

**A HYBRID MARKOV SWITCHING GARCH  
MODEL APPROACH FOR IMPROVING  
VOLATILITY DYNAMICS**

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**A HYBRID MARKOV SWITCHING GARCH  
MODEL APPROACH FOR IMPROVING  
VOLATILITY DYNAMICS**

by

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## **Dedication**

I dedicate this thesis to my beloved parents, family, and my daughter, Junairah Hossain.

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## LIST OF SYMBOLS

$\omega$	Constant coefficient
$y_t$	Observations at time $t$
$\varepsilon_t$	White noise at time $t$
$\gamma$	Scaling factor of ExpAR model
$r_t$	Returns of the assets at time $t$
$\mu$	Average return
$h_t$	Variance return at time $t$
$\sigma_t^2$	Variance return at time $t$
$I_{t-1}$	Information set at time $t - 1$
$s_t$	State variables at time $t$
$P$	Transition probability matrix
$\Gamma$	Gamma function
$\nu$	Degree of freedom
$\pi$	Invariant probability measure
$\mathbb{R}$	Set of real number
$\ \cdot\ $	Matrix norm
$\rho(\cdot)$	Spectral radius of a matrix

## LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BIC	Bayesian Information Criterion
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
ExpAR	Exponential Autoregressive
FIGARCH	Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GED	Generalized Error Distribution
GFC	Global Financial Crisis
IGARCH	Integrated Generalized Autoregressive Conditional Heteroskedasticity
IMF	International Monetary Fund
IPM	Invariant Probability Measure
LL	Log Likelihood
MCMC	Markov Chain Monte Carlo
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroskedasticity
ML	Maximum Likelihood
MSGARCH	Markov Switching Generalized Autoregressive Conditional Heteroskedasticity
RS	Regime Switching
SETAR	Self-Exciting Threshold Autoregressive
STAR	Smooth Transition Autoregression
TAR	Threshold Autoregressive
VaR	Value-at-Risk
WUI	World Uncertainty Index

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- Appendix A      PROOF OF LEMMA AND THEOREM
- Appendix B      THIRTY-FOUR SAMPLE'S CATEGORY, SAMPLE NAME,  
PERIOD, AND SAMPLE SIZE
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# **PENDEKATAN MODEL GARCH PERTUKARAN MARKOV HIBRID UNTUK MENAMBAHBAIK DINAMIK KEMERUAPAN**

## **ABSTRAK**

Analisis siri masa telah lama menarik perhatian penyelidik dalam pelbagai bidang. Sejak dua dekad yang lalu, siri masa telah dianalisis menggunakan model linear, yang mempunyai sejumlah kelebihan. Walau bagaimanapun, persoalan sama ada terdapat kaedah lain yang dapat membantu memahami dan meramalkan data sebenar daripada model linear yang telah dikemukakan. Data siri masa sejarah menunjukkan tidak linear, bukti perubahan berstruktur, dan turun naik ekstrim. Dalam kes ini, model linear tidak dapat menjelaskan turun naik dan meramalkan nilai masa depan. Model keluarga GARCH menjelaskan ketidakstabilan dan ramalan dengan sangat baik untuk data siri masa tidak linear tetapi runtuh ketika berlaku perubahan struktur dan pergolakan pasaran. Penyelidikan ini bertujuan untuk membentuk model siri masa tak linear baharu yang terdiri daripada model min bersyarat tak linear, ExpAR, dan model varians bersyarat tak linear, MSGARCH. Model hibrid ini dikembangkan untuk menggambarkan ketidaklinearan dalam persamaan min dan varians semasa perubahan struktur dan keadaan pasaran yang melampau. Akibatnya, ia dapat menjadi kaedah yang berguna untuk menyuai, menggambarkan, dan menangkap risiko penurunan dalam data siri tak linear. Di samping dapat menawarkan beberapa peningkatan dari segi penyuaian dan penjelasan dinamik kemeruapan jika dibandingkan dengan model penanda aras. Disebabkan pelancaran model baharu, data siri masa serupa telah dijana dari model baharu dan model penanda aras. Selepas itu disuaikan ke dalam model-model ini. Kemudian, data siri masa nyata dimasukkan ke dalam model-model ini dan prestasi



mereka dibandingkan. Model terbaik dipilih berdasarkan kebolehjadian maksimum dan kriteria maklumat minimum. Nilai pada risiko juga digunakan untuk menilai kemampuan model baharu untuk menangkap risiko penurunan. Hasil yang dianggarkan dari data simulasi menunjukkan bahawa prestasi model baharu melebihi model penanda aras. Secara aplikasi empirikal, secara keseluruhan, model baharu ini mengungguli model penanda aras dan menggambarkan risiko penurunan dengan memuaskan.

# **A HYBRID MARKOV SWITCHING GARCH MODEL APPROACH FOR IMPROVING VOLATILITY DYNAMICS**

## **ABSTRACT**

Time series analysis has long attracted the attention of researchers in a variety of fields. Past two decades, time series have been analyzed using linear models, which have a number of advantages. However, the question of whether there are other methods that can help understand and predict actual data than linear models have been presented. The historical time series data show nonlinearity, evidence of structural changes, and are extremely volatile. In this case, linear models are incapable of explaining volatility and predicting future values. The GARCH family models explain volatility and forecasting very well for nonlinear time series data but collapse when structural breaks and market turbulence are present. This research aims to incorporate a new nonlinear time series model comprised of the nonlinear conditional mean model, ExpAR, and the nonlinear conditional variance model, MSGARCH. This hybrid model was developed to capture nonlinearity in both the mean and variance equations during structural changes and extreme market conditions. As a result, it can be a valuable method for fitting, illustrating, and capturing downside risk in nonlinear time series data. Moreover, it can offer some enhancement in both fitting and explaining volatility dynamics compared to the benchmark model. Since the launch of the proposed model, similar time series data has been generated from the proposed model and the benchmark model. Then the generated data are fitted into these models. Later, the real-world time series data were fitted into these models and their performance was compared. The best model was chosen based on maximum likelihood and minimum information criteria. The

Value-at-Risk was also used to assess the proposed model's ability to capture downside risks. The estimated results from simulation data revealed that the proposed model outperforms the benchmark model. In empirical applications, overall, the proposed model outperforms the benchmark model and captures downside risks satisfactorily.

# CHAPTER 1

## INTRODUCTION

### 1.1 Background of the study

The study of time series in finance and economics is one of the topmost interests by the academician and researchers of various subjects. But most of the research was concentrated primarily on linear modeling. The autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) are the most commonly used linear models. These models were introduced by Box and Jenkins (1970). Though the real-world time series data exhibit not only linearities but also nonlinearities and hence, usually a question has been arisen that whether the existing models can be capable of enlightening and forecasting the volatility dynamics of such time series better than existing linear models.

The Threshold Autoregressive (TAR), Self-Exciting Threshold Autoregressive (SETAR), and Exponential Autoregressive (ExpAR) model are typical nonlinear models in conditional mean. In contrast, the most popular and representative nonlinear models in the conditional variance are the Autoregressive Conditional Heteroskedasticity (ARCH) model of Engle (1982) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model of Bollerslev (1986). Moreover, combining linearities or nonlinearities in conditional mean and nonlinearities in conditional variance has become another popular class of hybrid model in the preceding two decades.

Volatility is a common phenomenon in the modern financial market, especially the stock market index. Volatility in the stock market is a natural consequence because of variations in activity level at a market. These activities, such

as trading volume, new information, and market expectation, will cause shifts in stock market variance daily returns. In the stock market, volatility clustering is known as one of the stylized features which indicate large and small shifts in the return will also follow by large and small shifts. However, structural breaks in the volatility are found in many financial and economic assets, and thus overlooking this characteristic can have great impacts on the accuracy of the volatility forecasts. Many researchers and experts care about only the single-regime conditional volatility model, whereas Danielsson (2011) refers to these models as one of the reasons for the financial crisis. In recent studies have shown that GARCH family models might fail to predict actual variant in the volatility during volatility dynamics changes regimes over time (Bauwens et al., 2014; Bariviera, 2017; Ardia et al., 2018). A way out to this issue is to allow the GARCH parameters to vary over time corresponding to a hidden discrete Markov process, which is termed as Markov-switching GARCH (MSGARCH) model. This approach precedes volatility predictions that can promptly adapt to changes in the unconditional volatility (Hamilton, 1989; Marcucci, 2005; Ardia, 2008).

Under the above circumstances, this study intended to establish a comprehensive volatile model to enhance the ability to capture volatility dynamics even in the time of the financial crisis period. The reason for developing a new model is also based on the subsequent arguments of Section 1.2.

## **1.2 Motivation of the study**

In this recent era, all types of financial markets, such as stock markets, digital currency markets, energy markets, precious metal markets, and different categories of financial institutions and instruments, have rapidly grown both in number, value,

and volume. This rapid progression has simultaneously elevated risks and uncertainty in the financial procedure and potentially generate the essentiality of proper risk management for the investors. At the same time, the markets become frenzy causes high volatility and bubbles. Stock returns show sharp jumps not only as a result of structural changes in the financial sector but also as a result of shifts in future assumptions arising from conflicting information or disparate preferences (Arellano, 2016). True volatility is influenced by shocks that never last long, resulting in mean-reverting conduct. As a result, a reliable volatility model for stock return can have a different approach to dealing with shocks. Most economic and financial time series exhibit at least one of the five characteristics mentioned below: trend, seasonal patterns, outlier, clusters, and nonlinearity are all examples of nonlinearity. According to Franses and van Dijk (2010), four traditional stylized facts exist in time series of returns: (i) large returns appear more regularly than expected (fat tail or leptokurtic), implying that the kurtosis is greater than three, or that the distributions' tails are heavier than the Normal distribution; (ii) large returns have a tendency to happen in clusters, suggesting the existence of potentially time-varying volatility or risk; (iii) significant negative returns occur more frequently than significant positive returns; (iv) volatile periods are always followed by high negative returns. For returns, characteristics (i) and (iii) point to the suitability of models of varying regimes (Franses and van Dijk, 2010). Characteristics (ii) and (iv) point to the importance of models that permit the explanation of time-varying uncertainty, with the effects of negative and positive past returns potentially differing. The residual variances in the data shift with time, making the ARMA model or any linear model unsuitable for use (Amri et al., 2020). Therefore, the urge of the nonlinear model or

combination of the linear and nonlinear model or combination of nonlinear in mean and nonlinear in variance model.

After the introduction of Bitcoin by Nakamoto (2009), the new era of virtual currency was started as a new monetary resource that operates a peer-to-peer automated cash system allowing online transactions directly to transfer one person to another without involving any financial institutions. For that reason, there is no need for any associate authority for Bitcoin (and other cryptocurrencies) like most of the financial assets and thus no necessity of tangible representative. The most attractive uses of Bitcoin (and other cryptocurrencies) are very low transaction costs, peer-to-peer technology, strong security, and globalization, and free of centralized control. Despite low transaction costs (Kim, 2017) and diversification benefits (Corbet, Lucey, et al., 2018; Glaser et al., 2014), and highly speculative uses, causing high volatility as well as bubbles (Cheah & Fry, 2015; Dyhrberg, 2016b; Corbet, Meegan, et al., 2018; Hafner, 2018). However, the acceptability of Bitcoin and other cryptocurrencies reduce due to lack of computer knowledge, lack of conviction about the cryptocurrency transaction system of its users, very high volatility compared to other financial assets, and limited area of acceptable financial institutions to take Bitcoin and other cryptocurrencies as an alternative currency. Nonetheless, Bitcoin and other cryptocurrencies' popularity increases significantly because of frequently addressing by media (both in print and electronic), investors, policymakers, financial institutions, politicians, researchers, and government. From the inauguration of Bitcoin to 19th May 2017, the prices stayed below USD2000. However, its price rose over USD19000 on 16th December 2017 due to the frenzied market exhibiting the highest volatility and this increasing figure is another proof of the acceptability of Bitcoin. The questions arise with Bitcoin and other cryptocurrencies' climbing

popularity, how its price is correlated with monetary assets (such as stock prices, energy prices, precious metal prices, and bond prices) is the topmost concern of comprehending for the investors, researchers, regulators of the governing body, policymakers, and government of a country. Another question, is Bitcoin and other cryptocurrencies valuable like other assets, or is it comparable with other assets to include in the portfolio?

Recently researchers focused on volatility dynamics as well as risk management of Bitcoin returns. Chu et al. (2017) found in their research the existence of volatility clustering and concluded the GARCH family model could perform well within the sample. In volatility dynamics, there exist long memory, which was found by Phillip et al. (2018). Applying the traditional GARCH family model, researchers found volatility is persistent, but forecasting is poor. This was happened due to biases of estimation or neglecting regime changes on the volatility (Lamoureux et al., 2009). According to Ardia et al. (2019), Bariviera (2017), and Balcombe & Fraser (2017) study on Bitcoin returns, they found a significant change in the regime and suggest that regime-switching models are the excellent choice of capturing volatility dynamics. Thies and Molnár (2018) found evidence of a structural break in Bitcoin data. Okorie and Lin (2020) have studied volatility connectedness among crude oil and cryptocurrency returns. They have seen that there is evidence of volatility spillover from the Bitcoin market to the crude oil market and vice-versa. Also, crude oil has hedging abilities on Ethereum which is in the short-run, and on Elastos as well as Bit-Capital-Vendor which is in long run. Over 1,000 GARCH family models were examined by Caporale and Zekokh (2019) on returns of cryptocurrency data to find out the best perform model. They have suggested that for better risk management, optimistic portfolio, securities



improvement, etc. one should consider asymmetry and regime switching in their model. Charles and Darné (2019) have taken a sample from July 2010 to March 2018, then divided this sample into two subsamples, one is July 2010-October 2016 for replication of Katsiampa's (2017) study and the other is the whole sample for reproduction purposes. Their analyses were the same as Katsiampa (2017) with only a few differences, but they found jumps in returns of Bitcoin, therefore GARCH-family models are not suitable for modeling. That's why they suggested that long-memory model and Markov-switching model are the best choice for analyses purposes. In the recent study of cryptocurrencies volatility dynamics and interconnectedness, Hossain and Ismail (2021) found cryptocurrency is time-varying, thus time-varying model can better explain volatility dynamics.

Nowadays, people are interested in Bitcoin and other cryptocurrencies due to global economic instability, and they want to keep their savings in a secure place. For this reason, the primary concern is to develop a reliable model for forecasting volatility and risk management. Most of the researchers focus on GARCH family models, which lead to poor forecasting both in volatility and risk due to neglecting regime changes in the conditional variances process (Runfang et al., 2017). Bitcoin can be served as a hedge or a safe-haven or a diversifier for stocks, bonds, exchange rates, etc. Bitcoin volatility and these features (hedge or a safe-haven or a diversifier) can be captured by the existing GARCH family model. But what happens when there is evidence of structural breaks in the sample period, is GARCH family model adequate to explain volatility dynamics during the breaks? Need to explore the answer to this question; if the answer is not then need to find a better model which can well capture volatility during the breaks and explain volatility and risk management.

Bangladesh stock markets volatility investigated by Roni et al. (2017) considering three crisis periods from November 2001 to November 2016. They found that volatility is persistent, and that TGARCH and GARCH are the best models based on model accuracy and error statistics, respectively. Bathia et al. (2020) applied the panel GARCH model and showed that the financial crisis of emerging stock economics was affected by cross-border assets flows during the post-global financial crisis. Nevertheless, during the global financial crisis Zekri and Razali (2019), Al Refai et al. (2017), Joseph et al. (2020), McIver and Kang (2020), Yamani (2019), and Belhassine (2020) also studied volatility dynamics using a different methodology. Recently, Broto and Lamas (2020) focused on the relationship among returns, liquidity, and volatility of US Treasuries and found spillover effects and lower persistence volatility after the crisis period. A study by Al-Rjoub and Azzam (2012) analyzed the stock returns of Jordan during the financial crisis and found an inverse relationship between volatility and stock returns. Tai (2018) analyzed the dot.com crisis in 1999–2001 and the subprime crisis in 2007–2009 and provided experimental evidence of international diversification. Researchers also employed the GARCH family model to discover the effect of the COVID-19 crisis in agriculture commodity prices, such as Tanaka and Guo (2020) explored wheat price volatility. While the financial crisis (in 2008) of the MENA region was investigated by Ahmed (2018), and he found regime shift characteristics within three countries. Hossain et al. (2021) studied the Bangladesh stock market crisis in 2011, they found in some cases GARCH family model explodes, i.e., the GARCH family model is not capable of explaining the Bangladesh stock market crisis.

I have seen that Bangladesh stock market crisis in 2011 and many researchers studied different crises throughout the world, but none of them considered structural break and regime shift characteristics in the sample period. As a result, different variance model performs well in different sub-sample period, therefore the problem arises. It is difficult to fit different variance models in different sup-period then find the best model as well as it causes computational costs. In this situation, the need for the MSGARCH model comes in light of a good combination of nonlinearity in the mean equation and nonlinearity in the variance equation.

Many researchers applied the regime-switching model in different field of finance and economics, among them Xie and Zhu (2021), Thongkairat et al. (2019), Maneejuk et al. (2018) studied metal price volatility; Boonyakunakorn et al. (2019), Liao et al. (2019), Sampid et al. (2018), Sajjad et al. (2008), Arouri et al. (2016) studied stock markets volatility; Urom et al. (2020), Roubaud and Arouri (2018) studied stock, energy, and exchange rate volatility; Korley and Giouvris (2021), Wu et al. (2020), Lee and Chen (2006) studied exchange rate volatility; Xiao (2020), Zhang and Xu (2020), Zhang et al. (2019), Naeem et al. (2019) studied energy volatility. They found evidence of regime changes over time, but none of them consider the combination of nonlinearity in the mean equation and the variance equation. Therefore, it is time to see what happens if we combine two nonlinear models. Will this proposed model improve the results?

### **1.3 Problem statement**

From the discussion in the previous sections, the need for a new hybrid model becoming vital especially when there is evidence of structural changes. In the presence of structural changes, the MSGARCH model is the only candidate for

fitting real-world data. But this real-world data is not linear, therefore the need for the combination of nonlinearity in the mean equation and nonlinearity in the variance equation, so that it can capture volatility dynamics more accurately than the existing models. To establish a new comprehensive model, we need to focus on several matters. Firstly, when a new model introduces, it is crucial to simulate the model for a different parameter value to see the significant difference with the benchmark model, which could be demonstrated by this model. Secondly, it is important to see the performances of the proposed model when fitting into real-world data. In this case, the question arises as can it capture volatility dynamics better than the existing models, can it produce low standard errors than the existing model? Thirdly, need to see the ability of the proposed model in capturing downside risks. This is important because the financial crisis throughout the world was not so rare, most of all stock market was faced a crash due to various reasons. The volatility of the world stock market has increased radically from 2006 according to IMF's World uncertainty index (WUI) (Baker et al., 2016; Ahir et al., 2019; Ali et al., 2019). Previous financial crises for instance stock market crash in 1987, the global financial crisis (GFC) in 2007-2008, the Eurozone debt crisis in 2010, etc. was the witness of massive capital loss and bankruptcy of big financial institutions. The common reasons behind these crises were poor methods of measurement, meager risk management, and lack of knowledge of governing risks specifically miscalculating risk measures (Gropp, 2014). Hull (2018) argued that most of the previous financial enormous losses were possible to avoid if reliable VaR modeling was appropriately implemented.

Therefore, it is becoming vital to introduce an econometric model that takes into account the above-mentioned arguments with the purpose of producing a robust

and comprehensive volatile model which can explain volatility dynamics and capture downside risks. Although, there is no such model exists that can perfectly capture the volatility of financial and economic time series data, if a model can give some idea of volatility movement and minimize risks then it is considered as an efficient and significant model.

#### **1.4 Research questions**

Based on the comprehensive discussion of previous sections, the research questions of this study are presented as follows:

1. What are the simulation performances of the proposed model compared to the benchmark model? Can the two models simulate approximately similar time series data, and can the proposed model provide better results?
2. What are the performances of the proposed model when fitting real-world financial and economic data compare to the benchmark model?
3. Is the proposed model capable to capture downside risks more accurately than the benchmark model?

#### **1.5 Research objectives**

From the research questions, the objectives of this study are portrayed as follows:

1. To develop the proposed model and benchmark model, generate similar time series data then estimate results using the simulated data and compare two results to find the best model.

2. To fit real-world time series data into the proposed model and benchmark model then compare the two estimated results and choose the best model based on maximum log-likelihood and minimum information criterion.
3. To capture downside risks by applying 5% VaR backtesting and see which model capable of capturing downside risks more accurately.

## **1.6 Significance of this present study**

This study signifies and enriches existing literature in many ways. Since this hybrid econometric model is a combination of nonlinear conditional mean and nonlinear conditional variance equations, therefore capable of capturing real-world volatile market movement more accurately than the existing models. However, previous research was only focused on linear model or conditional variance models or a combination of both, therefore these models were well fitted in the tranquil markets. But when the market was in turmoil, these models were not much efficient in explaining the volatility of the markets which leads to poor forecast results (see, e.g., Lamoureux and Lastrapes, 1990; Bauwens et al., 2014). MSGARCH model can grab this unstable movement (Caporale & Zekokh, 2019; Charles and Darné, 2019), but this is not sufficient enough to explain volatility and to capture downside risks. The proposed hybrid model is well enough to demonstrate volatility even in the chaotic market situation and grab downside risks more accurately, which leads to better forecast. It is of key importance to pick a reliable model for grabbing volatility and forecasting the risk before an investment. In quantitative finance, the investors would like to allocate their capital among a succession of uncertain investment opportunities (Ardia et al., 2018). Therefore, the investors can get a true picture of the volatility movement and downside risks, so that they can make a correct decision

about hedge or diversification or a safe-haven. The proposed model is the improved version of the existing models which uncovered the door of present literature of volatility and risk management in a new dimension.

### **1.7 Limitations and Future research**

Since there is no such model present in the literature which perfectly applicable in financial and economic time series data and able to demonstrate everything accordingly. Therefore, the presence of limitations in any model is natural and inevitable. In the aftermath, the proposed hybrid has some limitations that indicate further improvement needed which is left as future works. Firstly, choosing the right gamma ( $\gamma$ ) value for the ExpAR model is difficult. There is no established algorithm for the gamma parameter such that it can automatically take a value during the estimation step of the ExpAR model. Since this value has a great influence on the estimated results, thus needs an appropriate method to choose the right value. Secondly, here we only considered a normal distribution, but I need to observe what will happen when considering other distributions such as skewed normal, student's t, skewed student's t, generalized error distribution (GED), and skewed GED. Thirdly, the model is going to be more complex when the number of orders increases, causes computational costs, thus here I only considered the first-order model. Lastly, we only considered the MSGARCH model in all states, but it is possible to apply different Markov switching GARCH models in a different state. The proposed model can be applied to check hedge or diversifier or safe-haven capabilities and to capture the volatility dynamics of some well-known crisis periods. I did not check the forecasting performance of our proposed model, I left it as my future work. I only consider thirty-four samples from different financial areas, but to establish a new

model it is important to fit a large number of samples with large sample size. I consider the Maximum Likelihood (ML) estimation procedure, but I need to check the Markov chain Monte Carlo (MCMC) method whether there is any improvement of the results. All these left as recommended future research for further improvement of the proposed hybrid model to make it more realistic.

## **1.8 Thesis organization**

This study was carried out by employing quantitative research techniques of simulating data and estimating results through simulation data, meanwhile fitting real-world historical time series data and compared the results with the benchmark model. This research is structured as follows:

- In Chapter 1, a brief discussion on the background and motivation of this study followed by the research problem, research questions, research objectives, significance, and limitations with future recommended works are presented.
- In Chapter 2, a summary of the previous literature works related to the present study and some reviews sector-wise like digital currencies, stock markets, metal prices, and energy markets are described. This chapter gives insight into the theoretical and empirical understanding of the improved volatile model.
- In Chapter 3, the theoretical construction of the proposed hybrid model based on the exponential autoregressive (ExpAR) model and Markov switching GARCH model are portrayed. Characteristics of the model and various constraints are also discussed in this chapter.



- In Chapter 4, approximately similar data generated from the new and benchmark model, graphical view of this data, and estimated results from this data are displayed here. For practical analysis purposes, real-world data fitted into both models and the other two models- MSGARCH and GARCH model and reported estimated results in this chapter. A brief discussion on the results and the reason for choosing the MSGARCH model and benchmark model are explained here.
- In Chapter 5, it is the final chapter containing a summary of the whole study and a brief discussion on the research questions, contributions, and concept of future works.

## CHAPTER 2

### LITERATURE REVIEW

#### 2.1 Introduction

Time-series studies have long been a topic of concern in a number of various areas, among them, finance and economics have become hot topics. Decade after a decade, time series have been studied using linear models. The use of linear models during analyzing time-variable phenomena has always been attributed to the reality that these models have various benefits, such as uncomplicatedness, the capability to estimate comparatively effortlessly, and to describe quite well a lot of time-series observed in the reality and to forecast well enough. However, the linear models are not always dominated over nonlinear ones, particularly in applications for financial and economic data. The reality is often nonlinear effects observed and, in such situations, it can be too stringent to presume that the linear model is appropriate for the time-series data. There are numerous time series characterized by nonlinearity, and thus the nonlinear models can be explained much better (Katsiampa, 2015).

Here I address the numerous popular and extensively used nonlinear and combination of linear and nonlinear time series models proposed in the literature. I discussed the various application of these linear and nonlinear models that are addressed in the existing literature. Finally, I discussed the need for two forms of nonlinearity combine in the conditional mean equation and in the conditional variance equation that are of special concern to us. A well-known portfolio management tools VaR and its various practical application are also discussed here.

## **2.2 Bitcoin and other digital currencies**

After the inauguration of Bitcoin in 2009, cryptocurrency markets have been spreading rapidly throughout the world. These digital currencies are spreading globally because of frequently mentioned by printed media, electronic media, financial and governmental institutions (Glaser et al., 2014). These digital currencies' popularity is increasing day by day due to security failure in the banking sector and the ongoing financial crisis throughout the world. For example, the Bangladesh bank robbery, also known as a cyber heist, happened in February 2016. About 1 billion US dollar transfer from Federal Reserve Bank of New York, this account belongs to Bangladesh bank (Das & Spicer, 2016). Such a security breach can be avoided in cryptocurrency. Cryptocurrency is using blockchain technology, in which less sensitive data will be provided in a transaction as compared to those involving standard currencies (Corbet, Lucey et al., 2019). The recent China-US trading war also another example of financial instability throughout the world. There is also another reason, many financial institutions (gradually this number also increases) are accepted cryptocurrency as a transaction media. Governmental restrictions, hacking problems, lack of computer knowledge, etc., could not create a barrier to the growth of cryptocurrencies' popularity. The investors, those who invested their money to buy precious metals, now invest their money to tend towards the cryptocurrency. Unlike conventional currencies, cryptocurrencies foundation is cryptographic proof, which has lots of advantages over usual payment systems (like debit and credit cards) and lowers operational costs, high liquidity, and secrecy. Among the cryptocurrencies, Bitcoin is the largest cryptocurrency, both in volume and capital. As of May 2019, there are more than 1800 cryptocurrencies existed (Y. Li et al., 2020).

Cryptocurrencies return much more volatile as well as riskier than traditional currencies and stock. As asset returns, cryptocurrencies have a place in financial markets and portfolio management (Dyhrberg, 2016a; Wu and Pandey, 2014). These assets are nonstationary and violate the normality assumption. Volatilities in the financial markets are intercorrelated and cross-correlated across assets returns, and markets are widely accepted (Jondeau et al., 2007; Ismail et al., 2013). Cryptocurrency returns are much more than other asset returns and have hedging capabilities when incorporated in stakeholders' portfolios. However, in recent days, fluctuations in the exchange rate have become vital concerns amongst researchers, stakeholders, economists, and financial institutions involved in these markets. One of the essential concerns for the investors to better understand cryptocurrencies markets and generate more knowledge to make an appropriate decision in improbability and risks is the study of cryptocurrencies interconnectedness well as volatility co-movements (see, Gkillas and Katsiampa, 2018). When the potential investors have sufficient information about correlation factors, covariances, and operational mechanisms of cryptocurrencies, they will get privileged opt-to-alter or diversify their investment to reach the desired goal.

Yermack (2013) has studied essential characteristics (the function of exchange facility, storage value, and transaction unit) of Bitcoin from an economic perspective. He found that it mostly fails to fulfil all essential characteristics compare to conventional currencies and cannot be a traditional currency. On a daily basis transaction, has zero correlation with worldwide accepted currencies, and compared to gold, it is incapable of risk managing and hedging capabilities. He also added that Bitcoin prices influence by geopolitical, government, digital crime, global socioeconomic events, and many other reasons. Most researchers have compared

Bitcoin with gold in their analysis (Grinberg, 2012; Dyhrberg, 2016a, 2016b; Zhu et al., 2017; Hossain et al., 2020). The researchers mainly focus on the correlation between Bitcoin and precious metals, compare behavior with traditional currencies, economic value, hedging properties, volatility co-movement, spillover effect, risk management, relation with energy, etc. Barber et al. (2012) have investigated Bitcoin in-depth to understand better its long-term stability, weakness, strengths, and security issues. They have found that there is a lack of simplicity, lack of flexibility, and difficulty making decentralization, and it is easily grabbed but challenging to subvert. They have concluded that if Bitcoin operates in the right way, then it can be treated as a decentralized currency.

Yelowitz and Wilson (2015) have analyzed Bitcoin based on its user characteristics of google search and categorized them into four types (such as speculative investors, Libertarians, computer programming enthusiasts, and criminals). They concluded that computer programming and an illegal activity positively influence Bitcoin price, whereas political and speculation terms do not have. Bergstra and Weijland (2014) have tried to classify Bitcoin from traditional currency, informational currency, or money-like commodity and concluded it as a money-like commodity. Cusumano (2014) has intuitively analyzed of Bitcoin ecosystem and found that it is less-alike like a currency but more as a computer-generated commodity. Cheah and Fry (2015) have studied Bitcoin in a speculative-bubble aspect and investigated whether there are trends of google search or not for additional perception, and they come to the conclusion that it is much prone to speculative bubbles and has no fundamental value. Zhu et al. (2017) have considered stock price, custom price, currency (US dollar), Federal funds, and gold price to see the influence on Bitcoin and decided; it has an influence of microeconomics index

and also assets price and cannot be a real currency. Another finding is, all variables exhibit long-term impact. US dollar has the highest impact on Bitcoin value, whereas the least influence is the gold price. Klein et al. (2018) have studied Bitcoin and gold and with other assets to observe their structure, correlation, and portfolio components. They have argued that it has asymmetric returns during market shocks and similar movements like other precious metals. They also argued that it is unable to hedging; therefore, it is not safe-heaven.

Based on the Whittle function, Adebola et al. (2019) have used parametric and semi-parametric techniques for fractional integration. Using bivariate relationships among cryptocurrencies and gold for fractional cointegration, they have inspected the level of persistence and probability of short-run and long-run stability between them. They have found an indication of mean-reversion in gold values and few cryptocurrencies, and in the long-run, a small amount of cointegration only in few cases. They concluded that there is significantly less connection between cryptocurrencies and precious metals, and one market cannot influence others. Katsiampa (2018) has used bivariate Diagonal-BEKK to analyze volatility dynamics and co-movement of two cryptocurrencies, Bitcoin and Ether, and concluded that cryptocurrency markets are interdependent, these currencies are prone to essential news, and Ether has hedging capabilities against Bitcoin. The literature on cryptocurrencies is minimal and concise; therefore, it needs much attention from academic viewpoints. Corbet et al. (2019) have review published research from 2009 to 2018 and found this area is immature and needs more attention to explore these newly attractive e-cashes. They have also found ten research gaps and included that Bitcoin is nothing but an asset, and there is no value like traditional currency. Guesmi et al. (2019) have investigated in pair bases such as Bitcoin and exchange

rates, Bitcoin and the stock market, and Bitcoin and commodity to observe spillover effect, portfolio diversifications, and hedge properties. They have found spillovers effect among Bitcoin and other assets (gold and stock), and Bitcoin, oil, gold, and equities have hedging capabilities against portfolio risk while Bitcoin decrease significantly portfolio risk compare to the risk of other assets portfolio. Okorie and Lin (2020) have studied connectedness and hedge properties between two markets, namely cryptocurrencies and energy (crude oil), by applying *VAR-MGARCH-GJR-BEKK* model. They have found presence of bi-directional spillover effect between energy market and Bit-Capital Vendor and uni-directional spillover effect from energy market to Bitcoin-Cash market. They have also found other cryptocurrencies markets have significant unidirectional spillover effect to energy market. They have added that they found evidence of hedging capabilities between these two markets.

Based on the Smooth-Transition-GARCH model, the asymmetric effects of cryptocurrencies were studied by Cheikh et al. (2019). They have observed robust evidence of reversed asymmetric impact for almost all major digital currencies, i.e., positive news looks like having more effect on cryptocurrencies volatility than negative news. They have also added that the asymmetric effect of digital currencies is similar to gold so that it can be treated as a safe-heaven. Caporale and Zekokh (2019) have examined four major cryptocurrencies, namely Bitcoin, Litecoin, Ethereum, and Ripple, from a different angle. They have fitted these four digital currencies on the 1000 GARCH family model, from which find the best-fitted one so that investors and policymakers can get the correct information. Their findings suggested that the Markov-switching GARCH technique is suitable for digital currencies modeling and the possibility of getting more relevant results. Charles and Darné (2019) have replicated Katsiampa's (2017) work in the same sample (2010-

2016); they fitted six GARCH family models and reproduced the same work for an extended period (2010-2018). Their results were similar to Katsiampa (2017), only with a minor difference, and found the existence of jump features on Bitcoin returns. They also found that these GARCH family models were not suitable for modeling extended periods of Bitcoin returns; therefore, they need to switch the model into Markov-switching models.

Chan et al. (2019) have inspected whether the presence of Bitcoin hedging abilities and risk diversification against five well-known stock indices using various frequency data (daily, weekly, monthly). They found that Bitcoin has powerful hedging abilities against all these indices when considering monthly data, whereas medium and high-frequency returns did not show any strong hedging capabilities. Canh et al. (2019) have considered structural breaks and, at the same time, spillover effects in seven major cryptocurrencies and modeled them with DCC-MGARCH. They have found in their empirical results, the presence of structural breaks in all cryptocurrencies and correlations between cryptocurrencies are positive and very strong with the existence of spillover effects. Their main findings were the limitation of diversifying advantages within cryptocurrency markets. Al-Yahyaee et al. (2019) have considered the Bitcoin price and gold price on oil investors and S&P GSCI-investors for diversifying properties and hedge abilities purposes and used five DCC-GARCH type models. They have observed that Bitcoin and gold exhibit diversification advantages against oil and S&P GSCI and robustness of hedge with risk reduction capabilities. Beneki et al. (2019) have only considered two cryptocurrencies (namely Bitcoin, Ethereum) to investigate volatility spillovers and hedge properties under the BEKK-GARCH model framework. Their findings revealed that Bitcoin volatility shows positive shocks on Ethereum and uni-



directional volatility-transmission from Ethereum returns to Bitcoin returns, which sustain not more than ten days, then weakens over two weeks. Tu and Xue (2019) have examined bifurcation properties among two cryptocurrencies (such as Bitcoin and Litecoin) in the BEKK-MGARCH model framework during 2013–2018. They have found a unidirectional effect from Bitcoin returns to Litecoin returns and the shock transmission direction before bifurcation being inverted after bifurcation. Bouri et al. (2018) have considered Bitcoin and five assets, namely commodities, equities, bonds, stocks, and currencies, to examine volatility spillovers from July 2010 to October 2017. They found that Bitcoin returns, and other asset returns were closely related to each other and substantial evidence of volatility spillovers between these two markets.

### **2.3 Bitcoin and gold hedging performances**

Bitcoin is a growing e-cash in the virtual markets and the largest both in volume and market capitalization. It occupied 89% of the market share from the total share of whole digital currency markets as of Bariviera (2017) and is considered the leading valuable and acceptable cryptocurrency. Bitcoin price volatility increases substantially over time compared to the regular currency. Blau (2017) has observed that Bitcoin volatility became double counter to the average volatility of 51 conventional currencies from the period between July 2010 and June 2014. To see the driving forces of Bitcoin prices, researchers got mixed findings. Blau (2017) has concluded that returns of Bitcoin were uncorrelated to speculative trading. At the same time, Dyhrberg (2016a) has tried to determine whether Bitcoin acts as a currency or a commodity and concludes that Bitcoin returns pointed a positive response to the US dollar and US Federal Funds rate. He also found risk management

abilities of Bitcoin against exchange rates of dollar-euro and dollar-pound, almost similar findings found in the case of gold by Tully and Lucey (2007). Thus, Dyhrberg suggested that Bitcoin could be categorized as not the same as gold and US dollar, something in between them and could be used as a portfolio management tool.

Capie et al. (2005) have assessed gold price with yen-dollar and sterling-dollar exchange rates and found golds hedging abilities against exchange rates, but this relationship moved across time and depended on political situations. An in-depth investigation of safe-haven and hedging features of gold has been done by Baur and Lucey (2010). Their studies found evidence of safe-haven and hedge properties of gold only on stocks, but there is no such effect on bonds. However, they also found that gold performs as safe-haven only for 15 days after markets fall. Baur and McDermott (2010) have extended this study and seen gold work as a safe-haven for equities, but the number of countries they examined was limited. By applying wavelet analysis, Bredin et al. (2015) have shown that gold provides safe-haven benefits for a maximum of one year, whereas Lucey and Li (2015) have found that the safe-haven abilities of gold are not stable, suggesting that the hedging ability of gold is stable, but safe-haven ability oscillates over time. Ciner et al. (2013) have testified that from 2000 to onwards, gold has the ability to work as a safe-haven for the UK pound and US dollar. Thus, the literature is enriched by assessing the safe-haven and hedging characteristics of gold, but there are scarcities of a detailed Bitcoin investigation.

In recent years, the researchers have gotten attention to enrich the literature of the association amongst Bitcoin with other monetary assets that resolve the answer to whether Bitcoin performed as a safe-haven, hedge, or diversifier counter to the other

monetary assets. An approach of quantile regression to investigate the correlation among global uncertainty and gold, Bouri et al. (2017) has shown that Bitcoin only serves as a hedge counter to global uncertainty in a short-run horizon in the time of bull markets. Applying the DCC model in their analysis, Bouri, Molnár, et al. (2017) have shown that there is inadequate evidence of safe-haven and hedging capabilities of Bitcoin, although they found strong evidence of efficient diversifier. Corbet, Lucey, et al. (2018) added that Bitcoin has its risks, which are challenging to hedge against, but still, it can play an essential role in the investor portfolio. However, Bitcoin could act as a safe-haven shown by Shahzad et al. (2019), while its time-varying function varies across markets. A very recent work of Platanakis and Urquhart (2019) has shown in their studies if investors include cryptocurrencies into their stock-bond-commodity portfolios, which radically enhances portfolio performance through extremely high risk-adjusted returns. Similar findings are obtained by Kajtazi and Moro (2019) in their studies. Hence, there is some evidence of Bitcoin hedging and diversification abilities, but a detailed examination is essential in the case of Bitcoin to fill up the lacks in literature.

#### **2.4 Crisis in financial markets**

The financial market, especially the stock market, plays an essential role in a country's economic growth. Moreover, capital markets are volatile due to the uncertainty of assets return, therefore causes the complexity of risk management. High volatility produces high risk; similarly, low volatility triggers lower risk. Much research has been done to capture the movement of volatility and forecasting (Paolella et al., 2019; Zivot, 2008; Bera and Higgins, 1993). Nevertheless, these studies are challenging because of the unpredictability of the stock price movement.