REGIME SWITCHES IN THE EXCHANGE RATE OF PAKISTAN: LOOKING FOR A BETTER FORECAST USING MARKOV- REGIME SWITCHING MODELS

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CERTIFICATE

This is to certify that this thesis entitled: **"Regime Switches in the Exchange Rate of Pakistan: Looking for A Better Forecast Using Markov- Regime Switching Models"** submitted by **Ms. Sara Bibi** is accepted in its present form by the School of Economics, Pakistan Institute of Development Economics (PIDE), Islamabad as satisfying the requirements for partial fulfillment of the degree in Master of Philosophy in Economics and Finance.

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Author's Declaration

I, Sara Bibi, hereby state that my MPhil thesis titled "Regime Switches in the Exchange Rate of Pakistan: Looking for a Better Forecast Using Markov Switching Models" is my own work and has not been submitted previously by me for taking any degree from Pakistan Institute of Development Economics or anywhere else in the country/world.

At any time if my statement is found to be incorrect even after my Graduation the university has the right to withdraw my MPhil degree.

Date: July 7, 2022

Signature of Student

Name of Student

Sara Bibi

Dedication

To my Parents,

To my Siblings,

To my Friends,

To my teachers

And to all those who indirectly have been influencing me to be what I am today.

ACKNOWLEDGEMENTS

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ABSTRACT

Volatility is integral characteristic of financial markets all over the world. Exchange rates of Pakistan have been highly volatile since last two quarters. The volatility of exchange market is more sensitive to bad news but resilient to good news, indicating that investors are more likely to be impacted by bad news than by good news. In this study, the data of Nominal exchange rate returns have been used to conduct analysis on the basis of GARCH-type models. To examine model effects under various distributions and orders for the sample series, we developed the autoregressive moving average (ARMA)-Generalized Autoregressive Conditional Heteroscedasticity model. We also choose a threshold-GARCH (T-GARCH) model, in contrast, to reflect the asymmetry characteristics of the financial-returns series. Furthermore, Markov switching GARCH model has been used to model volatility while being in two different states. Additionally, to analyze the error level and prediction results of various models, mean squared error (MSE), mean absolute error (MAE), and root-mean-square error (RMSE) are used. The results prove that the MS-GARCH model under Generalized-Error-Distribution outperforms other proposed models when predicting the Exchange rate returns series. According to our findings, switching models tend to hold good predictive powers in short term only. They may fail in long term i.e., more than a year.

Keywords: Nominal exchange rate, GARCH, volatility, Regime switching, forecast.

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LIST OF ABBREVIATIONS

APARCH	Asymmetric Power Autoregressive Conditional Heteroscedasticity
ARCH	Autoregressive Conditional Heteroscedasticity
ARCH-LM	Autoregressive Conditional Heteroscedasticity Lagrange Multiplier
ARMA	Autoregressive Moving Average
FMCG	Fast Moving Consumer Goods
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GDP	Gross Domestic Product
MS-GARCH	Markov Switching Generalized Autoregressive Conditional Heteroscedasticity
MSM	Markov Switching Models
T-GARCH	Threshold Generalized Autoregressive Conditional Heteroscedasticity

CHAPTER 1

INTRODUCTION

Pakistan is a small open economy where informal sector has its major portion contributing in it. Quarter 1 of fiscal year 2022 has seen inflation rates at 8.6 as compared to 8.8 in the same quarter of fiscal year 2021. The economy has been under strict pressures of rising Fast Moving Consumer Goods (FMCG) demand due to up-surge of Covid-19. Energy inflation also rose due to increasing oil prices in global market. Increasing urban population and pressures on transit has higher energy demands to meet. Increasing demand, followed by all-the-time high prices, imposed import burden of US$ 17.5 billion[1]. These increasing demands with unchanging supplies in international markets has led to rupee devaluation as exchange rates had been very fluctuating in this whole time and showed a 7.7% depreciation in that quarter. Additional challenges arising from global logistics, particularly transportation bottlenecks, are contributing to the already-increasing pressure on costs. In countries like Pakistan, monetary policies are devised targeting the inflation. Therefore, fluctuations in exchange rate must be taken into account as they influence price levels in the economy.

Foreign exchange rates are defined as the price of a specific economy's money relative to another economy's money (Britannica). Foreign exchange rates are referred to as "floating" when aggregate supply and aggregate demand or future speculation influence them (conversion units). Imported goods will become more expensive for domestic consumers if a country imports a lot of goods because of increased demand, which will increase the country's exchange rate. As prices rise, demand declines, and the value of the national currency declines in relation to the currencies

[1] Facts and figures obtained from State Bank of Pakistan's review on State of the Economy.

of other nations, products become more expensive. The cost of the nation's goods decreases to international consumers, demand rises, and exports rise. For developing economies, where domestic consumption cannot be met by domestic production and need for importing goods arises, the impact reflects in domestic goods prices causing an inflationary pressure on the economy.

While addressing the problem of inflation, standard of living comes to mind. And to maintain the standard for a longer time, one needs to spend within his budget and maintain savings. This can only be done when the market prices in any economy are stable. As defined by Jason Fernando, “The consumer price index (CPI) statistics do not include rural populations, farm families, the armed forces, people who are currently incarcerated, or patients in mental hospitals who are unable to produce for the economy. Instead, they cover professionals, the self-employed, unemployed, people with incomes below the national poverty threshold, and retirees in the country”. The changes in price level of any economy are reflected in inflation rate. This rate then helps us forecast or foresee the situation economy will be facing after slight changes in price level. Governments then resort to devising new policies to curb inflation so that the living standards can be maintained. Studies find strong correlation between rates of inflation and the exchange rate fluctuations, especially in developing countries of the world (Yildrim, 2004). Pakistan, being a developing country, passes through same conditions as others and gets affected by exchange rate changes in its import prices. Since it has to target inflation to support growing population, exchange rate fluctuations destabilize the economy.

Many major economic variables, like the unemployment rate, production variables including GNP, GDP, and industrial production, consumption, price index, nominal and real exchange rates, stock prices, and so on, have significant nonlinearities. In this proposed study, we have examined how forecasting using Non-linear macro models is reliable. A non-linear model may give a spuriously good fit even when it is mis-specified. In this scenario, out-of-sample predictions are somewhat very poor. We have incorporated Markov-regime switching model to find whether the forecasting done on this basis is more robust and the model outperforms. The periodic regime switching that exchange rate undergoes is vulnerable to be found. We have taken daily time series data on Nominal Exchange Rate from 2013 and onwards. We supposed that series we have taken are not linear. We were supposed to analyze the abrupt changes in exchange rate of Pakistan. Consumer Price Index CPI in Pakistan increased to 161.88 points in March 2022 from 160.61 points in February 2022[2].

In literature, we analyzed researchers have focused on assuming that financial time series had undergone switching between two regimes only (Cheung & Erlandsson, 2005; Frömmel, MacDonald, & Menkhoff, 2005). It involves Markov regime switching model that best deals with the fluctuations of an economic financial variable across different regimes. These regimes may be political when we observe our variable of concern under political influence. And they can be termed as regimes of high and low volatility as well when we discuss the variable in the perspective of its financial properties. The economic policies of the country also impact the exchange rate determination in the market. These rates vary when a contractionary monetary policy is prevailing and are different when the governance changes its monetary policy to expansionary one. A Markov switching model is one way for identifying and estimating regime transitions (MSM). When (J. D. Hamilton, 1989) strongly disagreed with a random walk for the exchange rate in favor of an oscillating time-varying trend between a fixed positive and negative value, this technique found one of its initial uses in the foreign exchange market.

[2] Pakistan Bureau of Statistics

The "peso problem," the changing importance of chartists and fundamentalists in the foreign exchange market, differences between domestic and foreign monetary and fiscal policies, the presence of transaction costs and diversity of opinions are all factors that could lead to regime-switching behavior (Cheung & Erlandsson, 2005). We used Markov-Regime-Switching Models to analyze exchange rate dynamics. A sequence of stochastic processes is represented by a first order Markov model, in which the probability of each event transition is only determined by the state reached by the previous event. Exchange rates have shown volatility when there is a good or bad news in the market. Volatility is a property of financial time series according to which rates of return of that particular series vary along time intervals. To model this property, we need mechanism that can fit variance of data and let us forecast the future trends of data as well.

The study scheme that follows in this dissertation is as; chapter 2 incorporates the reviewed literature from oldest to the latest research done relevant to the subject of study. Chapter 3 deals with research strategy adopted to analyze and estimate specified models, methods of data collection, variable description, visual interpretation and research design with step-by-step explanation. Chapter 4 bears the detailed estimation techniques from beginning to end with obtained results and their interpretation. Chapter 5 includes the qualitative analysis of time-to-time monetary policy statements and stances, actions taken by monetary authorities (SBP) to manage financial risk and stability. Chapter 6 concludes the study with policy recommendations and limitations to the study.

1.1 PROBLEM STATEMENT

"Issue being the increasing inflation rates during last two quarters (Q1 & Q2 FY2021-22) of the economy, this research work is focused to devise efficient forecasting while determining the number of regimes in which exchange rate can switch. A non-linear model comparison of exchange rate is need of the hour to decide the efficiently reliable forecast of exchange rate returns".

1.2 RESEARCH PROBLEM

Managing Exchange rate of economy is a big challenge to least developed or developing countries. Curbing the inflation caused by imports, promoting exports, taking steps to stabilize the economy and encouraging foreign investors to invest in our economy become issues for Exchange rate management. With the advent of managed floating exchange rate in 1982, Pakistani Rupee value has been determined on daily basis. Since 1999, exchange rate is being determined on market situation. Exchange rate return risk increases transaction costs on goods and gains from international trade are reduced resultantly. Demand and supply forces determine exchange rates and the effects of this market determined exchange rate reflect in increased import prices leading to higher inflation rates. To mitigate this issue, forecasting needs to be enhanced in order to formulate effective monetary policy, bearing fruits that could reach to lowest earning individual of Pakistan economy.

1.3 OBJECTIVE/ AIM OF THE STUDY

The main objectives of this study are:

- To test and allow for switching between two regimes of nominal effective exchange rate.
- To test linearity of data against non-linearity where non-linear processes will be explored through Markov- Regime Switching models.
- To find answers about how monetary policies be conducted efficiently under the light of accurately inferenced inflation regimes.

1.4 RESEARCH QUESTIONS

- Does Exchange rate switch between two regimes: High volatility and Low volatility?
- Whether allowing two regimes improves the out-of-sample forecast performance or not?
- Is Markov-Switching GARCH model better in forecasting exchange rate volatility than Threshold GARCH Model?

CHAPTER 2

LITERATURE REVIEW

Financial data is prone to rapid shifts, necessitating a method that can be calculated theoretically to explain how such fundamental changes occur (Hamiltion, 2005). These fundamental changes often lead towards non-linear nature of data. To test the non-linearity of any time series, we perform certain tests. To describe the non-linear behavior of certain processes, tests for testing the linearity have been proposed by several authors (Subba Rao & Gabr, 1980). Real exchange rate behavior is determined through various real and monetary instruments of an economy. Using Small Open Economy model, (Chishti, Hasan, & Afridi, 1993) examined the Purchasing Power Parity theory for Pakistan and found the evidence against the PPP Theory. Also, that monetary expansion, proxies by domestic credit creation and the level of deficit financing cause disturbance in equilibrium level of real exchange rate. Absolute and relative prices, incomes and interest rates are found to be such shocks that influence exchange rate (Burney, Akhtar, & Qadir, 1992),(Gao, Ling, & Tong, 2018).

Johansen-Juselius cointegration technique found the PPP series to be integrating and nominal exchange rate cointegrated with Wholesale Price Index-based priced level. Using semiparametric and approximate maximum likelihood techniques, (Baum, Barkoulas, & Caglayan, 1999)analyzed WPI-based inflation rates of 22 countries and monthly CPI-based inflation rates for 27 countries. As (Khan & Qayyum, 2007) finds high degree of goods and foreign exchange market integration which is also seen by PPP validity. In the similar context, (Choudhri & Khan, 2002) are of the view that devaluations tend to increase inflation in Pakistan. In literature, we find (Teräsvirta &

Anderson, 1992) performed STAR Modelling technique on Logarithmic Production indices of 13 countries and Europe for the period of 1960-1986 and concluded that Business cycles are found to be asymmetric thus non-linear modelling is suitable for OECD countries' industrial output series except France.

Previously (Luukkonen, Saikkonen, & Teräsvirta, 1988) performed three tests to check the linearity of a univariate time series model against non-linear STAR and SETAR models. They concluded that test 3, S_3, is more powerful than test 2, S_2, and CUSUM test. Tsay's test is considered to be useful when there is no shift in the intercept between the two regimes. A very simple technique is introduced by (Terasvirta, 1994) to choose between STAR and linear modelling approach. Linearity is tested against STAR model and upon rejection of null of linearity, we move towards STAR. The technique is well suited for small samples. Using three economic variables, (Duekar, Owyang, & Sola, 2010) utilized 1968-2010 data on inflation, unemployment and interest rate US economy and concluded that STAR is best alternative to Markov switching when operated at constant threshold (Kim, Zhang, & Wu, 2015), (Petruccelli, 1992). Exponential AR model behaves as does the threshold AR model. In addition, it allows the parameters to smoothly change over time instead of "jump" abruptly as expressed in TAR models (Teräsvirta & Anderson, 1992). ESTAR model is more appropriate in examining non-linearity of inflation series (Rehman, Iqbal, & Rehman, 2011).

STAR model is preferred as compared to Markov switching after Bayesian predictive densities forecasts were obtained (Deschamps, 2008). Exchange rate adjustment can be modelled by LSTAR, ESTAR models (Drissi & Boukhatem, 2020). In the cited study, mean-reverting process in real exchange rate adjustments in which tendency varying with sign and magnitude of deviations is evident from the results. Author concludes that central banks of emerging countries should be given some credence so that their domestic currencies can be managed in certain fluctuations ranges. Within the inactive arbitration band, the nominal exchange rate may depart from PPP equilibrium in the near run. Non-linear models outperform the linear models (Moshiri & Forouton, 2006).

Volatility in the financial markets has been a great stimulus for financial econometrics since long time. The generalized autoregressive conditional heteroskedasticity (GARCH) model, created by Bollerslev in 1986, incorporates the autoregressive conditional heteroscedasticity (ARCH) model. Initially used in macroeconomic research, regime-switching models are now widely used in risk analysis and asset pricing (J. D. Hamilton, 1989). Markov-switching models bear two main advantages: estimate of the state specific parameters and estimations of the probabilities of state occurrences in each of the sample periods using filtering and smoothing methods. Regime switching models may not apparently vary much from the structural break models but they actually do. Parameters in Regime switching models vary across different regimes while they change at different times in structural change models. Determination of number of regimes is not only dependent on sample size of the data but also on the frequency.

Studies such as (Cheung & Erlandsson, 2005) find evidence on data frequency dependency. Engel raised a question on the reliability of Markov-switching models in forecasting exchange rates and their behavior (Engel, 1994). The study was carried out taking 18 exchange rates and concluded that a random walk gives more reliable and superior forecasts of exchange rates than a Markov-switching model. According to (Kobor & Szekely, 2004), the identification of high-volatility periods and a better understanding of their characteristics, as well as the estimation of volatility increases and spillovers to other economies, enable policymakers to develop better strategies for high-volatility periods, including prudential regulations.

Soon after Hamilton came with his work of Markov-switching models, (J. Hamilton & Susmel, 1994) incorporated ARCH to model volatility in different states rather than just assuming two states. Researchers like (Gray, 1996) further improved the idea by generalizing it to Markov-switching-GARCH models and (Klaassen, 2002) extends the MRS-GARCH model by discriminating between two regimes with differing amounts of volatility. Three large United States Dollar foreign exchange rate series, based on daily frequency, were used to assess the model's effectiveness and the results demonstrated much superior out-of-sample volatility forecasts than traditional constant regime GARCH forecasts. The projections of the Value-at-Risk (VaR) using the Markov-switching ARCH model (J. Hamilton & Susmel, 1994) were examined by (Tang & Gau, 2004). They found that the ARCH model with Markov-switching provides better VaR forecasts than other VaR models that just include time-varying variables.

A study done by (Tovar-Silos & Lamar, 2016) used both a normal and a t-probability distribution, a regime-switching ARCH (SWARCH) for the Peso exchange rate computation. Since it provided a higher log likelihood, the t-distribution specification was chosen. The probability of existence of two regimes in the ARCH model of the Mexican Peso exchange rates was found to be supported by significant statistical evidence. Using KSE daily frequency data (2005-2012), another research into the predictive performance of regular GARCH (GARCH, EGARCH, and GJR) models and Markov regime-switching GARCH (MRS-GARCH) models has been done (Iqbal, 2016). For both classes of models, normal and non-uniform (Student-t and GED) errors are taken into account, and volatility and VaR projections are produced for one day to one month ahead. The MRS-GARCH model with two, low and high, volatility regimes can match the KSE data, according to the findings. The MRS-GARCH and EGARCH models with Student-t errors outperform other models in predicting KSE index return volatility and Value at Risk for both short as well as long-time horizons.

In 2017, (Abdullah, Siddiqua, Siddiquee, & Hossain, 2017) investigated exchange rate volatility for Bangladesh using daily observations over a 7-year period for taka–US dollar exchange rate return. Due to the leptokurtic fat-tailed structure of exchange rate return series, it is typically appropriate to estimate volatility models using a skewed distribution—such as Student's t—rather than a normal distribution. The main focus was on determining if the taka–US dollar exchange rate return has the same nature as the Bangladeshi taka–US dollar foreign exchange rate return and whether the results might be improved using Student's t-distribution. This piece of research work used the GARCH, APARCH, EGARCH, T-GARCH, And IGARCH models to evaluate the volatility dynamics of the taka–US dollar exchange rate returns. The results of the models were compared to Student's t-distribution using the regular normal distribution assumption for the residuals.

In her research work, (Almisshal, 2021) concludes that the symmetric GARCH (1,1) and asymmetric GJR-GARCH (1,1) models are the best appropriate models for estimating volatility of the USD/TRY exchange rates. The Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) tests have been used to forecast volatility. According to the findings, the GJR-GARCH (1,1) static prediction is the best model for predicting future patterns for both USD and EUR against Turkish Lira. (Naseem, Fu, & Mohsin, 2018) inspected relative performance of symmetric and asymmetric GARCH family models based on five residual distributions in perspective of capacity to predict KSE-100 index volatility of Pakistan.

We summarize literature review with an insight that Markov-switching GARCH model and asymmetric/symmetric GARCH family of models are suitable for forecasting exchange rate volatility and relying on obtained forecasts. Regime switching modelling technique allows us examine volatility of assets in different states i.e., high volatile state and low volatile state.

2.3 THE EXCHANGE RATE REGIMES' HISTORY OF PAKISTAN

FIXED/PEGGED EXCHANGE RATE REGIME (1947-1981)

Pakistan has had a fixed exchange rate regime since independence in 1947, and its currency (PKR) was pegged to the pound sterling until 1971(Javed & Ahmed, 2016). Imports were initially liberalized significantly, and a wide range of items were placed under an open general license (OGL). In 1949, the majority of countries in the sterling area were chosen to devalue their currencies but Pakistan decided not to devalue its currency despite the fact that current account deficit was 2.5 percent of GDP. However, Pakistan suspended the OGL and imposed restriction on imports to improve terms of trade. As terms of trade improved, the trade policy was again liberalized in June 1950. In July 1950, the Korean War broke out. As a consequence, exports increased even more and Pakistan enjoyed current account surplus. After the war the recession set in. Export and export prices fell but with the liberal import policy imports remained unchanged. The country's balance of payments situation had deteriorated, and there had been mounting demand to weaken the currency. Therefore, in July 1955, it was decided to devalue the PKR for the first time by 31 percent in terms of pound sterling and 42 percent against US dollar (from Rs. 3.3 to Rs. 4.76), to stimulate exports. As a result, volume of exports increased by 52 percent in 1955-1956. Subsequently, exports began to decline and continued until the end of fifties. This devaluation adversely increased the import bill of food grains, which in turn increased their retail prices.

MANAGED FLOATING EXCHANGE RATE REGIME (1982-1998)

When the PKR strengthened by 25.12 percent against the French franc and 22.9 percent against the pound sterling in 1980-81, Pakistan lost its non-dollar export market. The overall appreciation of PKR was 7.94% against international currencies. It raised the import bills to $5,636.2 and deficit in balance of trade increased to $ 3,108.5 million in FY 1982. In these circumstances, the decision was made in January 1982 to delink the PKR from the US dollar and enable it to float against a trade-weighted currency basket. The exchange rate system was changed from a fixed to a flexible exchange rate system, in which the exchange rate is controlled by the foreign exchange market's demand and supply positions. However, the rate of currency exchange system of Pakistan was never entirely flexible; it had a restricted (managed) exchange rate system in place. It's an amalgam of a fixed and flexible exchange rate system where market forces decide the level of currency price and the central bank has no authority to engage in the foreign exchange market through open market operations (OMO) and foreign exchange operations (FXO) to avoid exchange rate volatility.

FLEXIBLE EXCHANGE RATE REGIME (JULY 2000 and onwards)

Until now, this exchange rate mechanism has remained unchanged. The foreign exchange market sets the value of currency in a flexible exchange rate system. This mechanism, in theory, helps to maintain exchange rate stability by allowing for self-correction in response to market demand. In actuality, with a floating exchange rate, the exchange rate is extremely volatile and can have a significant impact on local economies. When a country is in a negative economic spiral, the flexible exchange rate system puts downward pressure on the local currency, lowering citizens' purchasing power. Exchange rate volatility surged drastically with the implementation of the flexible exchange rate regime, and the PKR fell from Rs. 57.5 to Rs. 60.9 per US dollar. However, the other economic fundamentals remain the same. High volatility is controlled by State Bank of Pakistan by using monetary instruments. In comparison to previous exchange rate regimes, the exchange rate has witnessed significant volatility during this time.

2.2 RESEARCH GAP

We find that a lot of work has been done exploring the exchange rate pass-through on prices of goods, its impact on Wholesale price index, oil prices, unemployment rate, interest rate and inflation. The work has been carried out using techniques of threshold autoregression TAR, smooth transition autoregression STAR, GARCH, error correction model ECM and so on. The studies under review show that researchers assume regime switching upto a maximum of two. Carrying on this base, we go for exchange rate volatility in different regimes. Since Pakistan has undergone serious pandemic situation of Covid-19, we can go for post-recession and post-Covid time period analysis of this exchange rate fluctuations. The study incorporates the latest data on nominal exchange rate of Pakistan with US dollar.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 RESEARCH STRATEGY

In periods of economic boom and recession, the behavior of economic time series is markedly different. The solution of a time series is stationary and converges to a "limit point" as it approaches infinity if the data is assumed to be linear. Since linear models follow a symmetric joint distribution, they become less suitable for asymmetric data. The data exhibiting sudden changes/outbursts of large amplitude at irregular time points cannot be handled through linear models. To begin the analysis, we inspect the data visually. The variable chosen for analysis is nominal effective exchange rates (NEER) of Pakistan. Visual investigation has let us know the expected outliers or breaks causing the non-linearity in data and saved our time specifying the model.

Financial time series exhibit properties like non-stationarity, volatility, fluctuations over time, response to unpredicted shocks etc. Unit root tests have been performed to check the data stationarity. Non-linearity in data is tested afterwards. Furthermore, two models are specified, one being Markov Switching GARCH and other being Threshold GARCH. Purpose of doing so is that we can forecast exchange rates and the model comparison at same time. The forecast best reliable and closer to actual has led us towards best model selection. Since nominal effective exchange rate is a time series that sees major fluctuations when suffered from a big shock at a particular time, we can say that it switches between regimes. We assumed that nominal exchange rate can switch between two regimes. The order of Markov Process is determined.

3.2 METHOD OF DATA COLLECTION

Data on nominal effective exchange rates are taken from IMF-IFS[3] and the Economic data portal of State Bank of Pakistan. Daily data are used for the analysis from July 2013 to April 2022. This study is primarily quantitative based on data already available. For qualitative analysis, a brief analysis on State Bank of Pakistan's monetary policy statements and its efforts to stabilize exchange rates through various actions is done.

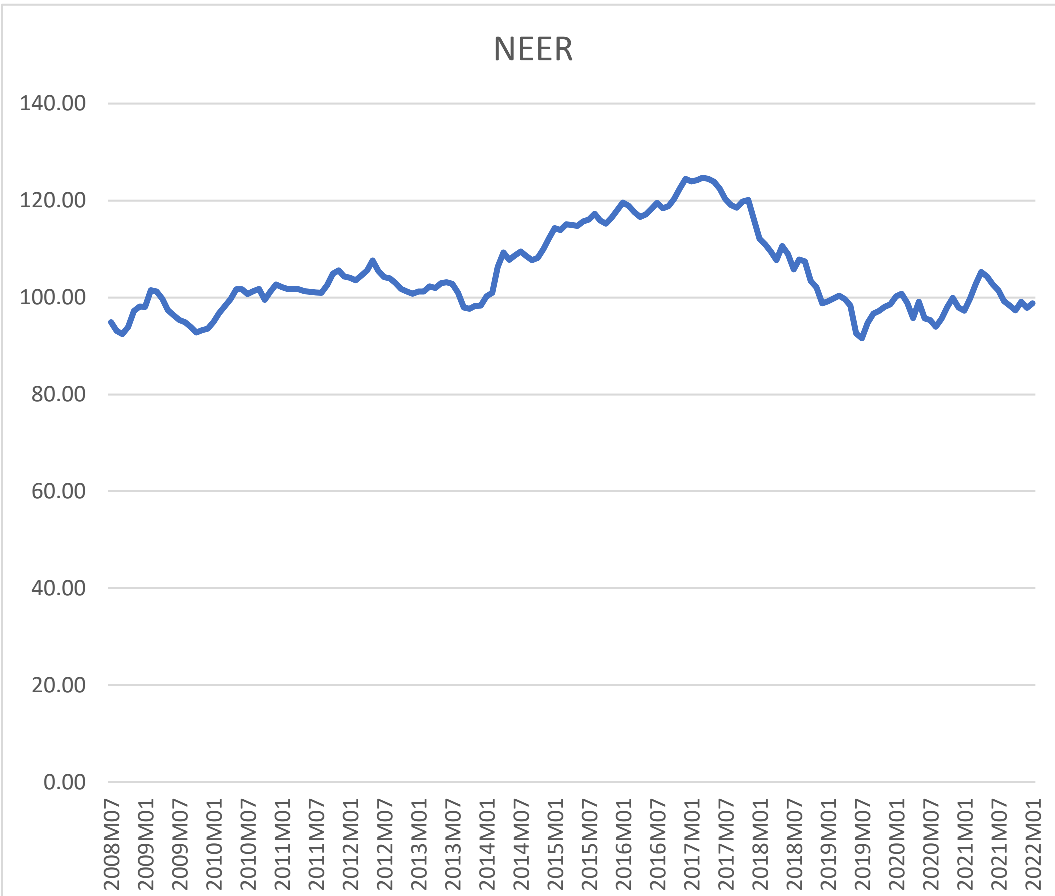

Figure 3. 1 *:* Monthly Exchange Rate of Pakistan 2008 - 2022

[3] IMF-IFS: International Monetary Fund's International Financial Statistics database.

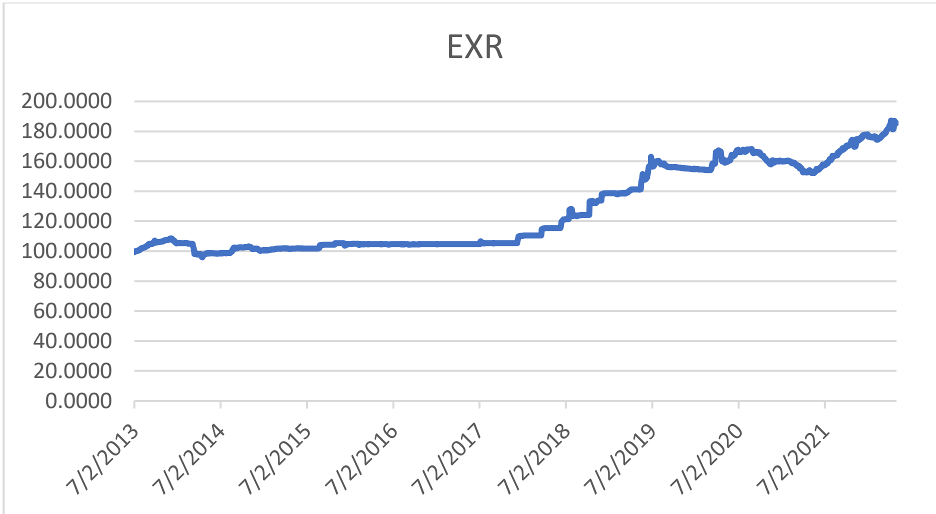

Figure 3. 2: Daily Exchange Rate 2013-2022

3.3 VARIABLE DESCRIPTION

The price of one currency in terms of another is called the exchange rate.[4] The nominal effective exchange rate (NEER) is a form of measuring a currency's nominal exchange rate relative to a

[4] "Economics of Money, Banking and Financial Markets", Frederic S. Mishkin

basket of other currencies using an unadjusted weighted-average calculation. NEER is also sometimes referred to as the “trade-weighted currency index”.

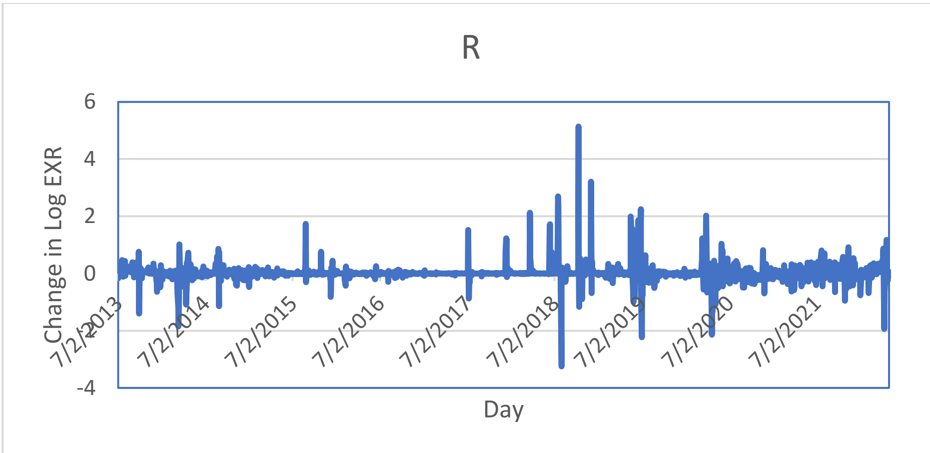

Figure 3. 3: Exchange Rate Return Series

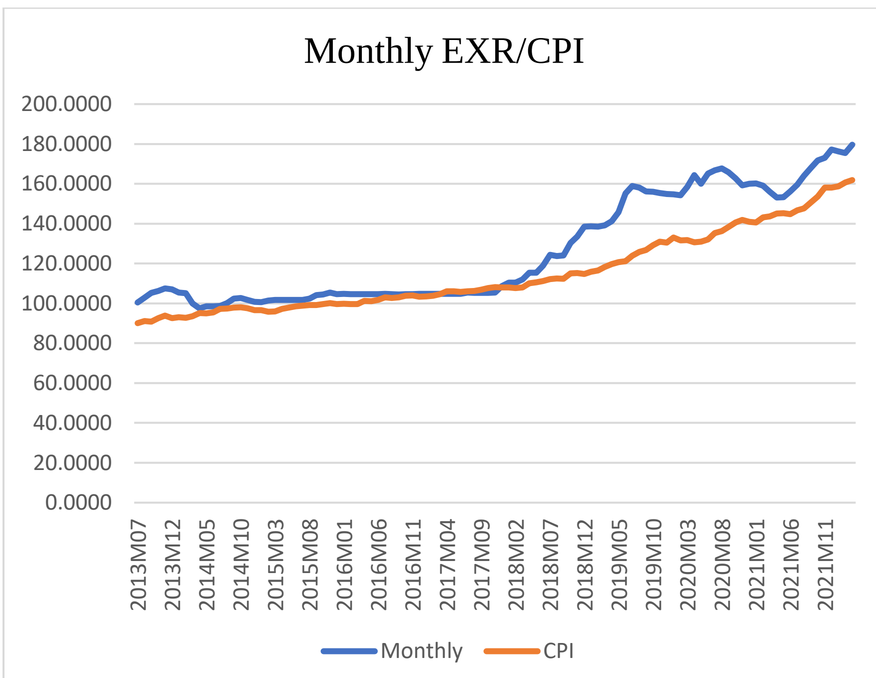

Figure 3. 4: Monthly Exchange rate and CPI of Pakistan

3.4 RESEARCH DESIGN

The study followed some steps mentioned below as our research design.

- ✓ Visual investigation of the data
- ✓ Tests of stationarity
- ✓ Tests of non-linearity
- ✓ Log transformation of the data
- ✓ Hypothesis Formulation
- ✓ Model Specification
- ✓ Model Estimation
- ✓ Tests for Model Adequacy
- ✓ Forecast (In Sample & Out Sample)
- ✓ Tests of Forecast Accuracy

Visual Investigation of the Data: Figures 3.1, 3.2 and 3.3 are drawn using the study sample data for visual investigation. The diagrams illustrate that post-Recession 2008, a slight upward mobility of exchange rate is seen after 2009 as economy started reviving. Foreign exchange reserves improved as a result of exceptionally good home remittances, stable commodity prices and flourishing industrial manufacturing.

Tests of Stationarity: We have performed test to check stationarity of data by incorporating Unit root tests. These include Dickey Fuller Test, Augmented Dickey Fuller Test, Phillips Perron Test and Beaulieu-Miron Test.

Dickey-Fuller (DF) Test: We applied Dickey Fuller Test on data to check the stationarity[5]. The null hypothesis that followed is;

H_0: $\alpha = 0$ $(i.e.,$ The series is non-stationary). H_1: $\alpha < 0$ $(i.e.,$ The series is stationary)

The test is run in three different forms i.e.,

a) the series is a random walk

$$\Delta y_t = \alpha y_{t-1} + \mu_t \qquad (3.4.1)$$

b) the series is a random walk with a drift

$$\Delta y_t = \beta_1 + \alpha y_{t-1} + \mu_t \qquad (3.4.2)$$

c) the series is a random walk with a drift and a trend

$$\Delta y_t = \beta_1 + \beta_2 t + \alpha y_{t-1} + \mu_t \qquad (3.4.3)$$

Augmented Dickey-Fuller (ADF) Test: When the series is a random walk, the conventional DF test is done using equation (1). Only if the series is an AR (1) process is the simple DF test valid. The assumption of white noise disturbances t is violated when the series is correlated at higher order lags. By assuming that the Yt series follows an AR (p) process and adding p delayed

[5] A stochastic process Y_t, where Y_t is a random variable and $t \in N$, is said to be stationary if for any positive integer k and any points $t_1, t_2, \dots\dots, t_m$, the joint distribution of $\{Y_{t1}, Y_{tm}\}$ is the same as the joint distribution of $\{Y_{t+1}, \dots \dots,$ Yt, i.e., the joint distribution is invariant under a time shift. A process Y_t is weakly or covariance stationary if COV (Y_m, Y_k) depends only on the time difference |m-k|.

difference terms of the dependent variable Y to the right hand of the test regression, the ADF Test provides a way to develop parametric correction for higher order correlation.

$$\Delta y_t = \alpha y_{t-1} + x_t' \delta + \beta_1 \Delta y_{t-1} + B_2 \Delta y_{t-2} + \cdots + \beta_\rho \Delta y_{t-\rho} + \mu_t \qquad (3.4.4)$$

Phillips-Perron Test: While moving towards next test of stationarity, we approach non-parametric technique. The problem of higher order correlation is addressed using this test. It builds on same null hypothesis as augmented dickey fuller. Null hypothesis formulated is “the time series we are using is integrated of order 1”. The regression equation for PP test is as follows;

$$\Delta y_t = \alpha y_{t-1} + x_t' \delta + \mu_t \qquad (3.4.5)$$

Beaulieu and Miron Unit Root Test: Beaulieu and Miron (1993) devised the test to examine the seasonal and non-seasonal unit root (i.e., unit root at zero, biennial, and annual frequency) in monthly time series. It was expanded to the Unit Root Test of Frances (1991) by generating 12 series to detect the complicated Unit Root individually. The unit root test in monthly data was proposed by Beaulieu and Miron. Since our primary focus of analysis is daily data, we do not perform BM test here.

Non-linearity of Data: Since exchange rates see many fluctuations due to changes in demand and supply of foreign currency globally, the data available to us is non-linear. There are several reasons behind these fluctuations. Including these are goods imports, capital movements to and from economy, open market operations, monetary policy of the economy, Forex trading and political atmosphere of the country. To check non-linearity, we performed tests of non-linearity on data. These include RESET test, Tsay, ACF, CUSUM, ARCH, McLeod and Li Test, Keenan and BDS tests.

Ramsey RESET Test: Nonlinearity can be detected using the regression error specification test (RESET). The residuals of a linear model should not be correlated with the fitted values or explanatory factors employed in the model, according to this test. As a result, the residual regression on these regressors should be statistically insignificant (Baghestani, 1991).

ACF test: To study the linear relationship between the values of y_t and y_{t-1}, the auto correlation function (ACF) is used. In ARMA model estimation, the auto correlation function (ACF) and partial auto-correlation function (PACF) are extremely useful in determining the right values of p and q. The ACF of the residuals is a useful diagnostic technique. However, when used in a nonlinear process, ACF can be deceiving, since it may miss the important asymmetry relationship that exists in the data. The autocorrelation function for all lags should be 0 when a sequence of observations is uncorrelated.

The BDS Statistic: The BDS Statistic is derived from the correlation integral. The BDS statistic can't tell the difference between a nonlinear deterministic and a nonlinear stochastic system, but it can tell the difference between random time series and time series created by low-dimensional chaotic or nonlinear stochastic processes.

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.078385	0.003045	25.73843	0.0000
3	0.141015	0.004869	28.95918	0.0000
4	0.183723	0.005839	31.46277	0.0000
5	0.209309	0.006132	34.13388	0.0000
6	0.222153	0.005960	37.27419	0.0000

Log-Transformation of the data

The data used in the study is log-transformed first to decrease the variability. Since financial data is prone to stylized facts and is generally skewed, either left or right, natural log is taken to make it closer to normal distribution. The study sample data is found skewed to the right before this transformation as can be seen in Figure 4.1.

Hypothesis Formulation

We will formulate following hypothesis in our analysis.

Null Hypothesis: Markov Switching GARCH model forecasts exchange rate volatility better than TGARCH model.

Alternative Hypothesis: Markov Switching GARCH model does not forecast exchange rate volatility better than TGARCH model.

The ARMA Process

The ARMA model is a mixture of the MA and AR and it is well known as the stationary time series model. The basic expression is as follows:

$$y_t = \alpha_0 + \varepsilon_t + \sum_{i=1}^{q} B_i \varepsilon_{t-i} + \sum_{i=1}^{p} \alpha_i y_{t-i} \quad (3.4.6)$$

α and β are unknown positive and negative coefficients, while Y_t stands for the variable that is obtained at time t. ε_t stands in for the independent residual term. The ARMA model can compute variables that are affected by the past state as well as random factors that exists in the present as well as the future state. The ARMA model is well suited regarding the volatility studying and predicting high frequency time series because to this feature. The ARMA model can easily interpret the auto-regression and trend of the time series, however it only works well with stationary time series.

The ARCH Model

In conventional econometrics, it is frequently assumed that the variance of a discrete independent variable is constant. In reality, heteroscedasticity affects financial time series, which indicates that the data is steady over the long spell but unstable over the short term (Bollerslev, Engle, & Nelson, 1994). In order to model the mean and variance of sequences and determine the time variation, Engel developed the ARCH model in 1982. The following is a typical way to write the Autoregressive Conditional Heteroscedasticity model:

Mean equation: $$y_t = \Phi x_t + u_t \quad (3.4.7)$$

Variance equation: $$\sigma^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \cdots + \alpha_p u_{t-p}^2$$

OR $$\sigma_t^2 = \sum_{i=1}^{p} \alpha_i u_{t-i}^2 \quad (3.4.8)$$

In the mean equation, x_t is the explanatory variable observed during time period t, and u_t is a residual that is assumed to follow a normal error distribution in the standard model. The square of the error term at time t-1, which is linked to the variance of the residual sequence t at time t, is the basic building block of the ARCH model. The ARCH model could not be used to examine series with asymmetric or uneven effects because it presupposes that both high and low volatility have the same effect on the response variable.

The GARCH-type Models

The GARCH model, which Bollerslev suggested as a significant generalization of the ARCH model (Bollerslev, 1986), can more clearly capture the financial time series exhibit a propensity towards volatility clustering. To estimate time-varying volatility, conditional variance is also regarded in this model as a GARCH process. The definition of the equations is as follows:

$$y_t = \Phi x_t + u_t$$

$$\sigma_t^2 = c + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \qquad (3.4.9)$$

where the GARCH parameter is σ_{t-i}^2 and the ARCH parameter is u_{t-i}^2. The ARMA lag order of the model is represented by p and q, while the coefficient estimates of both the ARCH and GARCH terms are denoted by α_i and β_i, respectively. As a result, the ARCH model may be thought of as a particular kind of GARCH model. To estimate the sample series in the research that follows, we primarily use the GARCH family of models with one lag only (i.e., GARCH (1,1) model). The GARCH model has the advantage of reflecting and explaining heteroscedasticity, but it still cannot account for asymmetry.

Threshold GARCH model of Exchange Rate (Asymmetric Model)

Threshold generalized autoregressive conditional heteroscedasticity (TGARCH), presented by (Zakoian, 1994) and (Glosten, Jagannathan, & Runkle, 1993), is another model created to investigate leverage effects. $u_{t-1} > 0$ (positive news) and $u_{t-1} < 0$ (bad news) generate a differential influence on volatility in the TGARCH (1, 1) model. In this case, good news has an impact of (+) and negative news has an impact of (-). When $u_{t-1} > 0$, the uplift in volatility due to bad news is greater than the increase in volatility due to good news, indicating that there is a leveraging effect. We also need non-negative limitations for, and, just like in standard GARCH models.

$$\sigma_t^2 = \delta + \sum_{i=1}^{P} \alpha_i u_{t-i}^2 + \sum_{l=1}^{m} \gamma d_{t-i} u_{t-i}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-i}^2 \qquad (3.4.10)$$

Where $$d_{t-1} = \begin{cases} 1, & u_{t-1} < 0 \\ 0, & u_{t-1} \geq 0 \end{cases}$$

Equation 3.4.10 shows that the dependent conditional variance σ_{t-1}^2 of the preceding period t and the squared residual u_{t-1}^2 influence the value of σ_t^2. Furthermore, the model responds differently to positive and negative market news. The model's asymmetric or unbalance effect is represented by the notation $\gamma d_{t-i} u_{t-i}^2$. There is asymmetry of information in the time series as long as the asymmetry coefficient γ is not equal to zero. When unfavorable news breaks, $u_{t-1} < 0$ and $d_{t-1} = 1$. When good news is revealed, $u_{t-1} \geq 0$ and $d_{t-1} = 0$. The sequence has a leverage effect if $\gamma > 0$. The asymmetric effect does, however, lessen volatility if $\gamma < 0$.

A Markov Regime Switching Model

When used with actual data, all offered models retain the same structure. By doing so, one disregards the likelihood of many factors, such as economic situations, in the same period. Consequently, during periods of low (high) volatility, the estimated parameters from a GARCH model produce a conditional variance that is too large (low). (Cai, 1994) contends that structural changes are the cause of the significant persistence in variance. Using the Markov-Regime-Switching (MRS) framework developed by J. D. Hamilton (1989), this potential bias can be removed. Each regime has a different set of parameters based on a Markov-Chain. Markov-Regime-Switching ARCH models were first developed by (J. Hamilton & Susmel, 1994) and (Cai, 1994).

The benefits of this model being that it works for non-linear data as well. And concludes the effects of structural breaks of data along with this, we can easily estimate the probabilities of states that are involved. The Markov switching model offers a versatile way for approximating structural alteration in the data generation progression after the fact. It allows the data to determine the timing of changes, the occurrence of regimes, and the extent to which any particular variable matters in each regime. The persistence of various regimes can have asymmetries, and the expectation of the dependent variable can even be independent of the present state if the probability in state 1 equals 1 minus the probability in state 2 (Stillwagon & Sullivan, 2020). For R regimes with unobservable states St ∈ (1,2, …, R) at time t, the MRS-ARCH(q) process reads as follows.

$$y_t = \alpha(s_t) + \phi_1[y_{t-1} - \alpha(s_{t-1})] + \cdots + \phi p[y_{t-p} - \alpha(s_p)] + \varepsilon_t \qquad (3.4.11)$$

Where S_t = State t of Volatility, S_{t-1} = State t-1 of volatility. These states can take on values of either 1 & 2 assuming that 1 being high volatility state and 2 being low volatility state. Y_t, variance of exchange rate in t time and Y_{t-1} is variance of exchange rate in previous point of time. α and φ being the parameters which will be estimated.

Markov switching GARCH model of Exchange Rate (Symmetric Model)

Regime-switching is the phrase used to refer structural changes in time series data. When it is used with real data, all of the presented models are required to maintain the same structure. By doing this, one ignores the likelihood of other factors, such as diverse economic situations, within the sample period (Cai, 1994). As a result, during periods of depreciation and appreciation, the calculated GARCH model parameters produce a conditional variance that is too large (low). Markov-switching GARCH model was presented by (J. Hamilton & Susmel, 1994), Gray in 1996 and further extended by Klaassen in 2002 (Bauwens, Preminger, & Rombouts, 2010). To estimate and check for the conditional variances for the financial time series, we use GARCH model. Allowing the conditional variance to be an ARMA process, we let the error distribution process be such that Variance equation;

$$\varepsilon_t = v_t \sqrt{h_t}$$

Where $v_t = white\ noise\ process$, and $h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$

The model in our case will be as;

$$h_t = c + \sum_{i=1}^{q} a_i u_{t-i}^2 + \sum_{i=1}^{p} b_i h_{t-1} \qquad (3.4.12)$$

Determination of number of regimes

Popularized by Hamilton (1989), Markov switching models usually only go for two regimes estimation. However, the series may undergo more than two regimes. In case one, we have;

$$\Delta_{y_t} = c_i + \beta_i \Delta X_t + \varepsilon_{i,t} \quad if\ s = s_i$$

$$\Delta_{y_t} = c_j + \beta_j \Delta X_t + \varepsilon_{jt} \quad if\ s = s_j$$

This transition is considered to be governed by an ergodic first-order Markov Process, with the probability of regime switching determined solely by the present state. We obtain a Transition probability matrix as;

$$P = \begin{bmatrix} p11 & p12 \\ p21 & p22 \end{bmatrix}$$

To go for more than two regimes, the system of equation above can be extended as follows;

$$\Delta_{y_t} = c_i + \beta_i \Delta X_t + \varepsilon_{it} \quad \text{if s=}\ s_i$$

$$\Delta_{y_t} = c_j + \beta_j \Delta x_t + \varepsilon_{jt} \quad \text{if s=}\ s_j$$

$$\Delta_{y_t} = c_k + \beta_k \Delta X_t + \varepsilon_{kt} \quad if\ s = s_k$$

So, in this extended framework of more than two regimes, the transition probabilities will also change as follows;

$$P = \begin{bmatrix} p11 & p12 & p13 \\ p21 & p22 & p23 \\ p31 & p32 & p33 \end{bmatrix}$$

Measures of Forecast Accuracy

In-sample and out-of-sample forecast is made to check the model sufficiency and accuracy. Forecast of nominal effective exchange rate obtained through out of sample forecasting is added into original data and one step ahead forecasting technique is employed to generate more forecast entry. These forecast values are then tested for their accuracy. The measures of forecast accuracy found in literature are mean square error, MSE, root mean square error, RMSE, mean absolute error, MAE, mean absolute percentage error, MAPE, mean algebraic percentage error, MALPE.

$$MSE = \frac{1}{T} \sum_{t=1}^{T} \left(\sigma_t - \sqrt{\hat{h}_t}\right)^2 \qquad (3.4.13)$$

$$MAE = \frac{1}{T} \sum_{t=1}^{T} \left|\sigma_t - \widehat{\sqrt{h}}t\right| \qquad (3.4.14)$$

3.5 SIGNIFICANCE OF THE STUDY

The study incorporates brief review on Monetary Policies of State Bank of Pakistan. The forecast obtained for exchange rate can be useful for agents working with ministry of commerce to predict import and export prices. A revision could be done on discretionary-managed float exchange rate in light of obtained results. With a well reliable forecast, authorities can ponder on tightening or loosening the monetary control. The study finds its importance to investors of foreign currencies in stock markets. It is useful for traders who deal with foreign currencies while trading their goods. Exchange rate return forecast is helpful to anticipate the market stability for stakeholders.

CHAPTER 4

ESTIMATIONS AND RESULTS

The daily closing exchange rates are the foundation for this piece of work. Our data set, which covers the dates of 02 July 2013 until 30 April 2022, was obtained from the financial database of the State Bank of Pakistan[6]. It comprises 2172 business days. Since the quantity of time series data will have an effect on the fitting outcomes, we choose to employ a high frequency data for modelling. To begin our analysis, we perform some basic tests on our financial series in order to check whether it has the stylized facts.

We can see in Figure 4.1 that the relative fluctuations in PKR/USD exchange rate exhibit periods of large swings in some time periods (2018-2019) and periods of more mild swings in others (2020-2021), demonstrating the phenomena of volatility clustering. 2018-2019 saw a change in political culture of Pakistan as the government now had been in hands of a first-time elected leader Ex-Prime Minister Imran Khan with a different foreign and trade policy. 2020-2021 had been Covid-19 hit fiscal year. This volatility has its statistical grounds as well.

Statistical reasoning[7] behind this volatility measure is as follows;

X_t = PKR/ US \$ Exchange rate series

X_t^* = Log of Exchange rate series

$dX_t^* = X_t^* - X_{t-1}^*$ = relative change in exchange rate

[6] Daily data on exchange rates is unavailable before 2013. So, the analysis begins with data from July 2013 and onwards.
[7] "Basic Econometrics", Damodar N. Gujarati & Dawn C. Porter

$d\bar{X}_t^* $ = mean of dX_t^*

$R = dX_t^* - d\bar{X}_t^*$ = Returns on Exchange rate

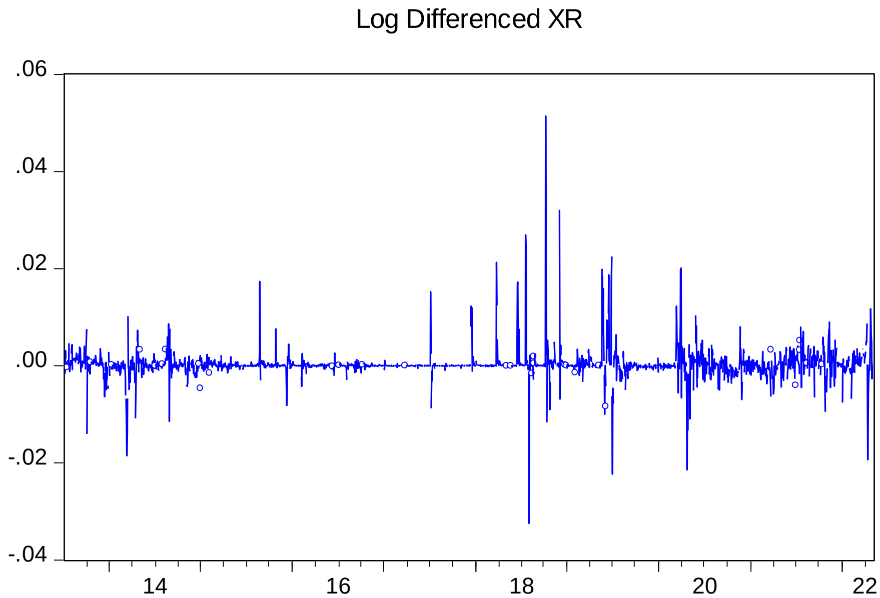

Figure 4. 1: Exchange rate return series

Before modelling, the time series must be pre-processed. To prevent erroneous regression in model estimation, the stationarity of the sequence must be established. The optimum lag order for the ARMA (p, q) model must then be determined using an autocorrelation test in order to achieve the best fitting results. The sequence's ARCH effect test verifies that the GARCH model is accurate. The series basic statistics are obtained first and are mentioned in the following Table 4.1.

Table 4. 1: Descriptive Statistics

	Sample	Mean	Std.	Skewness	Kurtosis	J-B Statistics	P-Value
EXR	2172	127.087	27.598	0.544	-1.367	276.23	0.0000
R	2172	0.028	0.311	3.159	59.204	319341.7	0.0000

Descriptive statistics obtained confirm the positive skewness of our sample data. The series under consideration has less Kurtosis than the Normal distribution. We performed ADF test on our exchange rate series with daily frequency to find out whether it is stationary or non-stationary, where p delayed differences to be 2, equation (1.1.5). Series is stationary at first difference. Probabilities of the coefficients are mentioned in parenthesis below.

$$\Delta exr_t = \quad C + \quad \underset{(0.002)}{\overset{}{\alpha exr_{t-1}}} + \quad \beta_1 \Delta exr_{t-1} + \mu_t \qquad (4.1.1)$$

$$\begin{array}{ccc} 0.026 & -0.675 & 0.068 \\ (0.002) & (0.000) & (0.001) \end{array}$$

Table 4. 2: ADF Test with Intercept & Trend and intercept

Augmented Dickey Fuller (ADF) Test			
H0: Exchange Rate Return as a unit root			
Intercept		Trend and Intercept	
Test statistic	Probability	Test statistic	Probability
-28.01798	0.0000	-28.07243	0.0000

The ADF unit root test is performed to test the return series of daily NEER and the test results are presented below in Table 4.1. The results demonstrate that the series has no unit root in the sample, with the t-statistics being significantly below critical values at the 1 percent, 5 percent, or 10 percent significance thresholds, and it is stationary time series. Same results are obtained when Phillips-Perron and KPSS tests are performed.

$$\Delta y_t = \alpha y_{t-1} \quad + x_t' \delta \quad + \mu_t$$

-0.642820 + 0.002822 + 0.2911

(0.0000) (0.0033)

Table 4. 3: PP Test

Phillips-Perron (PP) Test			
H0: Exchange Rate Return as a unit root			
Intercept		Trend and Intercept	
Test statistic	Probability	Test statistic	Probability
-31.61281	0.0000	-31.57999	0.0000

Table 4. 4: Unit Root Tests Summary

	ADF		PP		KPSS	
	Level	1st Difference	Level	1st Difference	Level (LM-stat)	1st Difference (LM-stat)
EXR	1.23 (0.9984)	-28.02*** (0.0000)	1.38 (0.9990)	-31.02* (0.0000)	5.51 (0.4630)	0.51** (0.7390)
Critical values 1% 5% 10%	-3.4331 -2.8626 -2.5674	-3.9623 -3.4118 -3.1278	-3.4331 -2.8626 -2.5674	-3.9623 -3.4118 -3.1278	0.7390 0.4630 0.3470	0.7390 0.4630 0.3470

Serial correlation causes traditional risk estimations to be underestimated, leading to erroneous financial return expectations. When there is time dependence in the returns, serial correlation, a type of non-normality, manifests itself in the financial asset returns. The null hypothesis states that “there is no serial-correlation up to p-lag” is tested using the Ljung-Box Q-statistics. The number of degrees of freedom for the chi-square with which the Q-statistic is asymptotically distributed, is equal to the number of auto-correlations being tested. If the test's associated p-value is less than 0.05, the null hypothesis that there is no serial correlation is rejected, and it is therefore possible that there is serial correlation in the returns. For obtaining the ideal lag order for the ARMA model, Ljung-Box Q (LB-Q) statistics, auto-correlation (AC) graph, and partial auto-correlation (PAC) graph are used.

Table 4. 5: ACF, PACF & LB-Q stats table

Auto-correlation	Partial Correlation		AC	PAC	Q-Stat	Prob
|*** |	|*** |	1	0.359	0.359	279.54	0.000
|* |	| |	2	0.076	-0.061	291.98	0.000
| |	| |	3	0.017	0.012	292.63	0.000
| |	| |	4	0.019	0.015	293.39	0.000
| |	| |	5	0.020	0.010	294.30	0.000
| |	| |	6	-0.020	-0.036	295.20	0.000
| |	| |	7	-0.024	-0.004	296.41	0.000

Financial return stylized facts typically indicate significant deviations from the normal distribution. A rigorous evaluation of how far the skewness and kurtosis vary from the normality assumptions of symmetry (zero skewness) and a fixed peak of 3 is provided by the statistic established by (Bera, Jarque, & Lee, 1984). The data from the Jarque-Berra (JB) test are calculated as:

$$JB = \frac{T}{6}[S^2 + \frac{(k-3)^2}{4}] \tag{4.1.2}$$

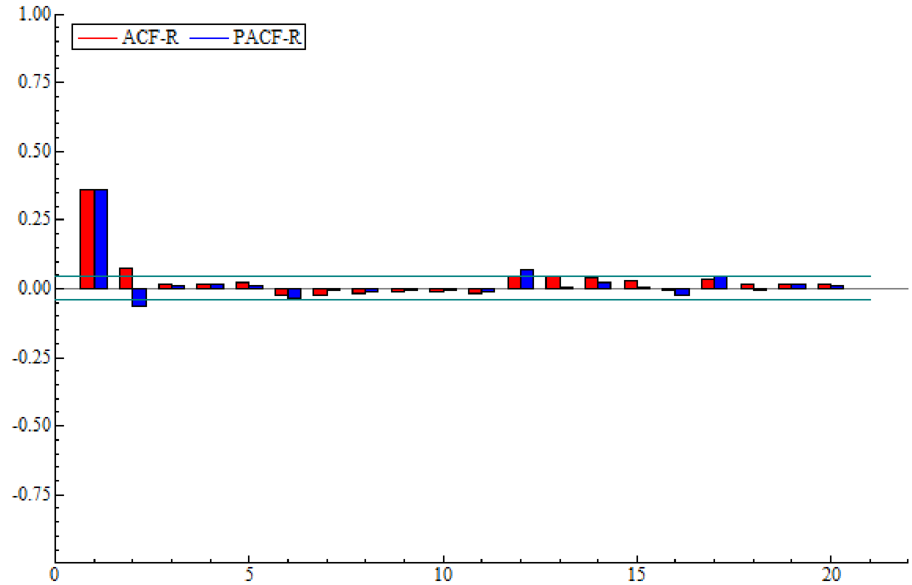

Figure 4. 2: Autocorrelation & Partial Autocorrelation Function

Where S, is the sample skewness. The third moment or skewness is an indicator of asymmetry in the return distribution. And k, is the sample kurtosis. The fourth moment or kurtosis is a measure of the peak-ness of the distribution. Figure 4.4 illustrates the phenomenon of non-normal distribution of return series data. We have obtained J-B stats as 319341.7 with p-values equal to 0.0000. The stats and p-value clearly signals the rejection of null hypothesis. The financial time series distribution is more topped than the normal density, has fatter tails, and excess kurtosis, and exchange rate series are not normally distributed. Since the exchange rate return series displays outliers, the volatility models are generated using a framework based on the Generalized Error Distribution.

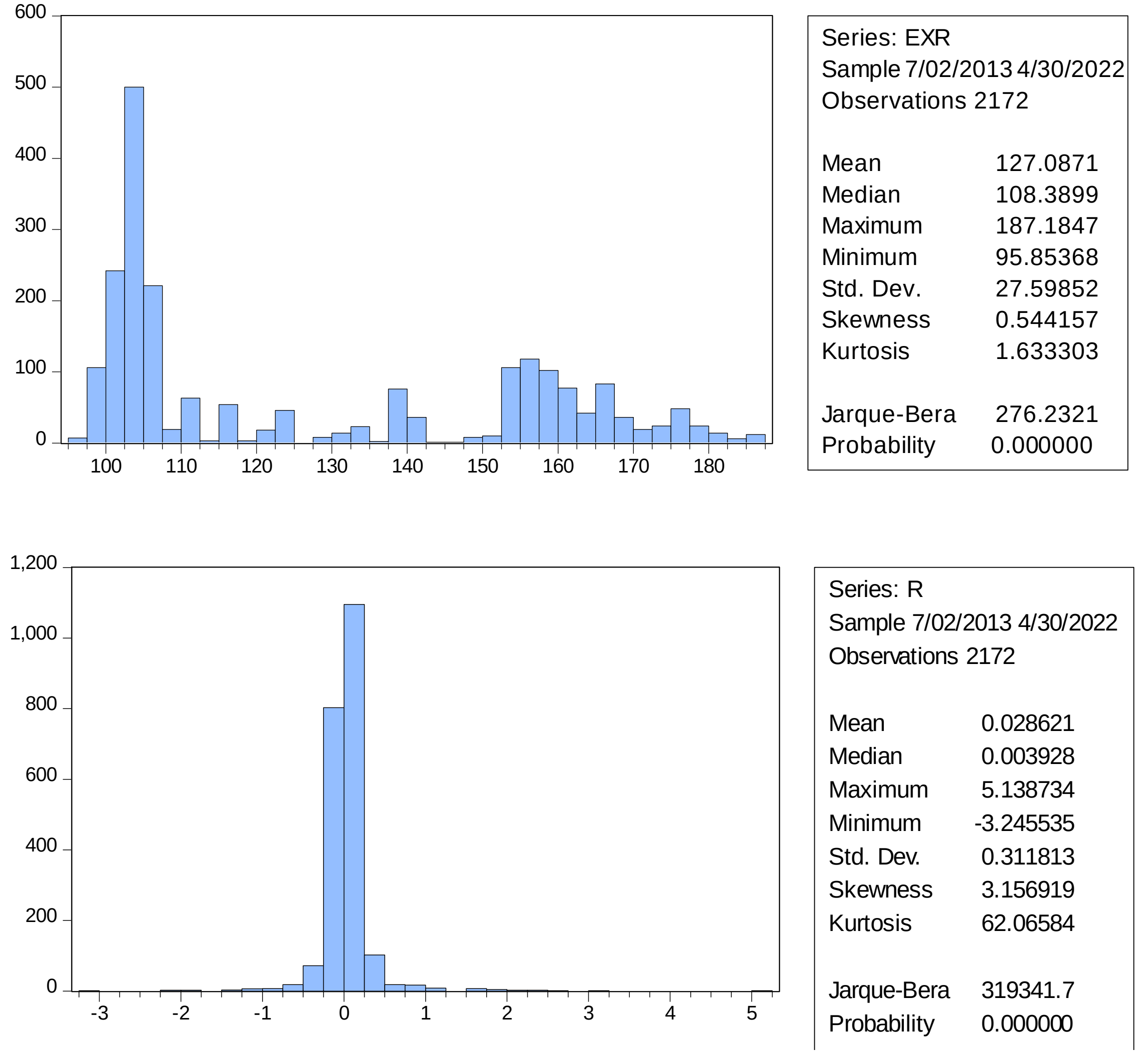

Figure 4. 3: Descriptive statistics of Daily Exchange Rate & Returns series

In Figure 4.3, Q-Q Plot of the exchange rate return series is shown. Strong corroboration of our findings comes from scattered points at the left tail and right tail that strongly deviate from the typical distribution. It directly represents the effect that once the market becomes highly volatile, it is more likely to stay that way than to calm down, and vice versa, by making the conditional variance depend on the past squared innovations. Thus, GARCH models allow us to capture the relevant conditional volatility inherent in the exchange rate in addition to estimating the path for the time-varying conditional variance of the exchange rate.

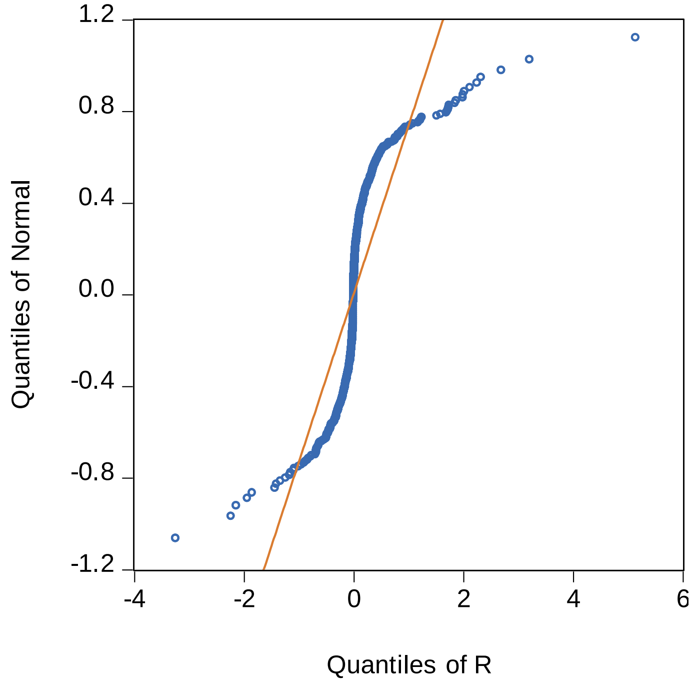

Figure 4. 4: Q-Q Plot of Exchange Rate Return series

In Table 4.3, Q-Statistics are taken into account for identifying autocorrelation and are linked to probability values. If the probability value is not greater than 0.05 and the series exhibits auto-correlation, the null hypothesis is rejected. The Q-statistics test findings show that all of the probability values are less than 0.05, representing that the squared residual series have auto-correlation and exchange rate returns series has a strong ARCH effect.

Model Selection

For the sample data, GARCH (1,1), GARCH (1, 2), and GARCH (2, 1) are established. After comparing the obtained results, the best suitable model is then selected for the returns time series under the normal distribution, Student's t-distribution, and GED. This section presents the estimation findings from the empirical analysis in Table 4.1.

Based on the AIC and SC values, the GARCH (1,1) model under the Generalized error distribution is the most suitable model for exchange rate return samples. We use the Generalized error distribution to generate GARCH (1,1) in order to estimate the EXR return series.

The GARCH (1,1) model for R's variance equation is as follows:

$$\sigma_t^2 = 0.0001 + 0.1497u_{t-1}^2 + 0.4116\sigma_{t-1}^2$$

The estimation results show that the model fits well at the 1% level of significance, which is supported by the fact that the coefficients and p-values of the ARCH and GARCH terms all vary round zero.

Table 4. 6: ARCH-LM Test results

	F-stats	p-values	Observations*R-squared	p-values
R	0.0065	0.9358	0.0064	0.9358

The joint relevance of the squares of error terms for all lag orders is revealed by the F-statistic. The sample sizes T and R-squared are combined to form the Chi-square statistic: Since all of the p-values are higher than 0.05, the null hypothesis can be accepted. This data supports the GARCH (1,1)'s applicability and the absence of the ARCH effect.

The total of the GARCH and ARCH parameters for the return series is 0.5613. The quantity should satisfy the constraint requirement of the parameter by being less than but close to 1. This shows how volatility has an ongoing effect but one that could weaken with time. The GARCH (1,1) model with Generalized error distribution outperforms other models in terms of capturing exchange market volatility, but it is unable to account for the asymmetric effect due to the model's intrinsic flaws. In order to clarify the volatility characteristics of the Pakistan Exchange rate, we employ the TGARCH model next.

Table 4. 7: GARCH Model estimations under Normal, Student's t and GED distributions

	GARCH (1,1)			GARCH (2,1)			GARCH (1,2)		
	Normal	Std t	GED	Normal	Std t	GED	Normal	Std t	GED
Constant	0.016 (0.0000)	0.0004 (0.7279)	0.0001 (0.0000)	0.008246 (0.0000)	0.000195 (0.4234)	0.000149 (0.0000)	0.027289 (0.0000)	0.000236 (0.4886)	0.00015 (0.0000)
u_{-1}^2	0.017 (0.0000)	27.689 (0.7295)	0.1497 (0.0000)	0.433844 (0.0000)	12.60902 (0.4253)	3.273345 (0.0000)	0.316409 (0.0000)	15.48711 (0.4911)	3.34136 (0.0000)
u_{-2}^2				-0.32688 (0.0000)	-0.24746 (0.8259)	-0.10462 (0.7270)			
σ_{-1}^2	0.670 (0.0000)	0.4183 (0.0000)	0.4116 (0.0000)	0.826587 (0.0000)	0.425790 (0.0000)	0.419026 (0.0000)	-0.01157 (0.1791)	0.305964 (0.0000)	0.357549 (0.0002)
σ_{-2}^2							0.453759 (0.0000)	0.06518 (0.0541)	0.029033 (0.5506)
standard. Error	0.2912	0.2957	0.2930	0.2915	0.2954	0.2929	0.2934	0.2954	0.2943
AIC	0.144	-2.263	-2.127	0.116	-2.278	-2.129	0.13407	-2.27936	-2.12896
SC	0.157	-2.273	-2.112	0.132	-2.260	-2.111	0.14978	-2.26104	-2.11064
HQ	0.148	-2.279	-2.122	0.122	-2.271	-2.122	0.13981	-2.27266	-2.12226

*Info 1> 1. * GED: Generalized Error Distribution. 2. AIC: Akaike Info Criteria. 3. SC: Schwarz Criteria 4. HQ: Hannan-Quinn Criteria. 5. u_{-1}^2 , u_{-2}^2 : ARCH terms 6. σ_{-1}^2 , σ_{-2}^2 : GARCH terms*

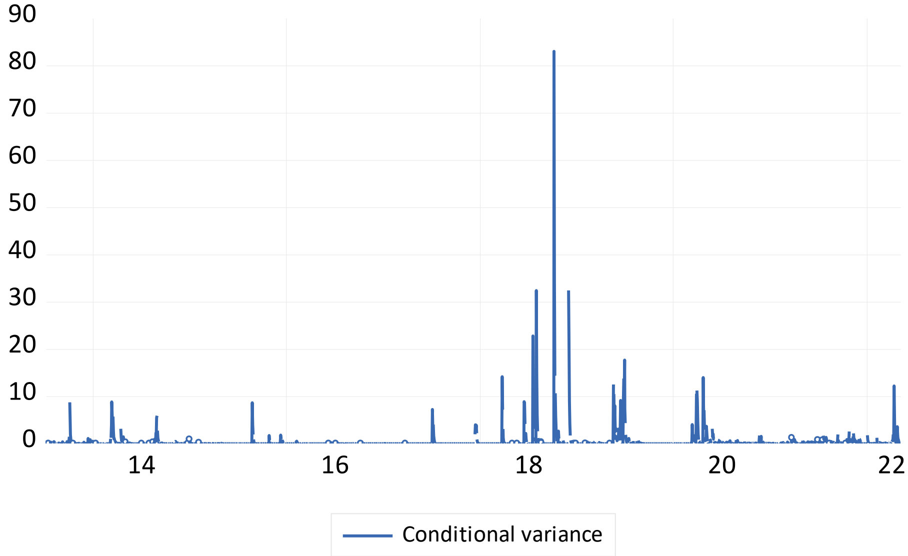

Figure 4. 5: Conditional Variance – GARCH (1,1)

T-GARCH Model Estimation

In order to find the TGARCH (1,1) model, we modify the GARCH model as described in the second section by include a dummy variable. The estimation results are shown in Table 4.7 and the series' variance equation is written as:

$$\sigma_t^2 = 0.0001 + 2.9711u_{t-1}^2 + 0.5345\, d_{t-1}u_{t-1}^2 + 0.4115\sigma_{t-1}^2$$

We found that the "leverage effect" is present because the coefficient of the asymmetric parameter γ is 0.5345. These results are evident and match with (Wang, Xiang, Lei, & Zhou, 2021). Additionally, the coefficient is all positive, demonstrating that positive news affects the market more significantly than negative news.

Table 4. 8: Empirical results of Threshold GARCH model

T-GARCH			
	Normal	Std. t	GED
Constant	0.01612 40.1529 (0.0000)	0.0005 0.9857 (0.3243)	0.0001 6.2691 (0.0000)
u_{-1}^2	0.2620 11.3546 (0.0000)	34.1250 1.0041 (0.3153)	0.9711 6.3940 (0.0000)
σ_{-1}^2	0.6714 82.6678 (0.0000)	0.4186 24.6547 (0.0000)	0.4115 17.6193 (0.0000)
γ	-0.1977 -8.10336 (0.0000)	2.6111 0.4707 (0.6378)	0.5345 0.7976 (0.4251)
Std error	0.2912	0.2957	0.2946
AIC	0.1294	-2.2784	-2.1285
SC	0.1451	-2.2600	-2.1101
HQ	0.1352	-2.2717	-2.1218

*Info 2 > 1. * GED: Generalized Error Distribution 2. AIC: Akaike Info Criteria 3. SC: Schwarz Criteria 4. HQ: Hannan- Quinn Criteria 5.* u_{-1}^2 *,* u_{-2}^2 *: ARCH terms 6.* σ_{-1}^2 *,* σ_{-2}^2 *: GARCH terms 7.* γ *: Threshold parameter*

According to the model's parameters, the results of the R series show that positive (good) news will have an impact on returns by an amount equal to $\alpha = 0.9711$ times, while negative news will have an impact equal to $\gamma+\alpha = 1.5056$ times. The statistic supports the idea that bad news has a considerably greater impact on exchange market volatility than positive news. Table 4.7 shows that the coefficients' p-values are almost all zero, indicating that the model is excellent at capturing volatility. Additionally, the ARCH-LM test verifies that the F-statistic and Chi-square statistic's p-values are more than 0.05, demonstrating the reliability of the TGARCH (1,1) model.

Table 4. 9: ARCH-LM Test for TGARCH model

	F-stats	p-values	Chi-square	p-values
R	0.00615	0.9375	0.00615	0.9375

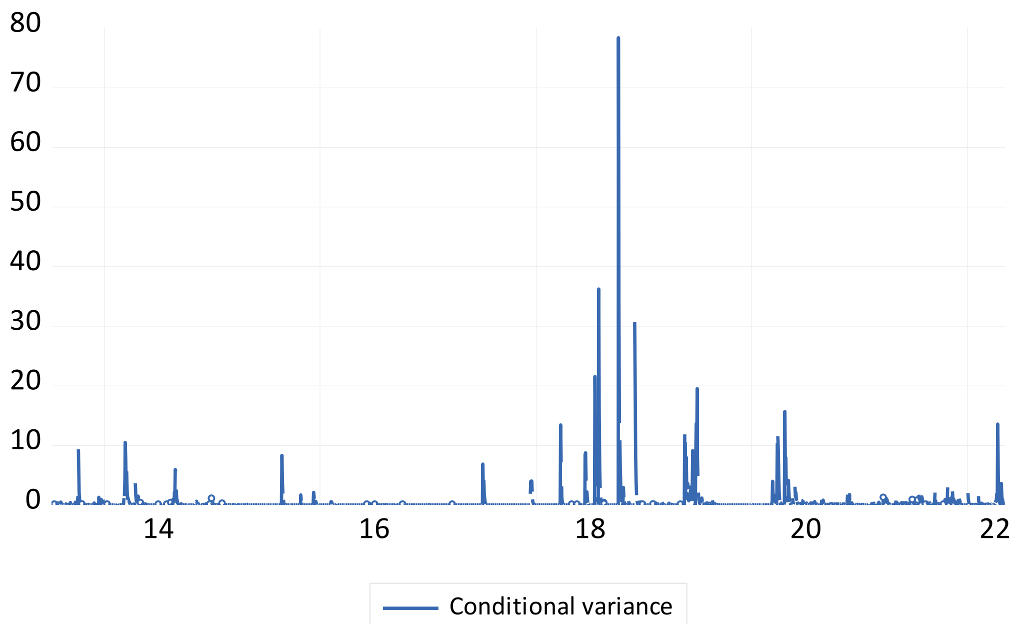

Figure 4. 6: Conditional Variance – TGARCH (1,1)

MS-GARCH Model

Similar to the conventional GARCH model, the MRS-GARCH model is estimated using three distinct error distributions. Regime specific equations below display the estimated parameters and corresponding p-values. The conditional mean is determined to be significant in the first regime, but for the Students'-t and GED distributions, it is impossible to rule out the possibility that this estimate is different from zero in the second phase. The significant values of transition probabilities indicate persistence of both regimes in MRS-GARCH models.

Conditional Variance equation in Regime 1:

$$h_t^1 = \underset{(0.0057)}{0.0426} + \underset{(0.0000)}{0.3582}\,(u_{t-1}^2)^1 + \underset{(0.0000)}{(-0.7903)}\,h_{t-1}^1$$

Conditional Variance equation in Regime 2:

$$h_t^2 = \underset{(0.0011)}{0.0031} + \underset{(0.0000)}{0.2112}\,(u_{t-1}^2)^2 + \underset{(0.0000)}{(-3.5115)}\,h_{t-1}^2$$

Regime probabilities are written in matrix below.

$$P = \begin{bmatrix} p11: P(s(t) = 1|P(s(t) = 1 & p12: P(s(t) = 1|P(s(t) = 2 \\ p21: P(s(t) = 2|P(s(t) = 1 & p22: P(s(t) = 2|P(s(t) = 2 \end{bmatrix}$$

$$P = \begin{bmatrix} 0.891457 & 0.108543 \\ 0.075013 & 0.924987 \end{bmatrix}$$

The estimations can be used to distinguish between two regimes, the first with low volatility and the second with high volatility. The constant expected duration, p and q, generally referred to as and, can be used to indicate the persistence of the regimes. In every instance, these transition probabilities are found to be considerable, demonstrating the permanence of both regimes.

One-step ahead regime probabilities are also calculated when the parameters are estimated. These probabilities show to what extent the variances will be staying in the particular regime.

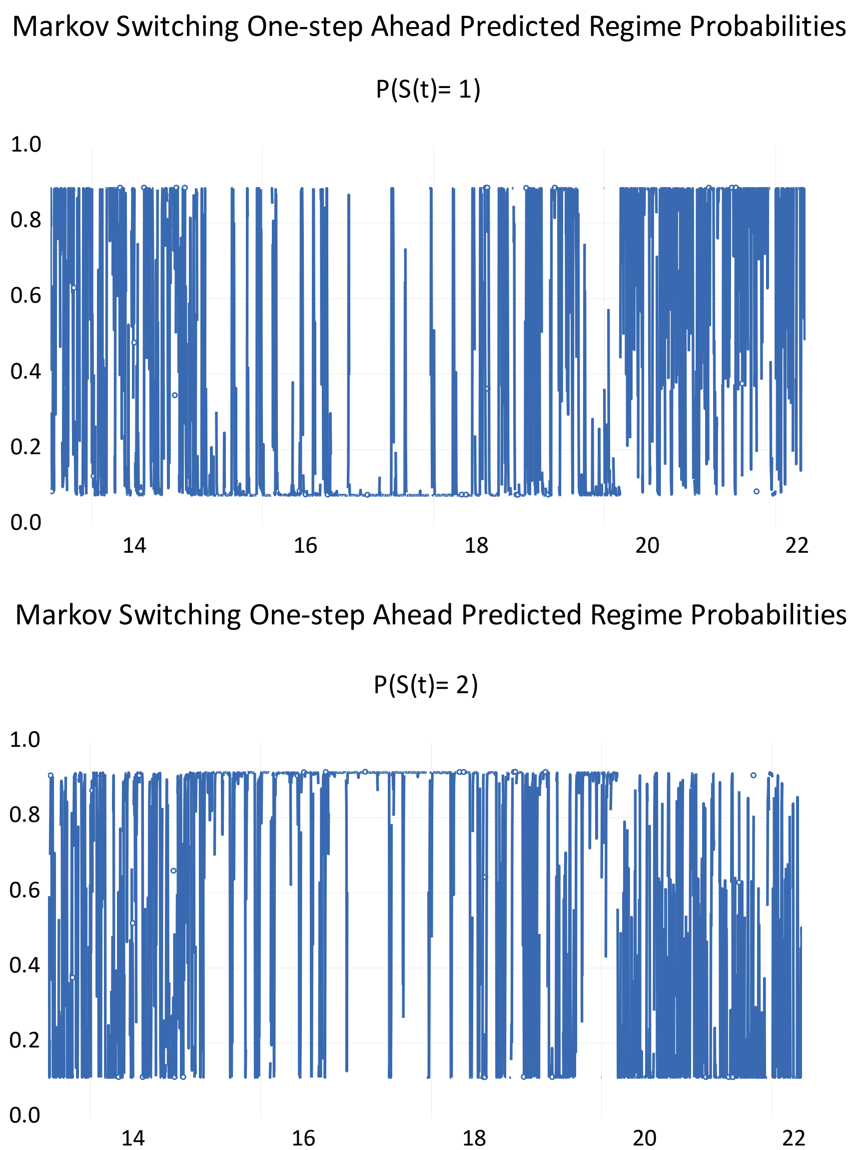

Figure 4. 7: Regime Probabilities

The unknown parameters of MRS-GARCH (1,1) model can be estimated using the maximum likelihood method. The log likelihood function is maximized to acquire these parameters.

$$\mathcal{L} = \sum_{t=1}^{T} \log [p1, t\ fr_t|S_t = 1 + P_{2,t} fr_t|s_t = 2] \qquad (4.1.3)$$

where $fr_t|S_t = 1$ is the conditional density of r_t given regime 1 occurs at time t and the ex-ante probability $p_{1,t}$ is calculated. Here $\hat{h}_{T,T+K}$ is the time t aggregated forecasts of the conditional volatility for the next k-steps, and $\hat{h}_{T,T+}\tau$ is the $\boldsymbol{\tau}$-step ahead forecasts of conditional volatility in regime 1 made at time t and can be recursively calculated.

$$\hat{h}_{T,T+K} = \sum_{\tau=1}^{k} \sum_{i=1}^{2} Pr(S_t = i|\Omega_{T-1})\hat{h}_{T,T+}\tau \qquad (4.1.4)$$

Table 4. 10: MS-GARCH Model Parameters Estimation

Parameters	Coefficients
C^1 (Regime 1)	0.042685 (0.0057)
C^2 (Regime 2)	0.003058 (0.0011)
$(u_{t-1}^2)^1$	0.358248 (0.0000)
$(u_{t-1}^2)^2$	0.211208 (0.0000)
h_{t-1}^1	0.790336 (0.0000)
h_{t-1}^2	3.511599 (0.0000)
P	9.213033
Q	13.33034
AIC	-1.538158
SC	-1.517217
HQ	-1.530501

The most accurate inference about the state in which the data generating process is at a given time is typically provided by smoothed probabilities, $P(S(t)=j|y_t)$, which are generated iteratively based on the entire sample.

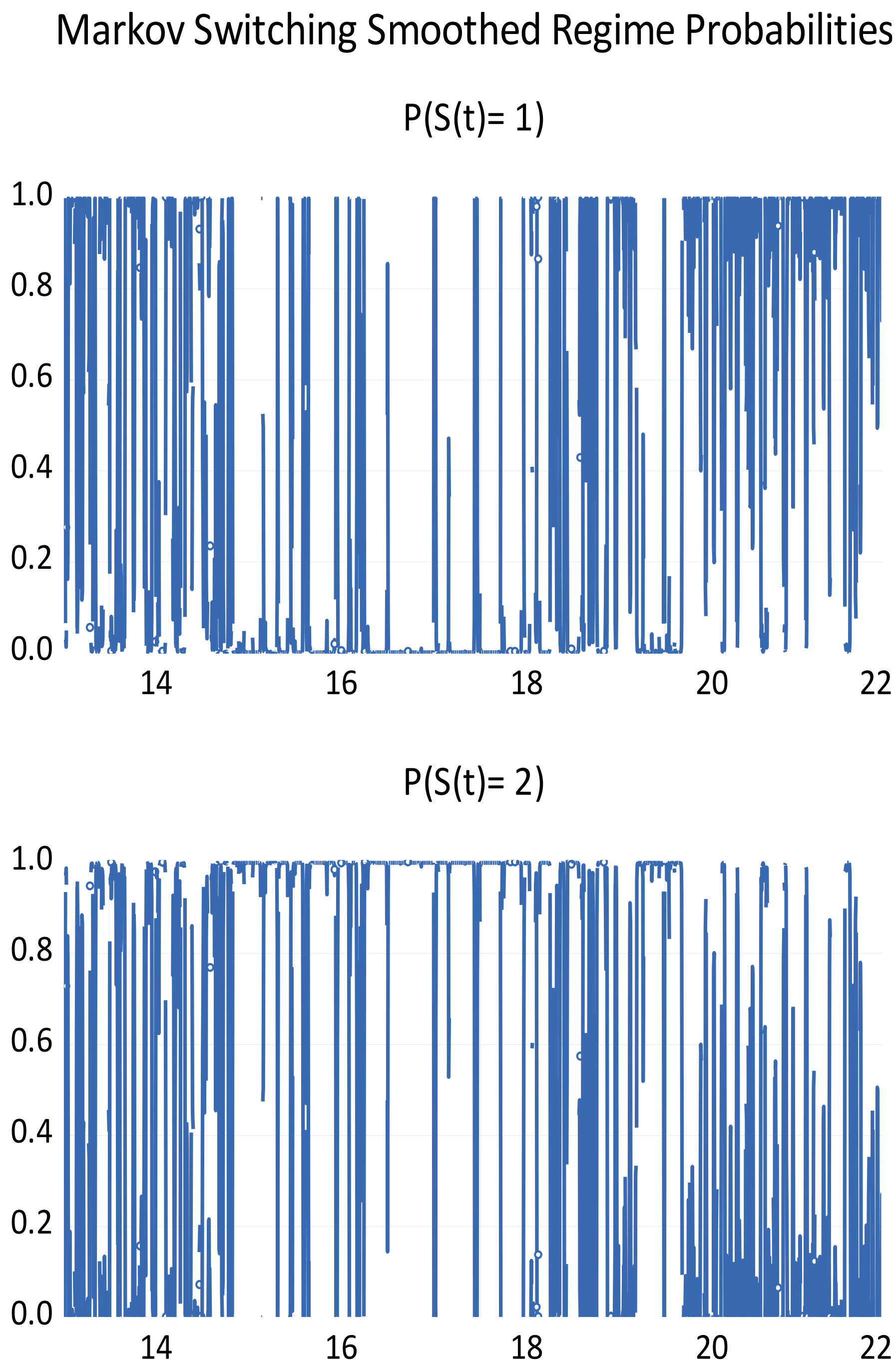

Figure 4. 8: Smoothed Regime Probabilities

Forecast Evaluation

In-sample and out-of-sample volatility prediction has been evaluated to check the model sufficiency and accuracy. Forecast of nominal effective exchange rate obtained through out of sample forecasting is added into original data and one step ahead forecasting technique is employed to generate more forecast entry. These forecast values are then tested for their accuracy. The measures of forecast accuracy i.e., loss function, found in literature are mean square error, MSE, root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), mean algebraic percentage error, (MALPE), Theil's U coefficient.

The volatility predictions from various GARCH models can be evaluated using a variety of statistical loss functions. However, comparing the predictive power of competing models is not an easy task because there is no one criterion for choosing the best model (Lopez, 2001). Therefore, three alternative statistical loss functions with various interpretations are used in this work. This can assist us in comparing the predictions of rival models and choosing the one that performs the best. For the evaluation, we use the mean squared error (MSE), root mean squared error (RMSE) and mean absolute error (MAE) of expectations for volatility. These are characterized as

$$MSE = \frac{1}{T} \sum_{t=1}^{T} \left(\sigma_t - \sqrt{\hat{h}_t} \right)^2 \qquad (4.1.5)$$

$$MAE = \frac{1}{T} \sum_{t=1}^{T} |\sigma_t - \sqrt{\widehat{h}}t| \qquad (4.1.6)$$

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^{T} \left(\sigma_t - \sqrt{\hat{h}_t} \right)^2} \qquad (4.1.7)$$

In-Sample Volatility Forecast Evaluation

For in-sample volatility forecast measurement in order to choose a best model, we performed one-step ahead, 5-step and 10-step ahead forecast analysis from a sample of daily exchange rate series ranging from 7/02/2013 to 3/25/2022. For one-step ahead forecast, we use two consecutive observations and go for variance forecast. Same technique is repeated for 5-step ahead forecast analysis, increasing the number of observations to be 5 this time. Here 5-step ahead means five working days in which nominal exchange rate has been observed.

One-step ahead forecast

Since we have to observe single day (3/24/2022-3/25/2022) variance forecast using the three proposed GARCH-type models, we see that minimum forecast errors have been observed in Markov Switching GARCH Model (MS-GARCH). Table 4.9 shows the obtained errors under Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) (Christoffersen & Jacobs, 2004).

Table 4. 11: One-step-ahead forecast evaluation

	MSE	MAE	MAPE	RMSE	Theil U2
GARCH (1,1)	0.006	0.078	62.78	0.08	0.29
TGARCH (1,1)	0.008	0.088	72.18	0.09	0.34
MS-GARCH (1,1)	0.002	0.041	29.97	0.048	0.113

Of the obtained forecast evaluation errors, we found that MS-GARCH gives the minimum error of model specification. Least the forecast error, higher the reliability of evaluation is.

5-step ahead forecast

We have used (3/14/2022- 3/18/2022) five working days return data to forecast variance and find optimal model with least error. Table 4.10 below shows various error criteria for GARCH, TGARCH and MS-GARCH under GED distribution. We conclude that still MSGARCH is only non-linear model which is best fitting our financial data having least values of MAE, RMSE, MSE and Theil's U coefficient.

Table 4. 12: In-sample 5-step ahead variance forecast analysis

	MSE	MAE	MAPE	RMSE	Theil U2
GARCH (1,1)	0.041	0.18	99.41	0.20	2.78
TGARCH (1,1)	0.040	0.18	99.45	0.20	2.79
MS-GARCH (1,1)	0.032	0.16	90.30	0.18	2.56

It is evident from table above that minimum errors under the three minimum error criteria MSE, MAE & RMSE are obtained through MS-GARCH modelling.

10-step ahead forecast

Using in-sample observations from exchange rate return series ranging between (3/14/2022- 3/25/2022), following values of loss functions are obtained (Table 4.11). Critically analyzing the values, we came to know that MS-GARCH model outperforms other two models of variance forecast. The difference among the forecast and real evaluations is represented by the loss function (McCloskey, 1985) value. The model's forecast reliability increases as the loss function value decreases.

Table 4. 13: 10-step ahead forecast analysis using in-sample data

	MSE	MAE	MAPE	RMSE	Theil U2
GARCH (1,1)	0.044	0.19	99.35	0.21	2.50
TGARCH (1,1)	0.044	0.197	99.40	0.21	2.51
MS-GARCH (1,1)	0.040	0.17	87.34	0.20	2.30

Brief Conclusion on In-Sample Forecast

In-sample forecast gives us an idea about the reliability of data. It has ensured us that investors and other stakeholders should seek help from the available data and future patterns obtained through conditional variance forecast.

Out-of-sample forecast

The most important part of modelling volatility of exchange rate is forecast of future prevailing volatility. Forecast of exchange rate volatility is crucial for stakeholders and investors in their portfolios. For the said purpose, we make out-of-sample forecasts using observation 4/05/2022-4/06/2022, 4/04/2022-4/08/2022, 4/04/2022-4/15/2022 for one-step, 5-step and 10-step ahead forecasts.

1-step ahead forecast

To obtain single day (4/05/2022-4/06/2022) variance forecast using the three proposed GARCH-type models of volatility, we obtained minimum forecast errors in Markov Switching GARCH Model (MS-GARCH). Table 4.12 shows the obtained errors under Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) and Theil's U coefficient.

Table 4. 14: 1-step ahead out-of-sample forecast evaluation

	MSE	MAE	MAPE	RMSE	Theil U2
GARCH	0.168	0.41	84.66	0.41	14.14
TGARCH	0.185	0.43	88.01	0.43	14.50
MSGARCH	0.13	0.36	72.79	0.36	12.29

5-step ahead forecast

Table 4. 15: 5-step ahead forecast errors evaluation

	MSE	MAE	MAPE	RMSE	Theil U2
GARCH	0.270	0.43	88.41	0.52	1.57
TGARCH	0.280	0.44	91.79	0.53	1.58
MSGARCH	0.221	0.38	81.17	0.47	1.45

10-step ahead forecast

Ten working days observations from exchange rate return series ranging between (4/04/2022-4/15/2022) have been used to forecast volatility, loss functions numbers are obtained as in Table 4.14 below. Critically analyzing the values, we came to know that MS-GARCH model outperforms GARCH (1,1) and TGARCH (1,1) models of variance forecast. The difference between the forecasted and real values is visibly present in the function's value. The model's prediction accuracy can be taken as credible since the loss function value decreases.

Table 4. 16: 10-step ahead forecast evaluation

	MSE	MAE	MAPE	RMSE	Theil U2
GARCH (1,1)	0.593	0.53	94.22	0.77	0.98
TGARCH (1,1)	0.608	0.54	95.77	0.78	0.99
MS-GARCH (1,1)	0.526	0.53	100.2	0.78	1.009

Concluding Forecast Evaluation

While evaluating one-step, 5-step and 10-step ahead forecast, we observed that MS-GARCH model for conditional variance forecast outperforms the other two GARCH type models as minimum errors are obtained through loss functions. Second more important observation is that all the three model types forecast with lowest error when the frequency of forecast is low (1-step and 5-step). However, we see that increasing the observation frequency from 5-step to 10-step has led us to a greater value of errors as compared to 1-step and 5-step.

SUMMARY

This chapter concludes with the estimation of Conventional GARCH-type models and their performance comparison with Markov Regime Switching models. Forecast evaluation obtained through these models are then compared using Loss functions. We conclude from the results of loss functions that GARCH-type models are reliable for short term volatility predictions and are less suitable for longer periods (Monthly, half-annual frequency etc.).

CHAPTER 5

QUALITATIVE ANALYSIS

This chapter presents a brief review of economy's working policies formulated and revised time to time to stabilize exchange rates and commodity prices. The context of qualitative analysis is policy papers and research papers based. Monetary policies statements and publications have been used to analyze foreign exchange rate forecast on price stability and inflation targeting by SBP. As defined by State Bank of Pakistan, "Financial markets are those where financial instruments including cash, bonds, stocks, and derivatives are traded. In order to decrease information asymmetries and enable central banks to implement and fulfil the goals of monetary and exchange rate policies, developed financial markets can play a critical role as an intermediary between lenders (savers) and borrowers (investors)".

SBP has directed its monetary policy stance primarily influencing the money markets and foreign exchange markets. SBP operationally focuses on regulating the over-night money market repo-rate[8] through the employment of several monetary policy tools in order to carry out its monetary policy (OMOs, Interest Rate Corridor (IRC), Reserve Requirements, Foreign Exchange Swaps). The rates for short-term period are used as a benchmark for lending to households and businesses and are converted into various longer term market interest rates, such as Karachi Inter-Bank Offer Rate (KIBOR). By lowering various uncertainties and improving the translation of short-term interest rates to pricing decision of longer-term loans, efficiency driven financial markets improve the efficiency and efficacy of monetary policy transmission.

[8] The rate at which overnight repo deals are transacted in the money market. https://www.sbp.org.pk/dfmd/FM-intro.asp

By their very nature, financial institutions are always going to be vulnerable to risks related to maturity change and taking risks. The most important thing is to keep risks at manageable levels so that the arrival of any potential shocks won't interfere with how smoothly the intermediation process runs. This heavily depends on the ongoing evaluation of the financial system within a suitable framework. Although it is still in development phase, the Financial Stability Framework (FSF), also known as the Macroprudential Policy Framework (MPPF), offers the framework for creating and putting into place a system to reduce instability risks at reasonable levels. This framework's five main components are as follows: (1) institutional arrangements (such as legal mandate, powers, and accountability); (2) techniques for identifying and assessing key systemic vulnerabilities; (3) toolkits available to address various risks; (4) post-implementation assessment; and (5) international coordination[9].

The branch-licensing policy has been updated by SBP with the goal of improving financial access to underserved communities. Additionally, new business models for the banking industry have been developed, such as Sales & Service Centers and Mobile Banking Units. The idea of a digital branch has been developed, and a pilot project for one of these branches has been launched at the Institute of Business Administration (IBA), Karachi.

In addition to granting licenses, SBP establishes minimum supervision requirements for financial institutions through Prudential Regulations (PRs). Corporate and commercial banking, small- and medium-sized enterprise financing, infrastructure financing, agricultural financing, microfinancing, housing financing, and consumer financing are just a few of the areas that PRs address. Additionally, the AML/CFT regime has been adjusted to comply with FATF guidelines,

[9] https://www.sbp.org.pk/reports/annual/arFY21/Vol-1/Chapter-3.pdf

and sanctions have been put in place to prevent the businesses and/or people on the blacklist from using financial services[10].

It demonstrates how monetary policy can reduce inflation to the extent that the money supply and the exchange rate can be stabilized. Any unexpected monetary growth will cause unexpected inflation the next year. The central bank's ability to manage money supply and inflation in the nation are directly impacted by the fiscal deficit and its financing structure. Government is responsible for controlling the budget deficit, choosing the least inflationary financing options, and acting swiftly and appropriately if there are supply shocks.

[10] AML/ CFT: Anti-Money Laundering / Combating the Financing of Terrorism
FATF: Financial Action Task Force

CHAPTER 6

CONCLUSION AND POLICY RECOMMENDATION

The chapter concludes the estimation results and policy analysis done in the context of foreign exchange rate forecast. By creating ARMA-GARCH models with various distributions and orders, the fitted outcomes of the various models are contrasted. The models with the best fitting performance were found to fall under the Generalized error distribution. The estimation outcomes of GARCH-type models show that the volatility of the foreign currency market is persistent over the study period, with a gradually waning influence over time. A significant "leverage effect"[11] was also noticed in the market, pointing to a significant knowledge asymmetry. The volatility of the exchange market is more sensitive to bad news but resilient to good news, indicating that investors are more likely to be impacted by bad news than by good news. For instance, from a time series perspective, the volatility of the foreign exchange market exhibits features of significant time-variation and clustering. These findings underline the importance of comprehending exchange rate volatility estimation, which has significant policy implications.

The study aids agents in the economy specifically those who invest in the markets, those dealing with forecast for asset pricing and risk management because exchange rate volatility (exchange-rate risk) has the potential to increase transaction costs and decrease gains from international trade. Results can aid investors in bettering their portfolio's worldwide diversification and locating the most advantageous hedging options. Exchange rate return forecasts will help anticipate the market stability for stakeholders. Inquiring upon whether monetary policy should respond to the exchange

[11] "well established relationship between stock returns and both implied and realized volatility" (Figlewski & Wang, 2000)

rate, there is conflicting evidence from simulated open-economy models with exchange rate uncertainty. Most of the time, policymakers are not sure of the type of shock that will affect the real exchange. Therefore, policymakers must assign specific odds to a temporary shock and a highly persistent or bubble shock. Way that it is simple to investigate how this kind of uncertainty impacts the best response of policy tools and how that response is influenced by the transition probabilities that define the shock. Contractionary monetary policy may be to blame for the reduction in the money supply and subsequent increase in interest rates. More investments will be attracted by an increase in interest rates, which will increase the value of one currency for another.

LIMITATIONS OF THE STUDY

The over-sensitivity of the conventional Markov switching model leads to cause instability in parameter estimation and mis-classification of regime shifts, which in turn impairs its predictability because financial time series like exchange rates are frequently quite noisy. Switching models according to our findings, tend to hold good predictive powers in short term only. They may fail in long term i.e., more than a year.

POLICY RECOMMENDATIONS

- The State bank should target for domestic inflation and leave the exchange rate to float for the economy with perfect exchange-rate pass-through.
- For greater transparency in the foreign exchange market, State bank could take the expected effects of exchange rate volatility into account when implementing monetary and interest rate policies.
- To deal with the changes brought on by exchange rate volatility, financial sectors also need to make efforts toward structural and institutional reforms.

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