

MODELLING AND FORECASTING THE PREDICTABILITY OF STOCK  
MARKET RETURN IN ASIAN COUNTRIES BY USING HYBRID ARIMA-  
GARCH MODELS

SIOW KENT WOH

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## **DEDICATION**

This thesis is dedicated to my parents, who taught me not to give up for every obstacles I have faced. It is also dedicated to my sisters, who support me to pay full focus on my studies.

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## **ABSTRACT**

Predictability of the stock market return has been a crucial topic over a decade. The ability to forecast and predict the stock market price allows investors to make investment decisions at the lowest risk and also allows policy makers to evaluate development of stock markets as to design rules and regulations. Thus, this study was conducted to serve two main purposes. First of all, hybrid models was developed between Autoregressive Integrated Moving Average (ARIMA) model and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) family model for daily stock market data. In GARCH family models, there are GARCH, EGARCH and TGARCH where GARCH is symmetric model and EGARCH and TGARCH are asymmetric models. As hybridization of ARIMA model with different GARCH family models have different level of performances, each of the established hybrid models are evaluated using AIC, MAE, RMSE as well as MAPE to identify the outperformed model. In this study, daily stock prices of nine Asian countries (China, Hong Kong, India, Indonesia, Korea, Malaysia, Philippines, Singapore, and Thailand) are being used. EViews and R studio software act as the tools to perform the analysis. Results show that hybrid ARIMA-EGARCH model outperformed. On the other hand, identification of the calendar effects of all the nine Asian countries is the second concern of this study. The results show that each of the Asian countries have different calendar effects.

## ABSTRAK

Kebolehan ramalan pulangan pasaran saham menjadi topik yang amat penting selama satu dekad kerana keupayaan ramalan harga pasaran saham membolehkan pelabur membuat keputusan pelaburan dengan risiko terendah. Selain itu, para pembuat dasar juga mendapat manfaat untuk menilai perkembangan pasaran saham dan bagi tujuan mereka bentuk peraturan. Oleh kerana itu, kajian ini dijalankan untuk dua tujuan utama. Pertama sekali, model hibrid telah dibangunkan antara model keluarga Autoregresif Bersepadu Purata (ARIMA) dan model keluarga Generalized Autoregressive Conditional Heteroscedasticity (GARCH) untuk data pasaran saham harian. Dalam model keluarga GARCH, terdapat GARCH, EGARCH dan TGARCH di mana GARCH adalah model simetri dan EGARCH serta TGARCH adalah model asimetrik. Oleh sebab hibridisasi model ARIMA dengan model keluarga GARCH yang berlainan mempunyai tahap prestasi yang berbeza, setiap model hibrid yang ditubuhkan dinilai dengan AIC, MAE, RMSE serta MAPE untuk mengenalpasti model yang mengatasi model lain. Dalam kajian ini, harga saham harian sembilan Negara Asia (China, Hong Kong, India, Indonesia, Korea, Malaysia, Philippines, Singapore, and Thailand) telah digunakan. Perisian EViews dan R studio digunakan sebagai alat untuk melakukan analisis kajian ini. Keputusan analisis menunjukkan bahawa model hibrid ARIMA-TGARCH lebih baik. Sebaliknya, pengenalpastian kesan kalendar dari sembilan negara Asia adalah tujuan kedua kajian ini. Hasilnya menunjukkan bahawa setiap negara mempunyai kesan kalendar yang berbeza.

## TABLE OF CONTENTS

	<b>TITLE</b>	<b>PAGE</b>
	<b>DECLARATION</b>	<b>iii</b>
	<b>DEDICATION</b>	<b>iv</b>
	<b>ACKNOWLEDGEMENT</b>	<b>v</b>
	<b>ABSTRACT</b>	<b>vi</b>
	<b>ABSTRAK</b>	<b>vii</b>
	<b>TABLE OF CONTENTS</b>	<b>viii</b>
	<b>LIST OF TABLES</b>	<b>xii</b>
	<b>LIST OF FIGURES</b>	<b>xiv</b>
	<b>LIST OF ABBREVIATIONS</b>	<b>xv</b>
	<b>LIST OF SYMBOLS</b>	<b>xvi</b>
	<b>LIST OF APPENDICES</b>	<b>xvii</b>
<b>CHAPTER 1</b>	<b>INTRODUCTION</b>	<b>1</b>
1.0	Introduction	1
1.1	Background of the Problem	2
1.2	Statement of the Problem	3
1.3	Objectives of the Study	4
1.4	Scope of the Study	5
1.5	Significance of the Study	5
1.6	Outlines of the Study	6
<b>CHAPTER 2</b>	<b>LITERATURE REVIEW</b>	<b>7</b>
2.0	Introduction	7
2.1	Stylized fact of time series data in stock market	7
2.2	Calendar effect (Day-of-the-week effect)	8
2.3	ARIMA models	11

2.4	GARCH family models	13
2.5	Hybrid models	16
2.6	Summary of Reviews	18
2.7	Conclusion	19
<b>CHAPTER 3</b>	<b>METHODOLOGY</b>	<b>21</b>
3.0	Introduction	21
3.1	Box-Jenkins Method	21
3.1.1	Stationary Time Series Model	22
3.1.2	Nonstationary Time Series Model	23
3.1.2.1	Nonstationary in Mean	23
3.1.2.2	Nonstationary in Autocovariance	24
3.1.3	Testing for Stationarity	25
3.2	Model Identification	27
3.3	Parameter Estimation	29
3.3.1	Ordinary Least Square Estimation	29
3.3.2	Maximum Likelihood Estimation	30
3.4	Diagnostic Checking	31
3.4.1	Jarque-Bera Test	32
3.4.2	Breusch-Godfrey Serial Correlation LM Test	34
3.4.3	ARCH-LM Test	35
3.5	Forecasting	36
3.6	Operational Framework on ARIMA Models	37
3.7	GARCH family models	38
3.7.1	Symmetric GARCH model	38
3.7.1.1	GARCH model	38
3.7.2	Asymmetric GARCH model	40
3.7.2.1	Exponential GARCH Model	40
3.7.2.2	Threshold GARCH Model	41
3.8	Hybrid Models	42
3.8.1	General Equation for Hybrid Models	42
3.8.1.1	Hybrid ARIMA-GARCH Model	43
3.8.1.2	Hybrid ARIMA-EGARCH Model	44

3.8.1.3	Hybrid ARIMA-TGARCH Model	45
3.8.2	Model Identification	45
3.8.3	Parameter Estimation	46
3.8.4	Diagnostic Checking	46
3.8.4.1	Correlogram Squared Residuals	46
3.8.5	Forecasting	47
3.8.6	Operational Framework on Hybrid Models	48
3.9	Evaluation on the performance for hybrid models	49
3.10	Identification of Calendar Effects	51
3.10.1	Sample Data	51
3.10.2	Ordinary Least Square	52
3.10.3	Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Family Model	53
3.10.4	Operational Framework on Calendar Effect Identification	55
3.11	Conclusion	56
<b>CHAPTER 4</b>	<b>EMPIRICAL RESULTS</b>	<b>57</b>
4.0	Introduction	57
4.1	Data used in study	57
4.2	ARIMA Models	63
4.2.1	Stationary Testing	63
4.2.2	Model Identification	67
4.2.3	Parameter Estimation	72
4.2.4	Diagnostic Checking	76
4.2.4.1	Jarque-Bera test	76
4.2.4.2	Breusch-Godfrey Serial Correlation LM Test	78
4.2.4.3	ARCH-LM test	81
4.3	Hybrid ARIMA-GARCH Model	83
4.3.1	Model Identification	83
4.3.2	Parameter Estimation	85



4.3.3	Diagnostic Checking	87
4.3.3.1	Jarque-Bera test	87
4.3.3.2	ARCH-LM test	89
4.3.3.3	Correlogram Squared Residuals	91
4.3.4	Forecasting	96
4.4	Forecasting of Hybrid Models	105
4.5	Calendar Effects (Day-of-the-Week)	115
4.5.1	Unit Root Test	115
4.5.2	OLS Result	116
4.5.3	Selection of appropriate GARCH model for the Sample data	117
4.5.4	EGARCH(1,1) Result	118
4.5.5	Interpretation and tabulation	120
4.6	Conclusion	121
<b>CHAPTER 5</b>	<b>CONCLUSIONS</b>	123
5.0	Introduction	123
5.1	Summary	123
5.2	Conclusion	125
5.3	Suggestion of future study	126
<b>REFERENCES</b>		127
<b>APPENDICES</b>		133

## LIST OF TABLES

TABLES NO.	TITLE	PAGE
Table 2.1	Summary of reviews on hybrid models for data with volatility	18
Table 3.1	Family of transformation	25
Table 3.2	Summary behavior of ACF and PACF plots	28
Table 3.3	Interpretation of MAPE	50
Table 4.1	Graph and descriptive statistics of daily stock prices for nine Asian countries	58
Table 4.2	ADF test for stock market prices for nine countries	64
Table 4.3	ADF test results after transformation and differencing	65
Table 4.4	Interpretation of ACF and PACF plots for each country	67
Table 4.5	Tentative ARIMA Models for each countries and corresponding AIC values	73
Table 4.6	Results of Jarque-Bera test	76
Table 4.7	Results of Breusch-Godfrey Serial Correlation LM Test	79
Table 4.8	Results of Breusch-Godfrey Serial Correlation LM Test (Model reselection for Malaysia)	80
Table 4.9	Results of ARCH-LM Test	81
Table 4.10	Hybrid ARIMA-GARCH model for nine countries	83
Table 4.11	AIC values of hybrid models	86
Table 4.12	Results of Jarque-Bera test	87
Table 4.13	Results of ARCH-LM test	90
Table 4.14	Correlogram of Standardized Residuals Squared	91
Table 4.15	Forecast results	96
Table 4.16	Forecasting Evaluation for hybrid model (China)	105
Table 4.17	Forecasting Evaluation for hybrid model (Hong Kong)	106
Table 4.18	Forecasting Evaluation for hybrid model (India)	106
Table 4.19	Forecasting Evaluation for hybrid model (Indonesia)	107

Table 4.20	Forecasting Evaluation for hybrid model (Korea)	107
Table 4.21	Forecasting Evaluation for hybrid model (Malaysia)	108
Table 4.22	Forecasting Evaluation for hybrid model (Philippines)	108
Table 4.23	Forecasting Evaluation for hybrid model (Singapore)	109
Table 4.24	Forecasting Evaluation for hybrid model (Thailand)	109
Table 4.25	OLS Results for Day-of-the-Week Country Indices Returns	116
Table 4.26	Selection of appropriate GARCH model for sample data	117
Table 4.27	EGARCH(1,1) Results for Day-of-the-Week Country Indices Returns	118
Table 4.28	Summary – OLS for Day-of-the-Week Effects	120
Table 4.29	Summary—EGARCH(1,1) for Day-of-the-Week Effects	120
Table 4.30	Established hybrid models	121
Table 4.31	Summary of Calendar effects	121
Table 5.1	Trading strategies for each country	126

## LIST OF FIGURES

<b>FIGURES NO.</b>	<b>TITLE</b>	<b>PAGE</b>
Figure 3.1	Example of distribution with skewness	32
Figure 3.2	ARIMA modelling approach	37
Figure 3.3	Flowchart of hybrid model development	48
Figure 3.4	Flowchart of calendar effect identification	55
Figure 4.1	Comparison between forecast and actual data for China's daily stock prices	110
Figure 4.2	Comparison between forecast and actual data for Hong Kong's daily stock prices	110
Figure 4.3	Comparison between forecast and actual data for India's daily stock prices	111
Figure 4.4	Comparison between forecast and actual data for Indonesia's daily stock prices	111
Figure 4.5	Comparison between forecast and actual data for Korea's daily stock prices	112
Figure 4.6	Comparison between forecast and actual data for Malaysia's daily stock prices	112
Figure 4.7	Comparison between forecast and actual data for Philippines's daily stock prices	113
Figure 4.8	Comparison between forecast and actual data for Singapore's daily stock prices	113
Figure 4.9	Comparison between forecast and actual data for Thailand's daily stock prices	114

## LIST OF ABBREVIATIONS

ACF	-	Autocorrelation Functions
ADF	-	Augmented Dicker-Fuller
AIC	-	Akaike Information Criterion
AME	-	Absolute Mean Error
AR	-	Autoregressive Process
ARCH	-	Autoregressive Conditional Heteroscedasticity
ARMA	-	Autoregressive Moving Average
ARIMA	-	Autoregressive Integrated Moving Average
BIC	-	Bayesian Information Criterion
EGARCH	-	Exponential Generalized Autoregressive Conditional Heteroscedasticity
EViews	-	Econometrics Views
GARCH	-	Generalized Autoregressive Conditional Heteroscedasticity
JB	-	Jarque-Bera
LM	-	Lagrange Multiplier
MA	-	Moving Average
MAE	-	Mean Absolute Error
MAPE	-	Mean Absolut Percentage Error
OLS	-	Ordinary Least Square
PACF	-	Partial Autocorrelation Functions
RMSE	-	Root Mean Square Error
SSE	-	Sum of Square
TGARCH	-	Threshold Generalized Autoregressive Conditional Heteroscedasticity

## LIST OF SYMBOLS

$\Phi_p$	-	AR polynomial
$\theta_q$	-	MA polynomial
$\varepsilon_t$	-	Error term at time $t$
$\delta$	-	Constant term
$\lambda$	-	Minimum residual mean square error value
$\Delta$	-	Lag order of the autoregressive process
$H_0$	-	Null hypothesis
$H_1$	-	Alternative hypothesis
$\hat{\theta}$	-	Tested time series
$\varepsilon_{t-i}^2$	-	Past squared return
$\sigma_{t-j}^2$	-	Past of conditional variance
$\alpha_0$	-	Mean of the volatility
$\alpha_i$	-	Size effect
$\beta_j$	-	Degree of volatility persistence
$\gamma_i$	-	Sign effect
$n$	-	Sample size
$\hat{\rho}_k^2$	-	Squared sample autocorrelation at lag $k$
$d$	-	Amount of differencing
$p$	-	Autoregressive part order
$q$	-	Moving average part order
$D_{dt}$	-	Dummy variables for each day of the week respectively
$\gamma_1$	-	Coefficient $\gamma_1$ to $\gamma_5$ represent the size and direction of the day of the week effect on volatility

## LIST OF APPENDICES

APPENDIX	TITLE	PAGE
Appendix A	Parameter Estimation for ARIMA model by using Ordinary Least Square (OLS)	133
Appendix B	Parameter Estimation for hybrid model by using Ordinary Least Square (OLS) and Maximum Likelihood Estimation (MLE)	182
Appendix C	Ordinary Least Square (OLS) results of Day-of-the-Week Effects	209
Appendix D	EGARCH results of Day-of-the-Week Effects	214

# CHAPTER 1

## INTRODUCTION

### 1.0 Introduction

In general, stock market is defined as a collection and presentation of information from the market where activities such as buying, selling and issuance of shares of publicly-held companies take place. Stock market of a country normally reflects the economic condition, therefore, modeling and forecasting the stock market becomes very popular. Investors, financial analysts as well as the researchers are craving for the forecast results as a guide for their investment activities. Most of the forecasting activities involves the usage of the past data, therefore, the historical stock market returns become functional at this point. Different countries have different figures on stock market due to distinct of economic situation particularly. Hence, applying the same forecast model on different countries will not be practical at this point.

Stock market data is commonly constructed as time series data with volatility. Volatility of the data basically indicates the unpredictability and the uncertainty in the stock market. There are many factors that affect the fluctuations of the stock market for example, the economic growth, political issues as well as natural and man-made disasters. There are two focuses in this study. It includes identifying the best model to



forecast the stock market performance as well as identifying the calendar effects of stock market to formulate an effective trading strategy.

## **1.1 Background of the Study**

In the aspect of stock market, the topic of calendar anomalies or calendar effects had been widely discussed by many researchers over the period of almost half a decade. One of the best known calendar anomalies is day-of-the-week effects. Day-of-the-Week effect literally explains the stock price in specific day having the tendency of achieving higher price compared to the others. For instance, when a country is having a Monday effect on stock market, it simply means that particular country's stock market is more likely to have higher price on Monday compared to the others trading days. Day-of-the-week effect was reviewed and stated that stock market had a negative returns on Monday and positive return on Friday (Kumar, 2017). In stock market, "positive return" refers to getting back more money in return than what the investor has invested. In contrast, "negative return" means investors are getting less money as return. As different countries are having different calendar effects, this study will analyze and compare the calendar effects of nine different Asia countries.

Volatility modelling and forecasting has been a crucial task in financial market as it held the attention of academics and practitioners over the last two decades (H. Zhang & Li, 2010). Most of the financial and economic applications are assigning their focus on the volatility of the stock market because the volatility helps to assess the risk and provide crucial information for investment purposes. A higher volatility simply means that a value can potentially deviates over a large range of values. In short, the higher the volatility, the riskier the security. In this study, the composite index of the stock market for nine different Asia countries (China, Hong Kong, India, Indonesia, Korea, Malaysia, Philippines, Singapore, and Thailand) will be used as the sample. The reason why these data were selected, mainly because this study have the interest

to find out their respective models and compare the calendar effects between all the countries.

In this study, Autoregressive Integrated Moving Average (ARIMA) will be applied for modeling purposes. However, this model has the disability of handling nonlinearity and volatility (Pai & Lin, 2005). Hence, in order to overcome this weakness, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) family model is implemented to handle the volatility (Maria Caporale & Zakirova, 2017). Performance evaluations will be executed towards the hybrid models of ARIMA and GARCH family models for comparison.

## **1.2 Statement of the Problem**

Over the past few decades, the calendar effect of stock market in different countries are not consistent which means the phenomena of volatility clustering in time series data varies in different sets of data (different countries). As the calendar effect of the stock market often acts as a guidance to allow investors to make profit, many methods and models were implemented to handle this kind of data in order to find out the calendar effect of stock market. In this study, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) will be used to find out the calendar effects.

In terms of modelling, Autoregressive Integrated Moving Average (ARIMA) model is one of the popular model which has been extensively used in the field of finance and economic. The capability of handling non-stationary data is one of the reasons why ARIMA was widely used. A recent study used ARIMA to predict stock price due to its capability to produce short-term forecasts (Adebiyi, Adewumi, & Ayo, 2014). However, ARIMA has a major limitation where the condition of linearity of data must be fulfilled (P. G. Zhang, 2003).

In order to overcome the limitation of ARIMA model, GARCH family model is introduced. GARCH is popular and frequently applied while dealing with time series data with volatility or non-linearity. As the results, both the linearity and the non-linearity can be captured by the combination of both models.

In addition, asymmetric reactions of the volatility will be the second concern when GARCH family models are applied. GARCH model will be used for symmetric models whereas EGARCH and TGARCH model will be used for asymmetric models in this study.

Conclusively, the combination of ARIMA and GARCH models is implemented to sort out the appropriate model for forecasting. At the meantime, the performances of the hybrid models will be evaluated in order to enhance the accuracy of forecasting.

### **1.3 Objectives of the Study**

The proposed objectives are stated as followed: -

- (1) To apply a hybrid ARIMA-GARCH model, hybrid ARIMA-EGARCH, and ARIMA-TGARCH model for the stock market data from nine Asian countries.
- (2) To compare the modelling and forecasting performances of ARIMA-GARCH, ARIMA-EGARCH, and ARIMA-TGARCH models for stock market from nine Asian countries.
- (3) To identify the day-of-the-week effects of stock market in nine Asian countries.

## **1.4 Scope of the Study**

The main focus of this study is to find out the appropriate forecast model for nine Asian countries (China, Hong Kong, India, Indonesia, Korea, Malaysia, Philippines, Thailand and Singapore) and their respective calendar effects. The composite index of all the nine countries were collected from the database of UTM library. The period of the data covers from year 1990 to year 2019. In terms of modelling, the hybridization of ARIMA model and GARCH family models will be used in order to handle non-stationary data and capture volatility of the stock market. AIC will be used to justify the performance of the model whereas RMSE, MAE and MAPE will be used to justify the performance of the forecasting.

## **1.5 Significance of the Study**

This study models and forecasts the stock market by using hybrid ARIMA-GARCH, ARIMA-EGARCH models as well as ARIMA-TGARCH models. By overcoming the limitation of handling volatility data in ARIMA model, complying GARCH family models, it is hoped that the model will have a better performances for future usage.

In addition, the identification of calendar effect of stock market provides a clearer picture to investors on whether they can earn abnormal returns in the stock market. If the investors can identify the pattern of the volatility, it would be easier for them to make investment decisions based on the forecast results.

Moreover, this study will be an aid for policy makers to evaluate the developments in the stock markets as to design and execute the rules and regulations.

By having appropriate developments, market efficiency would be enhanced undoubtedly.

## **1.6 Outlines of the Study**

This paper consists of five chapters and is organized as follows. Chapter 1 discusses the background of this research, problem statements, objectives, scope of study, and significance of study. Chapter 2 reviews relevant literatures and theoretical framework published by other scholars. Chapter 3 describes the research design, data collection and methodology. Chapter 4 reports the empirical results as well as the analysis and interpretation. Chapter 5 concludes with the findings and results.

## References

- Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Stock price prediction using the ARIMA model. *Proceedings - UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, UKSim 2014*, 106–112.
- Ahammad Hossain, Md. Kamruzzaman, & Md. Ayub Ali. (2016). ARIMA With GARCH Family Modeling and Projection on Share Volume of DSE. *Economics World*, 3(4), 171–184.
- Ahmad, M. H., Ping, P. Y., Yazir, S. R., & Miswan, N. H. (2014). A hybrid model for improving Malaysian gold forecast accuracy. *International Journal of Mathematical Analysis*, 8(November 2015), 1377–1387.
- Akhtar, S., & Khan, N. U. (2016). Modeling volatility on the Karachi Stock Exchange , Pakistan. *Journal of Asia Business Studies*, 10(3), 253–275.
- Babu, C. N., & Reddy, B. E. (2015). Prediction of selected Indian stock using a partitioning – interpolation based ARIMA – GARCH model. *Applied Computing and Informatics*, 11(2), 130–143.
- Baig, S., Mohsin, M., & Zia-ur-rehman, M. (2018). The volatility of Pakistan stock market : A comparison of Garch type models Volatility of pakistan stock market : A comparison of Garch type models with five distribution. *Amazonia Investiga*, 7(17), 486–504.
- Bekaert, G., & Wu, G. (2000). Asymmetric Volatility and Risk in Equity Markets. *Review of Financial Studies*, 13(1), 1–42.
- Black, F. (1976). *Studies of Stock Market Volatility Changes. Proceedings of the American Statistical Association*. 177–181.

- Chandra, M. (2006). The day-of-the-week effect in conditional correlation. *Review of Quantitative Finance and Accounting*, 27(3), 297–310.
- Cont, R. (2001). Empirical properties of assets returns: Stylized facts and statistical issues. *Quantitative Finance*, 1, 1–14.
- Cont, Rama. (2007). Volatility clustering in financial markets: Empirical facts and agent-based models. *Long Memory in Economics*, (April), 289–309.
- Daniel B. Nelson. (1991). Conditional Heteroskedasticity in Asset returns: A New Approach. *Econometrica*, 59(2), 347–370.
- Derbali, A., & Hallara, S. (2016). Day-of-the-week effect on the Tunisian stock market return and volatility Day-of-the-week effect on the Tunisian stock market return and volatility. *Cogent Business & Management*, 16(1).
- Dritsaki, C. (2018). The performance of hybrid ARIMA-GARCH modeling and forecasting oil price. *International Journal of Energy Economics and Policy*, 8(3), 14–21.
- du Toit, E., Hall, J. H., & Pradhan, R. P. (2018). The day-of-the-week effect: South African stock market indices. *African Journal of Economic and Management Studies*, 9(2), 197–212.
- Gay, R. D., Rates, E., Prices, O., & Prices, S. (2016). Effect Of Macroeconomic Variables On Stock Market Returns For Four Emerging Economies: Brazil, Russia, India, And China. *The International Business & Economics Research Journal*, 15(3), 1–8.
- Gbeda, J. M., & Peprah, J. A. (2018). Day of the week effect and stock market volatility in Ghana and Nairobi stock exchanges. *Journal of Economics and Finance*, 42(4), 727–745.

- Jadhav, V., Reddy, B. V. C., & Gaddi, G. M. (2017). *Application of ARIMA Model for Forecasting Agricultural Prices*. 19, 981–992.
- Jaisinghani, D. (2016). An empirical test of calendar anomalies for the Indian securities markets. *South Asian Journal of Global Business Research*, 5(1), 53–84.
- Kamalakannan, J., Sengupta, I., Chaudhury, S., Angadi, M., Institutes, A., & Kulkarni, A. (2015). *Time Series Data Analysis for Stock Market Prediction using Data Mining Techniques with R Available Online at www.ijarcs.info Time Series Data Analysis for Stock Market Prediction using Data Mining Techniques with R*. (August), 1–5.
- Keong, L. B., Ng, D., Yat, C., & Ling, C. H. (2010). Month-of-the-year effects in Asian countries: A 20-year study (1990-2009). *African Journal of Business Management*, 4(7), 1351–1362.
- Kumar, S. (2017). A Review on the Evolution of Calendar Anomalies. *Studies in Business and Economics*, 12(1), 95–109.
- Lim, C. M., & Sek, S. K. (2013). Comparing the performances of GARCH-type models in capturing the stock market volatility in Malaysia. *Procedia Economics and Finance*, 5, 478–487.
- Lin, Z. (2018). Modelling and Forecasting the Stock Market Volatility of SSE Composite Index Using GARCH Models. *Future Generation Computer Systems*, 79, 960–972.
- Makridakis, S., & Hibon, M. (1997). ARMA models and the Box-Jenkins methodology. *Journal of Forecasting*, 16(3), 147–163.
- Mandelbrot, B. (2002). The Variation of Certain Speculative Prices. *The Journal of Business*, 36(4), 394.



- Maria Caporale, G., & Zakirova, V. (2017). Calendar anomalies in the Russian stock market. *Russian Journal of Economics*, 3(1), 101–108.
- Marie-Eliette Dury, B. X. (2018). *Forecasting the Volatility of the Chinese Gold Market by ARCH Family Models and extension to Stable Models*. 1–31.
- Mondal, P., Shit, L., & Goswami, S. (2014). Study of Effectiveness of Time Series Modeling ( ARIMA ) in Forecasting Stock Prices. *International Journal of Computer Science, Engineering and Applications*, 4(2), 13–29.
- Montaño Moreno, J. J., Palmer Pol, A., Sesé Abad, A., & Cajal Blasco, B. (2013). El índice R-MAPE como medida resistente del ajuste en la previsión. *Psicothema*, 25(4), 500–506.
- Naylor, T. H., Seaks, T. G., & Wichern, D. W. (1972). Box-Jenkins Methods: An Alternative to Econometric Models. *International Statistical Review / Revue Internationale de Statistique*, 40(2), 123–137.
- Naz, F., & Ahmad, Z. (2016). *Forecasting of Indian Gold Prices using Box Jenkins Methodology*. 2(1), 75–83.
- Pahlavani, M., & Roshan, R. (2015). The Comparison among ARIMA and hybrid ARIMA-GARCH Models in Forecasting the Exchange Rate of Iran. *International Journal of Business and Development Studies*, 7(1), 31–50.
- Pai, P. F., & Lin, C. S. (2005). A hybrid ARIMA and support vector machines model in stock price forecasting. *Omega*, 33(6), 497–505.
- Patil, A., & Madhuri, G. (2017). Modeling Volatility Clustering of Bank Index: An Empirical Study of BankNifty. *Review of Integrative Business and Economics ResearchOnlineCDROM*, 6(1), 224–239.
- Srinivasan, A. (2011). *Application of information technology and statistical process control in pharmaceutical quality assurance & compliance*. 67

- Sutheebanjard, P., & Premchaiswadi, W. (2013). Analysis of Calendar Effects: Day-of-the-Week Effect on the Stock Exchange of Thailand (SET). *International Journal of Trade, Economics and Finance*, 1(1), 57–62.
- Urquhart, A., & McGroarty, F. (2014). Calendar effects, market conditions and the Adaptive Market Hypothesis: Evidence from long-run U.S. data. *International Review of Financial Analysis*, 35, 154–166.
- Wennstr, A., & Stockholm, S. T. (2014). *Volatility Forecasting Performance: Evaluation of GARCH type volatility models on Nordic equity indices*.
- Yaziz, S. R., Azizan, N. A., Ahmad, M. H., & Zakaria, R. (2016). Modelling gold price using ARIMA–TGARCH. *Applied Mathematical Sciences*, 10(October), 1391–1402.
- Zakaria, S., Abdalla, S., & Winker, P. (2012). *Modelling Stock Market Volatility Using Univariate GARCH Models : Evidence from Sudan and Egypt*. 4(8), 161–176.
- Zakoian, J.-M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control*, 18, 931–955.
- Zhang, H., & Li, S. F. (2010). Forecasting Volatility in Financial Markets. *Key Engineering Materials*, 439–440(June), 679–682.
- Zhang, P. G. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, 50, 159–175.
- Zivot, E. (2009). Practical Issues in the Analysis of Univariate GARCH Models. *Handbook of Financial Time Series*, 113–155.