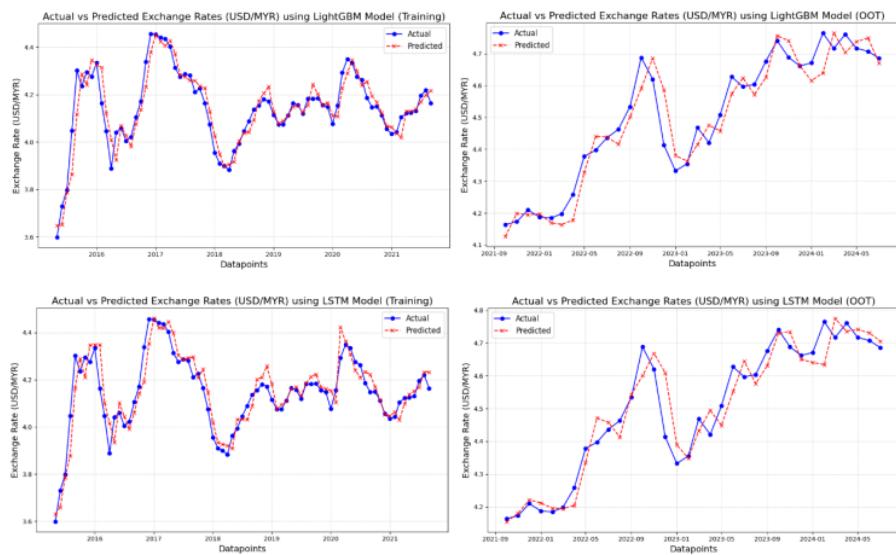


Figure 6 Actual vs Predicted USD/MYR Exchange Rates

Figure xx illustrates that all six models had closely predicted the actual ER values on the data. To evaluate the model performance, we had used the test data which is also

known as out-of-time (OOT) dataset and assessed it using key metrics including RMSE, MAE, MAPE, R² and training time. The detailed results are presented as follows.

Table 0.4 Summary of Model Evaluation Results

Models	RMSE	MAE	MAPE (%)	R ²	Training Time (sec)
ARDL	0.05977	0.04425	0.98253	0.90810	30872.70
SVM	0.05915	0.04291	0.95049	0.91000	1.59
RF	0.05716	0.04555	1.01273	0.91596	175.26
XGB	0.05699	0.04290	0.94695	0.91647	49.95
LGBM	0.05660	0.04513	0.99875	0.91759	17.95
LSTM	0.05823	0.04376	0.96639	0.91277	92.97

Table 4.1 depicted the results of the model comparison for predicting USD/MYR currency exchange rates. Among the six models evaluated, LGBM achieved the lowest Root Mean Square Error (RMSE) of 0.05660 and emerged as the most accurate model. It was followed closely by XGB with an RMSE of 0.05699 and RF at a value of 0.05716. These metrics indicate that these models provide the most precise predictions compared to the others. LSTM and SVM also performed well, with RMSE values of 0.05823 and 0.05915, respectively, while ARDL showed the highest RMSE of 0.05977, suggesting slightly less accurate predictions.

When evaluating the Mean Absolute Error (MAE), XGB and SVM delivered the best results with values of 0.04290 and 0.04291, respectively. These models demonstrated superior performance in capturing the absolute difference between predicted and actual values. ARDL and LGBM followed with slightly higher MAE values of 0.04425 and 0.04513, respectively. RF and LSTM had slightly higher errors, indicating less precise predictions in this regard.

In terms of Mean Absolute Percentage Error (MAPE), which measures prediction error in percentage terms, XGB achieved the lowest error (0.94695%), followed closely by SVM (0.95049%). LGBM, LSTM, and ARDL had slightly higher MAPE values, with

RF recording the highest MAPE (1.01273%). These results suggest that XGB and SVM are particularly effective for applications where percentage-based accuracy is critical.

¹²⁴ The coefficient of determination (R^2) highlights how well each model explains the variance in the data. LGBM showed the best performance with an R^2 of 0.91759, followed closely by XGB (0.91647) and RF (0.91596). ³² These models demonstrated their ability to capture the underlying relationships in the data. SVM and LSTM also performed well, with R^2 values of 0.91000 and 0.91277, respectively. ARDL, while slightly lower with an R^2 of 0.90810, still showed competitive performance.

Finally, the training time for each model varied significantly. LGBM was the fastest, requiring only 17.95 seconds, followed by SVM (1.59 seconds) and XGB (49.95 seconds). These models combine strong performance with computational efficiency, making them practical choices for real-world applications. In contrast, ARDL required the longest training time at 30,872.70 seconds, which may limit its practicality despite its decent performance metrics. RF and LSTM required moderate training times of 175.26 seconds and 92.97 seconds, respectively.

³ In summary, LGBM stood out as the best-performing model, balancing high accuracy and low computational cost. XGB and SVM also demonstrated excellent predictive performance and computational efficiency. While ARDL and LSTM delivered competitive results in terms of accuracy, their longer training times may make them less suitable for time-sensitive applications. RF showed solid performance but lagged slightly behind the top models in terms of accuracy and efficiency. These findings highlight the trade-offs between accuracy and computational cost in selecting the most suitable model for USD/MYR exchange rate prediction.

4.5 Model Interpretation

To understand insights from the models, the results were interpreted using different approaches. Firstly, the coefficients obtained from Autoregressive Distributed Lag (ARDL) models. By analysing these coefficients, the direction and magnitude of the impact of the macroeconomic factors on the USD/MYR exchange rates can be gauged. For instance, a positive coefficient for a macroeconomic variable would suggest that an increase in that variable is associated with an increase in the USD/MYR exchange rates.

Secondly, feature importance. This technique assessed the relative significance of each macroeconomic variable in predicting the USD/MYR exchange rates. It helped to pinpoint the most critical drivers of the fluctuations. Finally, the SHAP (SHapley Additive exPlanations) values. SHAP values provide a game-theoretic approach to explain the contribution of each feature to the prediction for a specific instance. They effectively break down the model's prediction into contributions from each feature, and reveal which features had the greatest impact on the model's decision for that particular observation.

In short, by combining these three methods, a comprehensive understanding of the models was achieved. ARDL coefficients provided insights into the overall relationships between variables, feature importance highlighted the most influential factors while SHAP values offered a detailed explanation of how individual features contributed to specific predictions.

4.5.1 ARDL Coefficients

ARDL Model Results						
Dep. Variable:	LER	No. Observations:	78			
Model:	ARDL(1, 1, 0, 0, 0)	Log Likelihood	219.278			
Method:	Conditional MLE	S.D. of innovations	0.014			
Date:	Mon, 13 Jan 2025	AIC	-422.555			
Time:	21:37:40	BIC	-403.805			
Sample:	05-01-2015 - 09-01-2021	HQIC	-415.055			
	coef	std err	z	P> z	[0.025	0.975]
const	0.3724	0.385	0.967	0.337	-0.395	1.140
LER.L1	0.9217	0.052	17.795	0.000	0.818	1.025
LKLCI.L0	-0.3348	0.068	-4.933	0.000	-0.470	-0.199
LKLCI.L1	0.2302	0.080	2.874	0.005	0.070	0.390
LOPR.L0	0.0418	0.014	2.935	0.005	0.013	0.070
LEXPUS.L0	0.0398	0.026	1.533	0.130	-0.012	0.092
LFFER.L0	-0.0058	0.002	-2.406	0.019	-0.011	-0.001

Figure XX showed the ARDL model results along with the coefficients. The model had obtained an AIC of -422.555 which indicates a reasonably good fit. From the ARDL model results, we can derive several key insights regarding the relationship between the USD/MYR exchange rate and the macroeconomic factors from both Malaysia and the U.S. The analysis is based on the coefficients, significance levels and the logged nature of the variables which means the coefficients can be interpreted as elasticities.²³⁷

First, the 1-month lagged exchange rate (LER.L1) has a highly significant positive coefficient of 0.9217 (p-value < 0.001) which indicates a strong persistence in the exchange rate over time. This suggests that the USD/MYR exchange rate is highly dependent on its own past values. It directly reflects the inertia or stickiness in exchange rate movements. This is a common characteristic in exchange rate modelling where historical rates heavily influence current values.¹²

Second, the current value of the Kuala Lumpur Composite Index (LKLCI.L0) has a significant negative impact on the USD/MYR exchange rate, with a coefficient of -0.3348 (p-value < 0.001). This implies that an increase in the LKLCI, which represents the performance of the Malaysian stock market, is associated with an appreciation of the Malaysian ringgit (a decrease in the USD/MYR rate). Conversely, the lagged value of the LKLCI (LKLCI.L1) has a positive and significant effect, with a coefficient of 0.2302 (p-value = 0.005). This indicates that while current stock market performance strengthens the ringgit, past performance has a delayed weakening effect which possibly reflects lagged investor reactions or delayed impacts on the economy.

Third, the current Overnight Policy Rate (OPR.L0), representing Malaysia's interest rate, has a small but significant positive effect (coefficient = 0.0418, p-value = 0.005). This indicates that an increase in the interest rate leads to a depreciation of the Malaysian ringgit relative to the USD. This is contrary to traditional economic theory which suggests that higher interest rates should attract capital inflows and strengthen the local currency. This counterintuitive result could reflect unique market conditions such as capital flight or higher inflation expectations offsetting the interest rate impact.

Fourth, the coefficient for the current U.S. Federal Funds Effective Rate (FFER.L0) is negative (-0.0058), which means that an increase in the U.S. Federal Funds Effective Rate is associated with a decrease in the USD/MYR exchange rate (an appreciation of the Malaysian ringgit relative to the U.S. dollar). This result is counter to conventional expectations which usually suggest that higher U.S. interest rates would attract capital to U.S. assets and strengthen the U.S. dollar. This phenomenon may result from capital flows to other emerging markets which are more attractive.

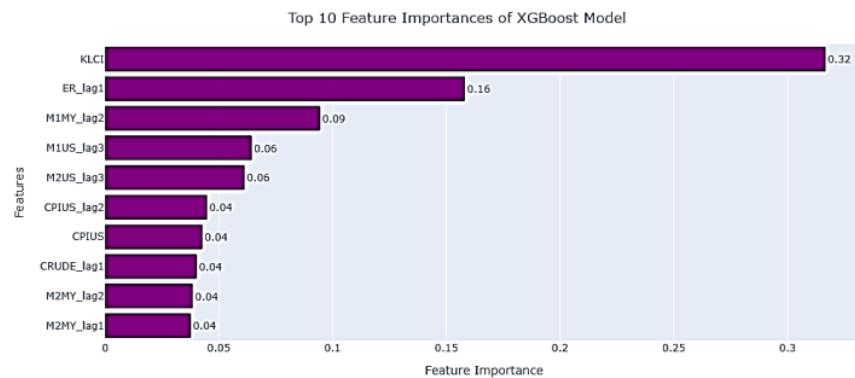
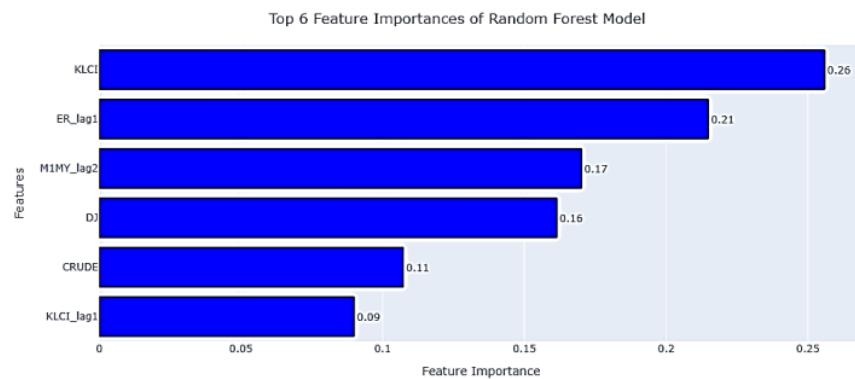
Finally, the coefficient for U.S. exports (LEXPUS.L0) is positive but not statistically significant (p-value = 0.133). This implies that, while there may be some positive

relationship between U.S. exports and the USD/MYR exchange rate, the evidence is not strong enough to draw definitive conclusions. This variable may require further investigation or refinement to better capture its impact on exchange rate movements.

Overall, the results highlighted the importance of both domestic (LKLCI, OPR) and international (FFER) macroeconomic factors in influencing the USD/MYR exchange rate.

63 4.5.2 Feature Importance

Feature importance indicates how much each feature contributes to the model prediction. It determines the usefulness of a specific variable for the predictions.



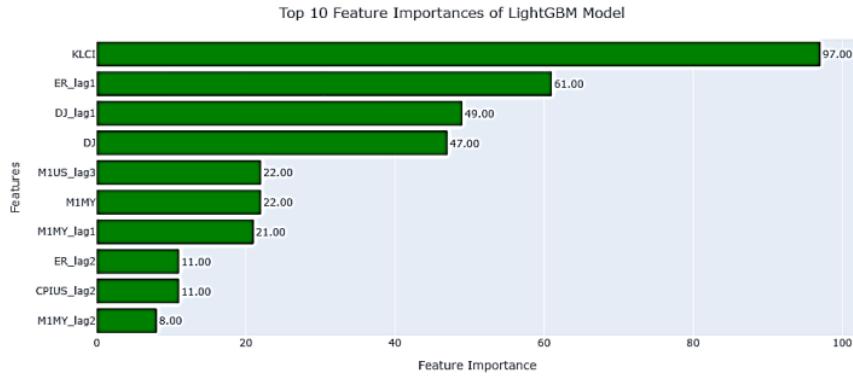


Figure 7 Feature Importance Charts (RF, XGB, LGBM)

The feature importance charts for the LightGBM, XGBoost and Random Forest models highlighted the relative contribution of each feature in predicting the target variable.

For the LightGBM model, the most important feature was KLCI which dominates with a significant contribution to predictions. The second most influential feature is ER_lag1, although its importance is much lower than KLCI. Other notable features include DJ_lag1 and DJ, which also play an important role. Features such as M1US_lag3, M1MY and M1MY_lag1 show moderate importance while lower importance is assigned to variables like ER_lag2, CPIUS_lag2 and M1MY_lag2.

In the XGBoost model, KLCI remains the most critical feature and mirrors its importance in the LightGBM model. ER_lag1 also emerges as a significant contributor, though its importance is about half that of KLCI. Features like M1MY_lag2, M1US_lag3 and M2US_lag3 show moderate importance. Meanwhile, features such as CPIUS_lag2, CPIUS, CRUDE_lag1 and M2MY_lag2 have lower but non-negligible importance, contributing less to the model's predictions.

The Random Forest model also identifies KLCI as the most important feature, although its contribution is slightly lower than in the other models. ER_lag1 ranks as the

second most critical feature, consistent with the LightGBM and XGBoost results. M1MY_lag2 and DJ also contribute meaningfully, while features like CRUDE and KLCI_lag1 have lower but still relevant importance.

When comparing the models, KLCI consistently emerges as the most influential feature, underscoring its strong impact on the target variable. ER_lag1 is the second most important feature across all three models, indicating the critical role of recent exchange rate movements in predictions. Other features such as DJ, M1MY_lag2 and M1US_lag3 show moderate importance across the models while features like CPIUS_lag2 and CRUDE generally contribute less.

In conclusion, the dominance of KLCI suggests that stock market performance, as represented by KLCI, is a key driver in predicting the USD/MYR currency exchange rates. The consistent contribution of lagged variables such as ER_lag1, DJ_lag1 and M1MY_lag2 highlights the value of historical data in modelling. The similar patterns observed across all three models reinforced the robustness of the identified key features.

1 4.5.3 SHAP Values

SHAP (SHapley Additive exPlanations) values are a tool for interpreting machine learning models and provide insights into the contribution of each feature to a model's predictions. They provide both global and local insights into model behaviour to enhance transparency and trust in machine learning applications.

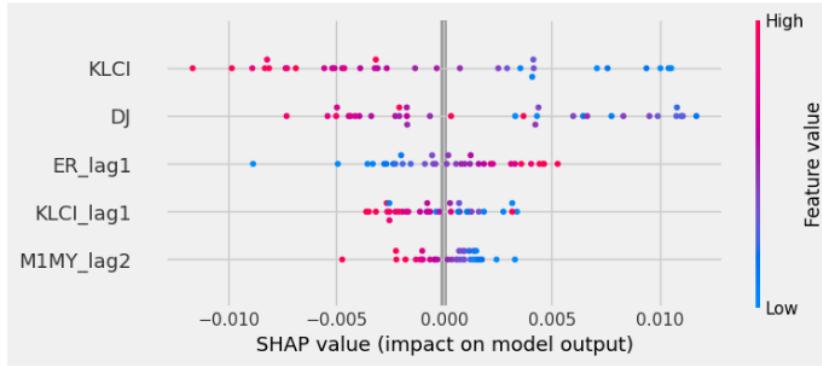


Figure 8 SHAP Summary Plot (SVM)

The SHAP Summary Plot derived from the SVM model in Figure provides insights ²⁹ into the influence of various features on the USD/MYR exchange rate predictions. Among the features, KLCI emerges as the most influential, with both strong positive and negative ¹⁷⁹ impacts on the model's output, as indicated by the wide range of SHAP values. This suggests that fluctuations in KLCI significantly affect the exchange rate predictions, underscoring its critical role in the model.

The DJ (Dow Jones Index) and ER_lag1 (1-month lag of the exchange rate) also exhibit moderate influence. Notably, higher values of ER_lag1 (red dots) are associated ²⁷ with positive impacts on the predicted exchange rate, highlighting the importance of recent exchange rate movements in shaping future trends.

In contrast, features like KLCI_lag1 (1-month lag of KLCI) and M1MY_lag2 (2-month lag of Malaysia's money supply, M1) show relatively low SHAP values concentrated around zero. This indicates that these features have limited overall impact on the predictions, although they may contribute marginally in specific instances.

Overall, the analysis highlights the dominance of KLCI and the relevance of ER_lag1 in the SVM model's predictive framework, while other features play secondary or minimal roles. This information can guide further feature selection and interpretation of macroeconomic factors affecting the USD/MYR exchange rate.

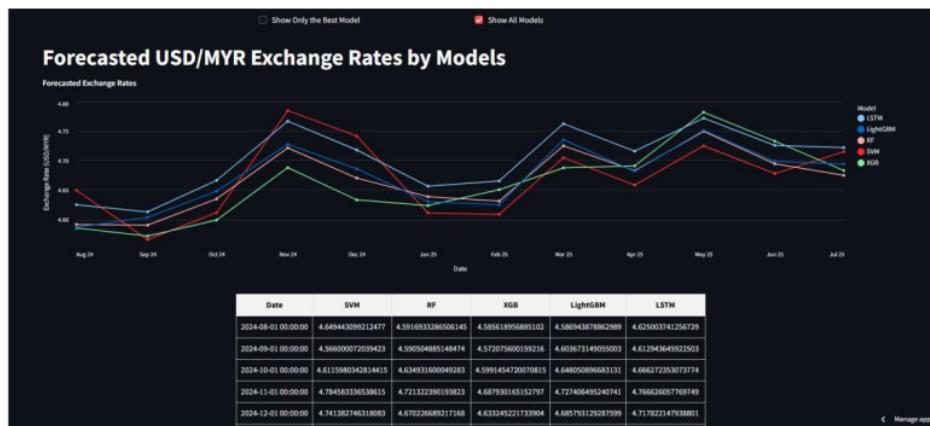
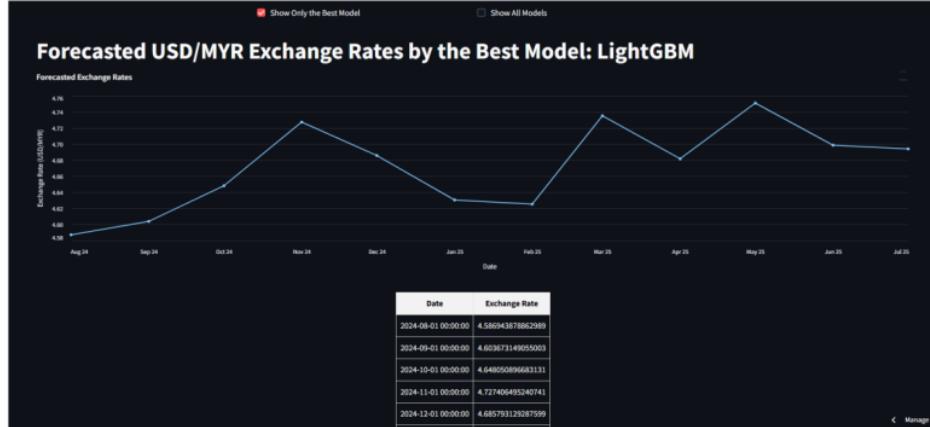
4.6 Deployments

The whole study was deployed in the Streamlit application at <https://usd-myrmodelling.streamlit.app/> where it provides the users an overview of the research, flexibility to interact with the data and apply the current macroeconomic factors to forecast the future USD/MYR currency exchange using the pretrained models.



Figure XX shows the landing page for the Streamlit application. The application is divided into five sections, namely “About”, “Dashboard”, “Forecasting Model”, “Source Codes” and “Contact Me”.

“About” page features a slide presentation to provide the users a glimpse into the background of the study and methodologies used. In the “Dashboard” section, users can interact with the data to create visualisations and generate ACF, PACF plots as well as decomposition graphs for each time series variable. “Forecasting Model” section will be the place for the users to use the current macroeconomic factors to predict the future currency exchange rates.



“Source Codes” section directs the users to the Github repository where all the Python and Streamlit working files are deposited. Last but not least, “Contact Me” section allows the users to direct any feedback or queries should they encounter difficulties in accessing the app or have new ideas for further improvements.

4.6 Benchmarking Against Other Studies

Studies	Models	RMSE	MAE	MAPE (%)	R ²	Observations
(Biswas et al., 2023)	LSTM	0.2526	-	0.244	0.9016	Surpassed the study in terms of RMSE and R ²

(Johari et al., 2021)	ARDL	0.1342	-	-	-	Surpassed the study in term of RMSE
(Erçen et al., 2022)	SVM	0.2252	-	3.906	0.9246	Surpassed the study in terms of RMSE and MAPE
(Joseph et al., 2022)	BPNN	0.3227	0.2897	7.000	0.846	Surpassed the results of neural network model for all metrics
This Research	ARDL	0.05977	0.04425	0.98253	0.9081	
	SVM	0.05956	0.04534	1.00007	0.90875	
	RF	0.05716	0.04555	1.01273	0.91596	
	XGB	0.05699	0.0429	0.94695	0.91647	
	LGBM	0.0566	0.04513	0.99875	0.91759	
	LSTM	0.05798	0.04318	0.95324	0.91354	

90 Table XXX compares the performance of various models developed in this research with those from prior studies for modelling USD/MYR exchange rates and macroeconomic factors. Metrics such as RMSE, MAE, MAPE and R² were used for evaluation. Among the previous studies, (Biswas et al., 2023) achieved an RMSE of 0.2526, a MAPE of 0.244% and an R² of 0.9016 using the LSTM model. (Johari et al., 2021) reported an RMSE of 0.1342 for their ARDL model. (Erçen et al., 2022) achieved an RMSE of 0.2252, a MAPE of 3.906% and an R² of 0.9246 with SVM. (Joseph et al., 2022) reported an RMSE of 0.3227, a MAE of 0.2897, a MAPE of 7.000% and an R² of 0.846 for their BPNN model.

In contrast, the models developed in this research demonstrated superior performance across all metrics. The ARDL model achieved an RMSE of 0.05977, a MAE of 0.04425, a MAPE of 0.98253% and an R² of 0.9081. The SVM model produced an RMSE of 0.05956, a MAE of 0.04534, a MAPE of 1.00007% and an R² of 0.90875. The Random

³ Forest (RF) model achieved an RMSE of 0.05716, a MAE of 0.04555, a MAPE of

²¹ 1.01273% and an R² of 0.91596. The XGBoost (XGB) model showed strong performance

³ with an RMSE of 0.05699, a MAE of 0.0429, a MAPE of 0.94695% and an R² of 0.91647.

³ The LightGBM (LGBM) model recorded the lowest RMSE of 0.0566, a MAE of 0.04513,

a MAPE of 0.99875% and an R² of 0.91759 which makes it the best-performing model

³ overall. Lastly, the LSTM model achieved an RMSE of 0.05798, a MAE of 0.04318, a

MAPE of 0.95324% and an R² of 0.91354.

These findings highlight the effectiveness of the models developed in this research in

⁶¹ capturing complex relationships between macroeconomic variables and exchange rates.

The results had also demonstrated significant improvements compared to prior studies.

²²⁹ 4.7 Summary

In this chapter, the results were discussed and benchmarked against previous studies.

²⁰ LightGBM had outperformed the other models achieving the lowest RMSE of 0.0566 and

the highest R-squared value of 0.91759. Lagged values of the USD/MYR currency

exchange rates and KLCI were proven to be the two key macroeconomic factors that

influence future currency exchange rates.

5.1 Introduction

In this chapter, an overall summary of this study is provided basically aiming in addressing the research objectives. The chapter is also accompanied by the limitations, lesson learned and future works that can be done.

5.2 Revisiting the Objectives

The objectives at Chapter 1 were revisited to identify if they had been achieved.

5.2.1 Objective 1

The first objective is to investigate the influence that each identified macroeconomic factor has on the paired exchange rates between United States and Malaysia.

As informed by the results returned from the models, the study has identified the Kuala Lumpur Composite Index (KLCI), Malaysia's primary stock market index, as a pivotal factor influencing the USD/MYR exchange rate. The KLCI serves as a barometer of Malaysia's economic and financial health, reflecting investor sentiment and market performance. Its significant impact suggests that fluctuations in Malaysia's financial markets, as captured by the KLCI, are closely linked to exchange rate movements. A robust stock market may strengthen the MYR by attracting foreign investments, while a declining market may have the opposite effect.

Additionally, the inclusion of lagged exchange rate values for the past one month (ER_lag1) underscores the autoregressive nature of exchange rates, where past trends and movements strongly inform future predictions. This highlights the importance of historical data in understanding currency dynamics and demonstrates that exchange rates often exhibit persistence over time.

Monetary policy variables, specifically the Overnight Policy Rate (OPR) for Malaysia
²³ and the Federal Funds Effective Rate (FFER) for the United States, emerge as critical determinants in exchange rate fluctuations. The ARDL model shows clear directional impacts which suggests that changes in these rates influence capital flows and investor behaviour. As Malaysia's central bank adjusts the OPR, it directly impacts the attractiveness of the MYR. Higher OPR levels may attract foreign investors seeking better returns on Malaysian assets, leading to MYR appreciation. Conversely, lower OPR levels may result in capital outflows and MYR depreciation. Changes in the US Federal Reserve's interest rate policy have global ramifications that affects the demand for the USD. A rise in FFER typically strengthens the USD against other currencies including the MYR due to increased investor interest in US-denominated assets.

While less dominant, commodity prices (CRUDE) and inflation rates (CPIUS & CPIMY) were also found to influence the exchange rate to a relatively smaller extent. As Malaysia is a net exporter of crude oil, changes in global oil prices can impact the trade balance and currency valuation. However, the study suggests that these effects are relatively modest compared to financial and monetary factors.

¹ Differences in inflation rates between the two countries affect purchasing power parity (PPP)¹⁰⁴ which in turn influences the exchange rate. The smaller influence of inflation in this study could be due to the relatively stable inflationary environment during the observed period.

These findings emphasise the dominance of financial market dynamics and monetary policies in shaping the USD/MYR exchange rate. Policymakers and market participants should prioritise monitoring financial market performance and central bank policies when analysing or forecasting exchange rate movements. Additionally, the observed secondary

influences of commodity prices and inflation rates suggest that while these factors are relevant, they may not be the primary drivers in the context of USD/MYR exchange rates.

192 This study provides a comprehensive framework for understanding and forecasting exchange rate dynamics. These insights can aid in designing more effective economic policies and investment strategies.

9 **5.2.2 Objective 2**

The second objective is to develop an econometric model that can predict the USD/MYR exchange rates using macroeconomic indicators.

This objective was achieved through a systematic approach involving model training, evaluation and deployment. Six distinct models were trained using a dataset spanning from January 2015 to October 2021. This period served as the training phase, where the models learned the underlying patterns and relationships between macroeconomic indicators and exchange rates. The models were then tested on unseen data from November 2021 to July 2024, enabling an assessment of their performance in real-world scenarios. This division ensured a rigorous evaluation of the models' generalisation capabilities and adaptability to new data.

The Support Vector Machine (SVM) model was included for its ability to identify patterns in high-dimensional spaces. Random Forest was chosen for its effectiveness in reducing overfitting and handling interactions between variables. Gradient boosting models such as XGBoost and LightGBM were utilised for their speed, accuracy and capacity to handle large datasets. Lastly, a Long Short-Term Memory (LSTM) model was used to capture temporal dependencies and trends in sequential data.

21 Model performance was compared using a comprehensive set of evaluation metrics. Root Mean Squared Error (RMSE) measured the average magnitude of prediction errors,

penalising larger errors more heavily. Mean Absolute Error (MAE) provided an average⁹² of absolute differences between predicted and actual values. Mean Absolute Percentage Error (MAPE) offered a percentage-based assessment of prediction accuracy, useful for interpreting errors relative to actual values. Finally, the R² (Coefficient of Determination)¹³ indicated the proportion of variance in exchange rates explained by each model. This comparison allowed for a balanced evaluation of the predictive accuracy and robustness of each model.

To enhance the usability and accessibility of these predictive models, a dashboard and forecasting application was developed using Streamlit. This platform provided an intuitive interface for users to input macroeconomic variables and generate exchange rate forecasts. By enabling users to generate forecasts based on updated macroeconomic data, the app supported informed decision-making for investors, policymakers and businesses.

This multi-model approach demonstrated the effectiveness of combining traditional econometric techniques with advanced machine learning methods for exchange rate prediction. The integration of these models into a user-friendly application bridged the gap between complex modelling and practical decision-making. This comprehensive framework not only achieved the research objective but also set a foundation for future advancements in exchange rate forecasting.

5.2.3 Objective 3

The third objective is to evaluate the performance of different econometric models in forecasting the USD/MYR exchange rates.⁶¹

A total of six models were assessed, including ARDL, SVM, Random Forest (RF), XGBoost, LightGBM and LSTM. Each model was trained on a dataset spanning January 2015 to October 2021 and tested on unseen data from November 2021 to July 2024.²³⁹

³³
Performance was measured using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and R². Additionally, training time was recorded to evaluate computational efficiency.

The ARDL model demonstrated robust explanatory power with an R² of 0.9081, indicating its ability to explain 90.81% of the variance in exchange rates. However, its training time was significantly longer (30,872.70 seconds) compared to other models due to the complexity of estimating long- and short-term relationships. SVM performed well, achieving an R² of 0.91 and the lowest MAE and MAPE among all models. Its training time was remarkably short (1.59 seconds) which makes it an efficient choice for quick implementations.

Random Forest achieved a strong R² of 0.91596, balancing accuracy with moderate training time (175.26 seconds). While its MAPE was slightly higher than other models, its robust performance and efficiency make it a reliable choice. XGBoost emerged as one of the top-performing models, with the lowest RMSE (0.05699) and MAPE (0.94695%) while maintaining a reasonable training time of 49.95 seconds. LightGBM performed exceptionally well in achieving the highest R² (0.91759) and competitive RMSE and MAE values. Its fast-training time (17.95 seconds) further enhanced its suitability for practical applications.

LSTM also delivered strong results, with an R² of 0.91277 and competitive RMSE and MAPE values. While its training time (92.97 seconds) was higher than XGBoost and LightGBM, LSTM's ability to capture temporal dependencies makes it a valuable model ³ for time-series forecasting. The results underscore the trade-offs between accuracy and computational efficiency across models. While ARDL offers interpretability and insights into relationships, machine learning models like XGBoost and LightGBM excel in predictive accuracy and efficiency.

In conclusion, XGBoost and LightGBM were identified as the most effective models for forecasting USD/MYR exchange rates due to their high accuracy, efficiency and ability to handle non-linear relationships. LSTM offers potential for sequential data modelling and ARDL provides insights into macroeconomic relationships, making it useful for understanding drivers of exchange rate movements. These findings provide a foundation for selecting appropriate models based on specific forecasting needs and resource constraints. SVM and LSTM have competitive RMSE values but slightly lower R² scores and efficiency. ARDL has good predictive accuracy but it is significantly slower to train with a long training time of 30,872.7 seconds. This makes it less practical for large-scale applications.

5.3 Implications of Results

5.4 Lessons Learned

5.5 Limitations

The study presents several limitations that should be considered when interpreting the results. Firstly, it does not account for the influence of unexpected geopolitical events, natural disasters or other external shocks that can significantly impact exchange rates.

¹These unforeseen events, such as wars, political instability or pandemics, can trigger sudden shifts in investor sentiment and risk appetite, leading to volatile currency movements. Additionally, the study's limited inclusion of market sentiment indicators and other qualitative variables may result in an incomplete understanding of exchange rate dynamics. Market sentiment, often driven by investor fear, greed and herd behavior, plays a crucial role in currency markets. Excluding indicators such as investor confidence indices, volatility indices and news sentiment analysis may limit the study's ability to fully capture the complexities of exchange rate determination.

Secondly, the models developed in this study, specifically trained on the USD/MYR exchange rate, may exhibit limited generalizability to other currency pairs or different time periods. The dynamics of different currency pairs are influenced by unique economic, political and financial factors. A model trained on the USD/MYR pair may not accurately predict the behaviour of other pairs, such as EUR/USD or GBP/JPY, which may exhibit different patterns and sensitivities to economic indicators. Furthermore, economic conditions, market structures and investor behaviour can evolve significantly over time. Models trained on historical data may not be robust enough to adapt to changes in economic regimes, such as shifts in monetary policy, changes in trade relationships and ¹⁸⁷ the emergence of new financial instruments. The generalizability of the models may also be constrained by the availability and quality of historical data. If the data used for model training is limited in scope or suffers from significant data gaps, ²²¹ the model's ability to accurately predict future exchange rates may be compromised.

These limitations highlight the need for further research that incorporates a broader range of factors and considers the potential for model instability over time.

5.6 Future Works

Future research could benefit from the inclusion of new variables to enhance the understanding and predictive capabilities of models analysing USD/MYR exchange rates.

¹² One way is the extraction of sentiment data from financial news or social media platforms using natural language processing (NLP) techniques. Sentiment data can capture market participants' perceptions and reactions to economic developments, policy announcements or geopolitical events. For instance, an increase in negative sentiment surrounding economic uncertainty or political instability could be a leading indicator of currency depreciation. By leveraging NLP tools, such as sentiment scoring or topic modelling,

researchers can quantify these qualitative factors and integrate them as predictors in econometric or machine learning models.

Additionally, incorporating geopolitical risk indices, such as the Baker-Bloom-Davis Economic Policy Uncertainty Index, could provide a systematic measure of uncertainty and risk perception. These indices are derived from news-based data and reflect the frequency of discussions about economic policy-related uncertainties. By including such indices, models can better capture the influence of external shocks and policy-related uncertainties on exchange rate movements. These variables, when combined with traditional macroeconomic indicators, can significantly enhance the robustness and relevance of exchange rate models.

Scenario-based modelling offers another compelling approach for advancing the analysis of USD/MYR exchange rates. This method involves simulating hypothetical scenarios that represent significant macroeconomic changes, such as policy shifts, trade disruptions or sudden changes in commodity prices. By evaluating the model's response to these scenarios, researchers can assess its adaptability and robustness in dynamic and uncertain environments. For example, a scenario simulating a sharp increase in interest rates in the United States could reveal the sensitivity of the USD/MYR exchange rate to monetary policy changes.²¹⁴

Such simulations also enable the evaluation of policy impacts and stress testing under extreme conditions, providing valuable insights for policymakers and stakeholders. Moreover, scenario-based modelling can help identify potential vulnerabilities in the model's structure and improve its flexibility by allowing adjustments to better capture non-linear and abrupt changes in economic relationships. By combining scenario analysis with advanced modelling techniques, researchers can ensure their models remain relevant

and effective in forecasting exchange rate dynamics amidst evolving global and local economic landscapes.

5.7 Summary

In conclusion, this study has evaluated the performance of multiple econometric and machine learning models including ARDL, VAR, Random Forest, XGBoost and SVM in modelling the relationship between macroeconomic factors and the USD/MYR exchange rate. Given the critical importance of exchange rate prediction for economic policy and financial decision-making, understanding the effectiveness of these models is important. This research confirms that ARDL is particularly effective for capturing both short-term dynamics and long-term equilibrium relationships while machine learning models like XGBoost demonstrated strong predictive accuracy due to their ability to handle non-linear interactions and feature importance. Random Forest and SVM, while slightly less precise, they were still managed to offer robust alternatives with varying strengths in handling complex relationships and overfitting challenges.

These findings underscore the value of integrating econometric insights with advanced machine learning techniques to enhance exchange rate forecasting accuracy.

Future research should focus on further refining these models, exploring additional macroeconomic variables and assessing their applicability in different exchange rate regimes. The comprehensive preprocessing of time series data, including stationarity transformations and hyperparameter tuning, simplifies the implementation and ensures scalability in real-world financial and policy environments. This integrative approach contributes significantly to the field of exchange rate modelling, providing actionable insights for policymakers, investors and researchers.

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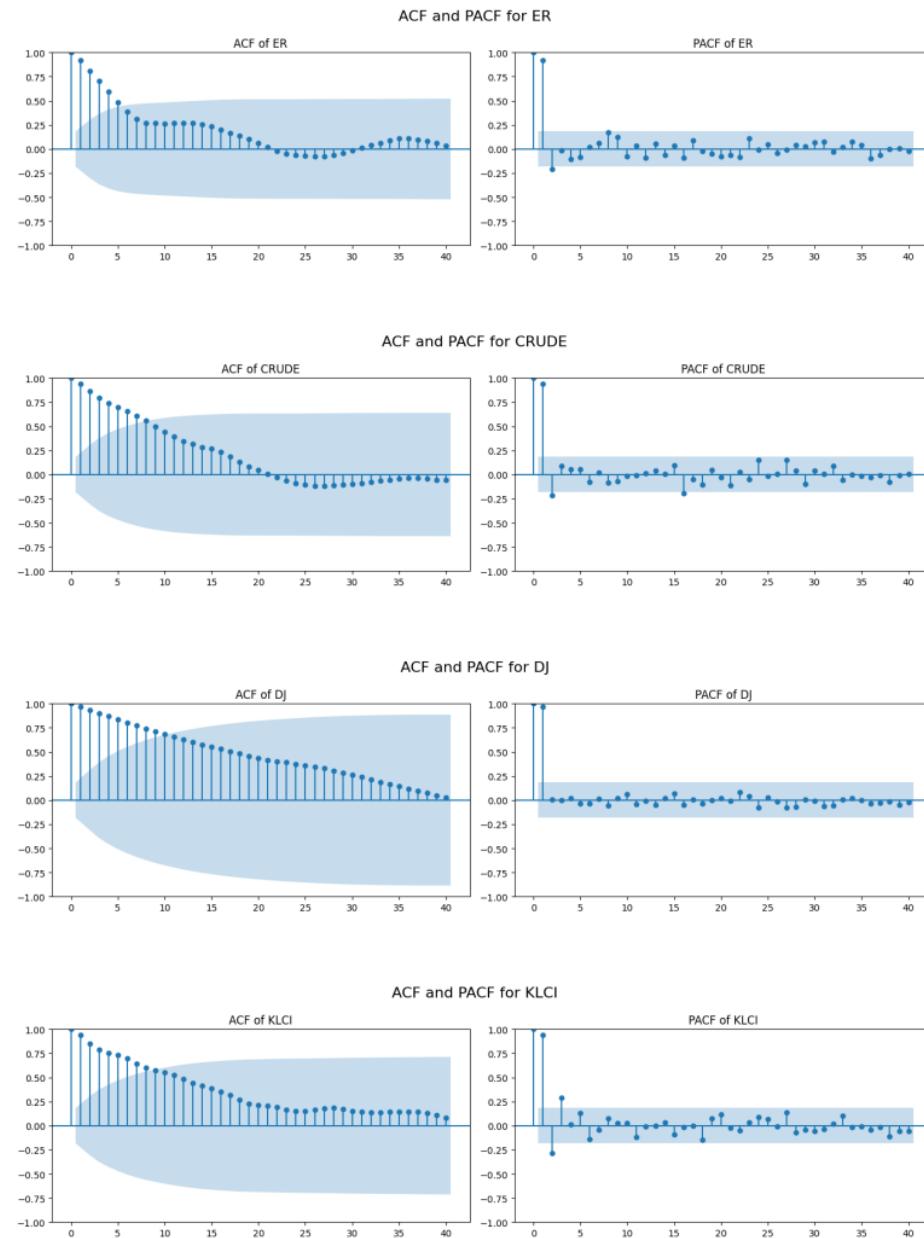
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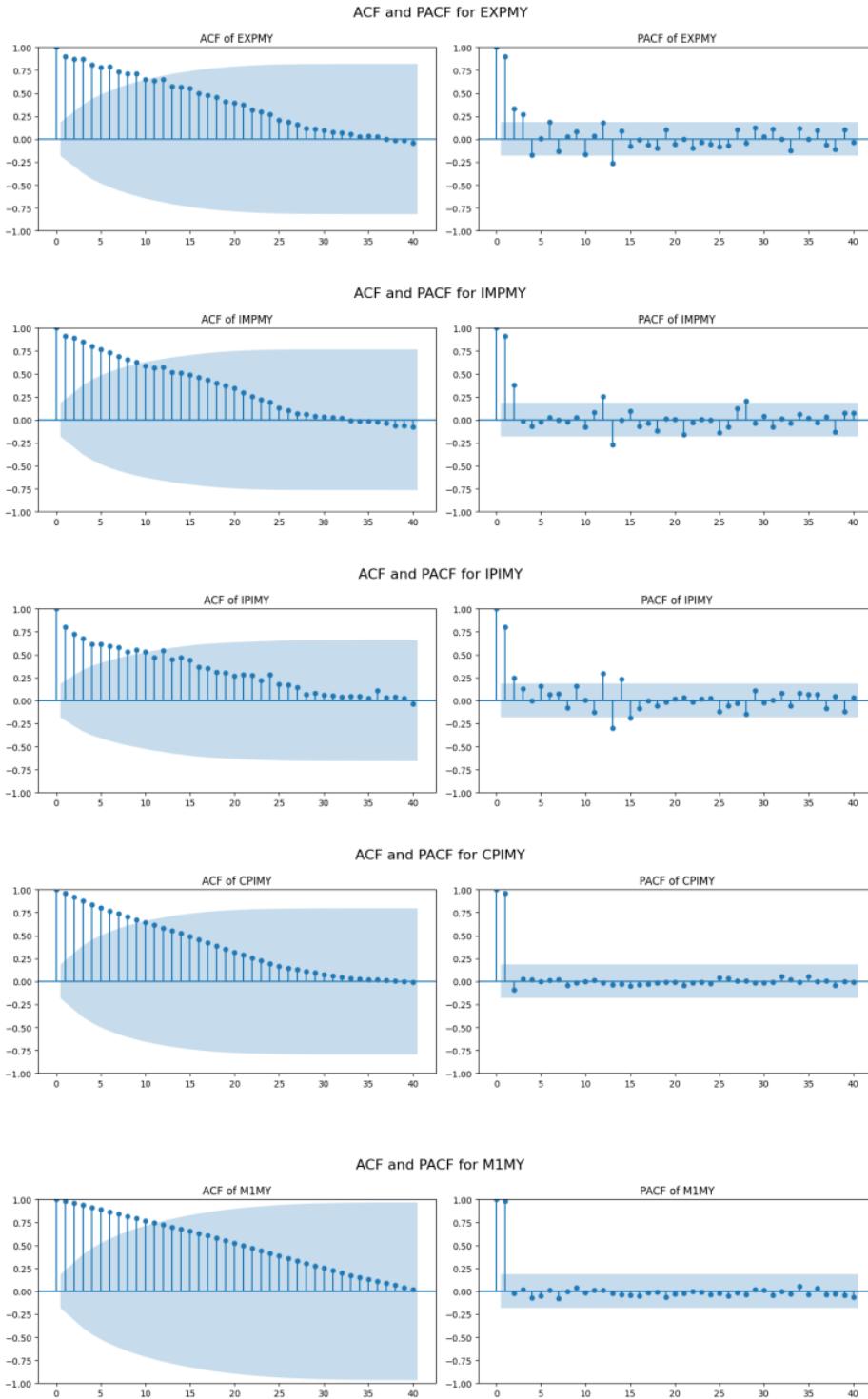
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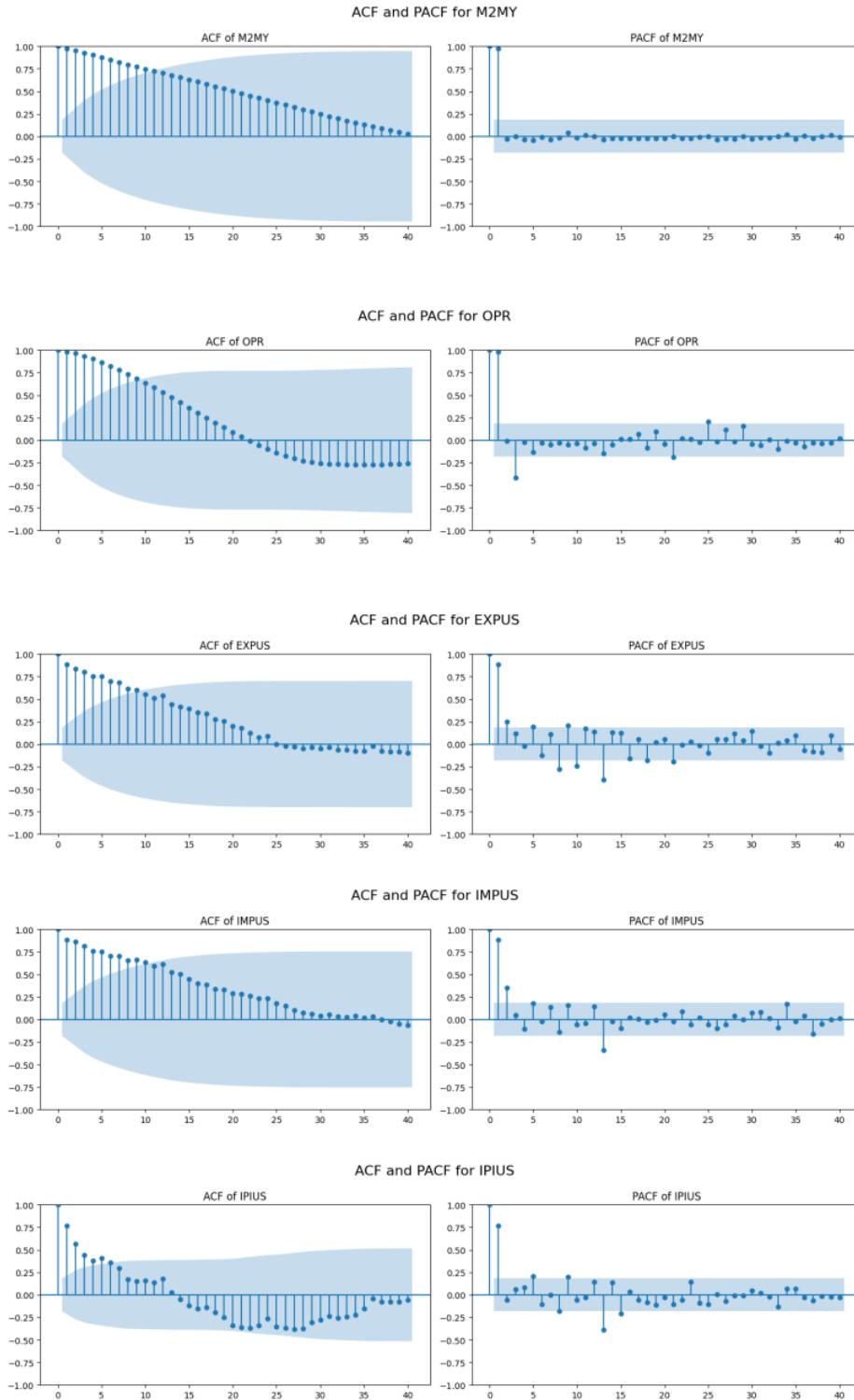
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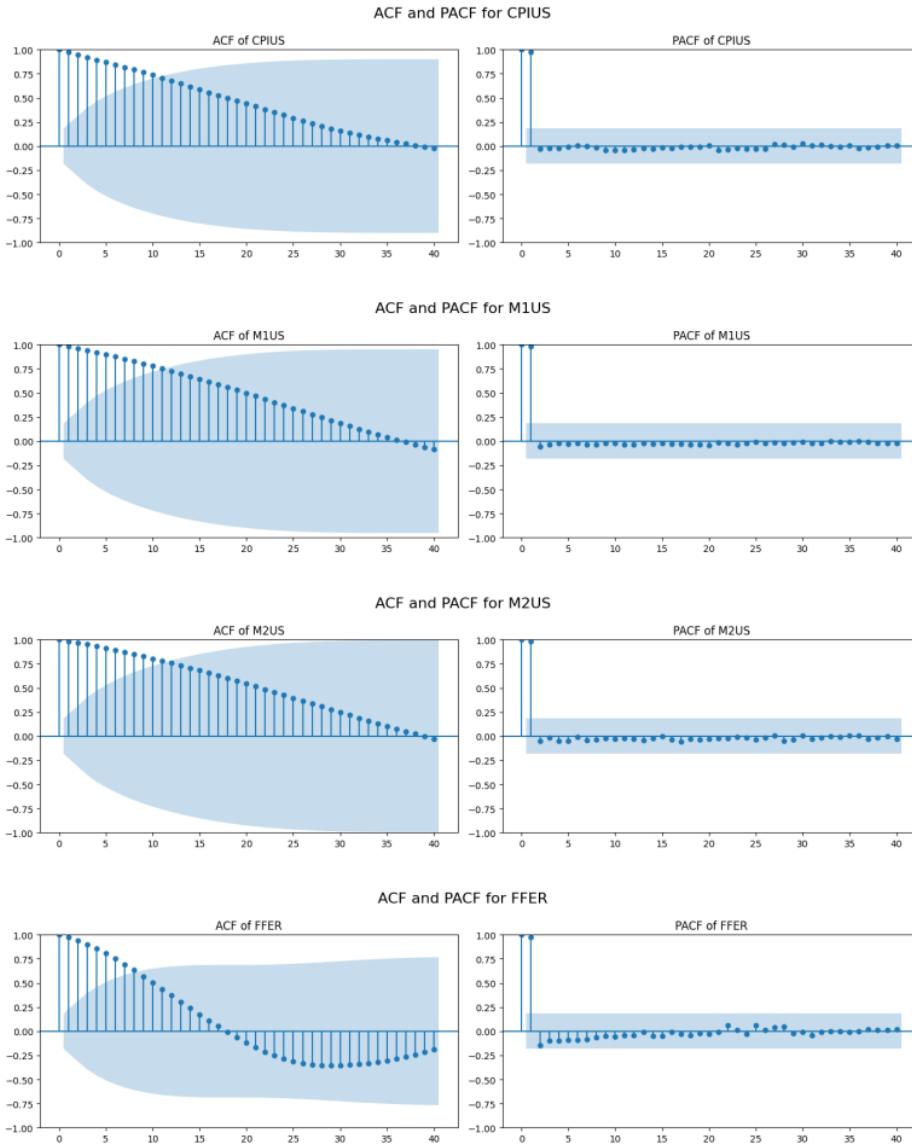
APPENDIX

Appendix A: ACF and PACF Plots









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