Forecasting Value at Risk for Energy Firms in Pakistan

Muhammad Asim Khan Khattak
10/M.Phil-EAF/PIDE/2015

Supervisor: Dr. Saud Ahmed Khan
Assistant Professor
PIDE

A dissertation submitted to the Department of Economics & Finance; Pakistan Institute of Development Economics Islamabad, in partial fulfillment of the requirements for the degree of Master of Philosophy in Economics & Finance**.**

DEPARTMENT OF ECONOMICS AND FINANCE

PAKISTAN INSTITUTE OF DEVELOPMENT ECONOMICS

ISLAMABAD, PAKISTAN

(2017)

PAKISTAN INSTITUTE OF DEVELOPMENT ECONOMICS, ISLAMABAD

CERTIFICATE

This is to certify that this thesis entitled **"Forecasting Value at Risk for Energy Firms in Pakistan"** submitted by **Mr. Muhammad Asim Khan Khattak** is accepted in its present form by the Department of Economics and Finance, Pakistan Institute of Development Economics (PIDE) Islamabad as satisfying the requirements for partial fulfillment of the Degree of Master of Philosophy in Economics and Finance.

Supervisor:

Dr. Saud Ahmed Khan
Assistant Professor
PIDE,
Islamabad.

Internal Examiner:

Dr. Atiq-ur-Rehman
Assistant Professor,
PIDE
Islamabad.

External Examiner:

Dr. Muhammad Jamil
Assistant Professor,
School of Economics
QAU,
Islamabad.

Head, Department of Economics and Finance:

Dr. Hasan Muhammad Mohsin
PIDE,
Islamabad.

ACKNOWLEDGEMENT

I still remember the day when during my Msc at the Lahore University; I stumbled upon the idea of applying for M.Phil Economics & Finance at PIDE. I realized overtime that LUCK is the biggest factor in shaping one's life. I was just lucky to get admitted.

My first good interaction at PIDE was with Mr. Shahzad who was really kind to provide all the information needed. As there are no separate buildings for each department at PIDE, I was guided through the reception in a very wrong way to the old block, then east block and finally met the representative of the Department of Economics & Finance who happened to be Mr. Shahzad, at his office on the top floor of west block. Mr. Shahzad supported in every possible way, from providing timely comprehensive information on various aspects of the program to being kind enough for providing company, specifically during the boring routine of research work.

The first two months of the program were very difficult because the coursework was rigorous. I was lucky to have been taught the courses of Finance by Dr. Arshad Hassan (during the entire program), the course of Macroeconomic Theory by Dr. Waseem Shahid Malik (1^{st} semester), Econometrics by Dr. Ahsan -ul- Haq Satti (1^{st} semester) and Financial Econometrics by Dr. Saud Ahmed Khan (2^{nd} semester). Dr. Abdul Rashid was kind enough to share the book along with solution manual for the course of Financial Theory, which helped a lot. I am indebted to Dr. Mehmood Khalid, Dr. Abdul Jalil, Dr. Hafsa Hina for allowing me to sit as non-registered student, in classes taught by them. The Head of Department (Dr. Hasan M. Mohsin) was supportive and always encouraged to do the best.

The whole experience of M.phil was the best and one of the biggest reason is the greatness of my class fellows. My class fellows are the best. Specially, Amna Malick who was key in bridging the gap of communication among us (class fellows). Mubashir Hassan and I used to

have those long sessions of study and I still remember the room filled with smoke. I hope, he overcomes the smoking problem. Abdul Wase used to say that he is not prepared for the paper but eventually would get higher marks, whenever result would announce. Mubashir and I were always surprised by Abdul Wase on the result day. Hafiz Waqas, Kashan, Sajid and others would laugh at me when during the long class of Macroeconomic Theory; uncertainty, sadness, confusion and tension were evident on my face. Eventually Raja Naveed who was my buddy in the old college days gave me the idea of recording lectures, which I did and while listening to recording, reading book and giving more and more time to Macroeconomic Theory, I realized that Dr. Waseem Shahid Malick was one of the best teacher. I wasn't able to grasp the new lecture because I didn't revise the previous one and things were all connected. Dr. Arshad Hassan teaching the courses of Finance (Financial Management, Financial Risk Management) was probably the best aspect of this program along with Dr. Waseem Shahid Malick teaching Macroeconomic Theory and Dr. Saud Ahmed Khan supervising my research work.

Dr. Saud Ahmed Khan was a source of continuous support, almost always available in office and the best part was being able to communicate not only through mail but text messages as well. So being able to continuously in contact really helped. He was instrumental in making me take a right decision of leaving the job as Research Assistant at APEX Consulting Pakistan. That decision meant more focused time for thesis and I was able to accomplish what I was supposed to.

Muhammad Asim Khan Khattak

M.Phil Economics & Finance (2015-17)

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

PACF	Partial Autocorrelation Function
ACF	Autocorrelation Function
SBLF	Sum of Binary Loss Function
SQLF	Sum of Quadratic Loss Function
VaR	Value at Risk

ABSTRACT

Value at Risk as a tool for measuring market risk has become very popular in the recent past. In Pakistan, the reporting of Value at Risk forecast by listed firms and mutual funds is not practiced. This study highlights the importance of Value at Risk forecast for the regulator, so that, a framework of forecasting and reporting the Value at Risk measure by a valid model could be made for the listed firms and mutual funds. It will contribute to increased information disclosure on the part of listed firms and mutual funds. This information disclosure has the potential to solve the problem of adverse selection due to asymmetric information about the worst possible loss (Value at Risk), which investors with commitments (of certain payments in future) are facing.

This study proposes the Variance-Covariance Method to be the best, using the volatility forecasts from valid GARCH type models (GARCH, GARCH-M, GJR), while accounting for the model risk. Variance-Covariance Method is compared with Historical Simulation and Monte Carlo Simulation for energy firms in Pakistan. Energy firms are selected from four sectors (Oil and Gas Exploration, Oil and Gas Marketing, Refinery, Power Generation and Distribution). Sum of Binary Loss Function and Quadratic Loss Function are used as evaluation criteria for comparing Value at Risk forecasts generated by these three methodologies.

CHAPTER I

INTRODUCTION

Corporations face risk and deal with it either passively or aggressively and as a result fail or succeed in achieving their objectives, however, the risks should be monitored carefully because of their potential for damage.

Risks faced by firms are classified into business and financial. Business risks are possible losses owing to the decisions firms make and the business environment in which they operate. Financial risks relate to possible losses owing to financial market activities.

One of the reasons for the phenomenal growth of risk management industry is attributed to the increased volatility of financial markets since the early 1970s. The breaking down of fixed exchange rate system in 1971, leading to flexible and volatile exchange rate system, the oil price shock starting in 1973, Black Monday, October 19, 1987, when the US stocks collapsed by 23% wiping out around 1 trillion dollars in capital, the Japanese stock price bubble deflating at the end of 1989, the Asian turmoil of 1997 wiping out 3/4th of the dollar capitalization of equities in Indonesia, Korea, Malaysia and Thailand, the Russian default in August 1998, terrorist attack on September 11, 2001 freezing financial markets for six days resulting in a loss of $1.7 trillion in value to the U.S stock market are some of the events where worst possible loss was faced by investor (Jorion, 2007). Most recent example of such a financial crisis is of 2008 Banking crisis. The unpredictability has been the only constant for all such events.

Market risk is one of the financial risks, faced by corporations, which is the probability of loss due to change in the market price and this study is focused on the market risk of stock. In the recent two decades the Value at Risk models, as a tool for measuring the market risk have become popular because these models give one single figure which tells us about the worst possible loss in a given time horizon with a specific confidence interval. See (Linsmeier and Pearson, 2000, Jorion, 2007) for detailed exposition of the concept.

The methodologies for forecasting Value at Risk are classified in to parametric & non-parametric in a broad way. There is need to forecast the mean and volatility by some process for parametric methodologies which include Monte Carlo Simulation and Variance-Covariance Method.

Historical Simulation is one example of non-parametric methodology and there are many other variants of Historical Simulation as well like Filtered Historical Simulation among others. In Historical Simulation the built-in assumption about the return series is that it will replicates the past. This assumption of Historical Simulation is violated if there exists volatility clustering in the return series. That's why applying a methodology which takes the volatility forecast as an input (like parametric methodology) is justified.

The biggest criticism on parametric methodology is when the volatility is forecasted by a static formula and the distribution of returns is assumed to be normal, whereas there is huge literature available which argues that the stock return series is leptokurtic, with heavy tails, sometime multi modal as well and exhibits volatility clustering and for these reasons a parametric model of Value at Risk using the mean and volatility forecast obtained by a static process and assumption of normality is not correct (Hung et al., 2008, Giot and Laurent, 2004, Fan et al., 2008, Cheng and Hung, 2011, Angelidis et al., 2004, Aloui and Mabrouk, 2010, Danielsson et al., 2016).

Still due to the problem of convergence being difficult to achieve, restriction on the persistence and parameters of a GARCH type model, sometimes one has to use the assumption of return series being distributed normally as a last resort for one of the parametric methodology like Variance-Covariance Method.

1.1 Research Gap

In case of Pakistan, there is not even a single study which has attempted to forecast the dynamic Value at Risk at the firm level. Potential investors are interested in stocks of firm. The measure of worst possible loss (Value at Risk) for investment in the stocks of firms are relevant instead of the worst possible loss on the market index. To replicate the return of market index requires huge diversified investment which tends to be a luxury most investors don't enjoy. Literature is silent about the best methodology among the Historical Simulation, Monte Carlo Simulation and Variance-Covariance Method.

In Pakistan the forecasting of Value at Risk for a given investment is not being practiced. Value at Risk forecasts are not reported by the firms. Due to this, investors are not able to make the best decision about their investment keeping in view the worst possible loss with a specific confidence interval and time horizon. Potential investors have commitments (of certain payments in future) and the information about the worst possible loss will certainly help in identifying the investment opportunity, which in the worst-case scenario doesn't disturb their commitments.

To cover the gap in literature in this regard, the first objective of this study is to forecast the dynamic Value at Risk by Historical Simulation, Monte Carlo Simulation and Variance-Covariance Method by accounting for the highlighted deficiencies. The second objective is to compare the Value at Risk forecasts generated by these three methodologies on the basis of two back testing criteria which are Binary Loss Function and Quadratic Loss Function and proposing the best methodology amongst.

1.2 Objectives of Study

In the light of previous discussion, the objectives of this study are following:

1) Forecasting dynamic Value at Risk by Historical Simulation, Monte Carlo Simulation and Variance-Covariance Method
2) Comparison of Value at Risk forecasts generated by these three methodologies on the basis of Binary Loss Function and Quadratic Loss Function in order to propose the best methodology amongst.

1.3 Significance of Study

The forecasts of Value at Risk are important so that the investors could allocate their resources keeping in mind the worst possible loss. Literature in case of Pakistan is silent about the best methodology among Historical Simulation, Monte Carlo Simulation and Variance-Covariance Method.

There is no law which forces the mutual funds or corporations to report the Value at Risk measure for investments in those firms. Investors have to invest without knowledge of the worst possible loss that they could be facing.

This study highlights the importance of Value at Risk forecast for the regulator, so that, a framework of forecasting and reporting the Value at Risk measure by a valid model be made for the listed firms and mutual funds. It will contribute to increased information disclosure on the part of listed firms and mutual funds. This information disclosure has the potential to solve the problem of adverse selection due to asymmetric information about the worst possible loss (Value at Risk), which investors with commitments (of certain payments in future) are facing.

1.4 Plan of Study

Chapter II provides the review of relevant literature. It highlights the historical discussion about risk in the finance literature, along with the critical review of Value at Risk methodologies, importance of Value at Risk in the context of Basel Accords, Information Asymmetry and finally discusses various studies of Value at Risk in the stock, metal and commodity markets.

Chapter III discusses the three methodologies of forecasting Value at Risk and data, used in this study. Chapter IV explains the results obtained by visual inspection and descriptive analysis, volatility models and the evaluation methods of Value at Risk forecasts. Finally, Chapter V provides the summary, conclusion and policy implications of the study.

CHAPTER II

LITERATURE REVIEW

Against the view of Keynes “Financial markets work like casinos”, Williams (1938) argued that speculators and investors buy stock for profit (capital gain) and income (dividend) respectively. The speculator can only benefit by selling the stock to investors at a higher price. Investor is only interested in buying a stock if the estimate of income to be generated favors this decision. In the end stocks trade at their intrinsic value determined by the present value of expected cash flows.

The work of Williams (1938) eventually became the basis for dividend discount model. The estimate of income to be generated from a stock varies from investor to investor. This translates into different investors willing to pay different price for the same stock. This is the sole reason for stock prices to vary overtime.

2.1 Risk in Finance: A Brief History

The risk wasn’t defined until 1952. The phenomenal work of (Markowitz, 1952) for the first time quantified risk faced by investors. The three main contributions of Markowitz include quantifying risk, proposing diversification as a tool to minimizing unsystematic risk and estimation of portfolio return and risk. Later Sharpe included the risk-free asset along with the risky asset and derived the relationship between systematic risk and return represented by the Security Market Line. Sharpe (1964), Lintner (1965) and Mossin (1966) developed the Capital Asset Pricing Model (CAPM) by extending the work of Markowitz.

CAPM developed by Sharpe (1964), Lintner (1965) and Mossin (1966) was based on several assumptions. Numerous studies relaxed the assumptions to propose different variants of the original CAPM like (Brennan, 1970) accounted for different tax rates on capital gain and dividend. (Jensen et al., 1972) show how CAPM is affected if there is no riskless asset, (Mayers, 1972) shows what form CAPM takes when there exist nonmarketable assets and (Merton, 1973) developed the model in continuous time to account for the fact that trading takes place continuously overtime. Several other empirical tests of the CAPM concluded that the single risk factor was not able to explain the returns. Ross (1976) developed Arbitrage Pricing Theory which accounted for more than one risk factor to be used in pricing the financial assets.

In Finance, there is huge discussion about return which is determined by variables other than systematic risk being named either anomaly or additional/ extra market factors by two school of thoughts. The one which named variables other than systematic risk or extension of Capital Asset Pricing Model as anomalies include Size Anomaly by (Banz, 1981); Price to Earning (P/E) Anomaly by (Basu, 1983) Momentum Anomaly by (Carhart, 1997) among others. The other school of thought which named the extension of CAPM as additional/ extra market factors include (Fama and French, 1996, Fama and French, 2016).

And now the Value at Risk as a tool to measure market risk is used extensively because it tells us about the worst possible loss in a given time horizon for a specific confidence interval. It gained popularity due to the fact that the Basel Committee has allowed financial institutions to use internal models for Value at Risk forecasts.

2.2 Critical Review of Value at Risk Methodologies

Historical Simulation is one of the simplest method being used which according to (Brooks and Persand, 2002) is misleadingly being called “Historical Simulation” and according to (Kuester et al., 2006) is also named as ‘’Naive Historical Simulation’’.

The idea is to get the 5^{th} percentile or 1^{st} percentile of the distribution of actual historical returns depending on the confidence interval being either 95% or 99% respectively as the Value at Risk. It is the most widely used method in risk management industry for forecasting Value at Risk (Dias, 2013, Danielsson et al., 2016).

This method assumes that the future replicates the past and we have numerous studies available which argue that the markets are efficient, prices adjust to the arrival of new information which is a random process and that is why assumption of future reflecting the past doesn't always hold. Hendricks (1996) argues that there is substantial difference between the Value at Risk forecasts obtained by different approaches of Historical Simulation on the same date, and in terms of variability across time, the approach with longer observation period tend to produce less varying results compared to those using short observation period but still there is no specific methodology among Equally Weighted Moving Average, Exponentially Weighted Moving Average and Historical Simulation, which performs well on all the performance criteria for the random portfolio of positions in the eight currencies namely British pound, Canadian dollar, Italian lira, Japanese yen and Swiss franc.

In a nutshell there are numerous studies which favor the parametric methods to forecast Value at Risk (Sarma et al., 2003, Bao et al., 2006). The performance of semi parametric method (Monte Carlo Simulation) in forecasting Value at Risk depends upon the distributional assumption of simulated returns and the statistical model used to estimate the mean and the standard deviation of returns (Khindanova et al., 2001).

Monte Carlo Simulation addresses the extreme assumption of Historical Simulation that the future replicates the past. Pritsker (1997) focused on accuracy versus computational time in detail using simulations for portfolios containing nonlinear instruments like foreign exchange options and provided a method for analyzing the accuracy of the Value at Risk forecasts as a percent of true Value at Risk even though true Value at Risk was not known. The simple methods like delta-gamma-minimization, delta, and delta-gamma-delta were less accurate but results on computational time favored these methods. One of the complex method (delta-gamma Monte Carlo) provided among the most accurate results and took relatively short time to compute. His study further concluded that all Value at Risk methods except for Monte Carlo with full repricing generated large errors as a percent of true Value at Risk for deep out-of-money options with a short time to expiration. Similarly Abad and Benito (2013) investigated the performance of different models of Value at Risk like Historical Simulation, Monte Carlo and Extreme Value Theory by using the daily closing prices data for the Spanish IBEX35, French CAC40, German DAX, UK FTSE100, US Dow Jones Industrial Average (DJAI), S&P 500, Japanese Nikkei 225 and Hong Kong Hang Seng (HIS) indexes and divided the sample in to stable and volatile periods. Their conclusion was that the Monte Carlo Simulation with the volatility forecast obtained by GARCH type models didn't give accurate results rather the parametric model (Variance-Covariance Method) was the best among the tested models.

The reason for difference in the conclusion of these two studies may be attributed to the different kinds of securities for which the forecast of Value at Risk has been obtained like in the study of (Pritsker, 1997) the Value at Risk forecasts have been obtained for portfolios containing nonlinear instruments (foreign exchange options).

The Variance-Covariance Method is also one of the parametric method used in the literature extensively and again the forecast of Value at Risk depends upon the statistical method used to get the forecast of mean, the standard deviation and distributional assumption of returns or innovation, if some GARCH process is used to forecast volatility.

There are numerous studies using the Variance-Covariance Method to forecast Value at Risk with the volatility being forecasted by GARCH process and the assumption about the distribution of return being student t, normal, heavy tail or generalized error distribution (Hung et al., 2008, Giot and Laurent, 2003b, Giot and Laurent, 2003a, Giot and Laurent, 2004).

Most of the models used for volatility forecast while forecasting Value at Risk lack one crucial aspect of the whole exercise and that is the model specification itself being time dependent. The model specification which is appropriate for one-time period may not be appropriate for other. The implication of this argument is that the model specification may change overtime (Chiu and Chuang, 2016).

When this happens, the volatility forecast or Value at Risk forecast obtained by a method using a specific model specification might not be accurate. Extending the already available models, Chiu and Chuang (2016) proposed a Switching Forecast Model to increase forecast effectiveness while examining six Asian stock markets. The objective was comparative analysis of risk forecasts. Based on Quadratic Loss Function, the Switching Forecast Model has been found to be appropriate compared to alternative models and enables the risk manager to adopt this model if the objective is not to rely upon volatility forecasts leading to Value at Risk forecasts from one model specification only.

2.3 Value at Risk in the Context of Basel Accords

The Basel Committee was founded in 1974 in response to the failure of Herstatt Bank in West Germany. Herstatt Bank went bankrupt in 1974. The first meeting took place in 1975. The committee is headquartered at the Bank for International Settlements in Basel. The committee has widened its membership from the group of ten countries at its inception to members in 28 jurisdictions.[1]

The objective of committee is to improve the quality of banking supervision. It also serves as a forum for discussion and cooperation on supervisory matters of banking.[2]

Initially the committee laid the foundations for supervision of internationally active banks.[3] The committee focused its activities on capital adequacy after laying the foundations for supervision of internationally active banks.[4] Consensus built on use of weighted approach for measuring risk. The ratio of capital to risk-weighted assets of 8% was called for in the 1988 Accord.[5] The 1988 Accord evolved overtime. First amended in 1991 for precise definition of general provisions to be included in capital adequacy calculation.[6] Similarly, in 1995 another amendment was made to include off balance sheet items. [7]

The focus of 1988 Accord was on credit risk but as it evolved overtime, the capital accord was amended to include market risks as well. This amendment is also known as ‘’Market Risk Amendment’’. Banks are exposed to foreign exchange and hold tradeable securities (equity, bond and commodities among others). The possibility of loss due to change in market prices (market risk) is inevitable. It was for this reason to

---

[1] http://www.bis.org/bcbs/history.htm
[2] http://www.bis.org/bcbs/charter.htm
[3] Principles for the supervision of banks’ foreign establishments 1983
[4] Basel I: The Basel Capital Accord 1988
[5] Basel I: The Basel Capital Accord 1988
[6] Amendment of the Basel capital accord in respect of the inclusion of general provisions/general loan-loss reserves in capital 1991
[7] Basel Capital Accord: treatment of potential exposure for off-balance-sheet items 1995

include a capital requirement for the market risk that a bank is exposed to, at the end of 1997.[8]

The unique aspect of this amendment was that the financial institutions were and still are allowed to use internal models (Value at Risk Models) for measuring market risk based capital requirement. The reason for allowing financial institutions to use internal models make sense because of the impossibility of having a universal model for valid Value at Risk forecasts, because the valid Value at Risk model depends upon the market, security, time period being volatile or nonvolatile, number of models being evaluated and number of back testing criteria being used (Dias, 2013, Yao et al., 2016).

2.4 Value at Risk and Information Asymmetry

Prices of stocks tend to be present value of expected cash flows. If we are interested in the chance of loss due to change in market prices of stock, then the components of prices have a unique importance. The two components are the expected cash flows and the discount rate.

Expected cash flows and ultimately the prices vary from one firm to another and depend upon certain variables like firm specific variables, industry specific variables, market specific variables and overall economic variables as well (Piotroski and Barren, 2004, Apergis et al., 2011, Ahmad et al., 2013). The expectation about the future cash flows of a firm may be different for different potential investors and day traders. Similarly, the discount rate is also a subjective term which depends upon the opportunity cost available to the investor. The expected cash flows of a firm and the discount rate used by investors, enable different investors to be willing to pay or receive different price for the same stock. But when it comes to selecting a stock for making an investment

[8] Amendment to the capital accord to incorporate market risks 1997

the information which is key and affects the decision of investor with commitments (of payments in future) is the forecast of worst possible loss.

As discussed earlier there is no universal acceptable model for generating the forecast of Value at Risk (worst possible loss) (Slim et al., 2016, Yao et al., 2016), it means that the information about the worst possible loss will vary from investor to investor, if its available or considered in the first place. This information asymmetry will lead to the problem of adverse selection.

If an investor has Rs. 100 to invest and the worst possible loss he could bear is Rs. 30 then he should invest in the stock where at least the forecast of worst possible loss is Rs. 30. If the investor ends up investing in a stock where he/ she suffers a loss of more than Rs. 30 then this would create a distrust in the market and lead to hindrance in further investment. The one who has the information will be able to make accurate decision about investing in the stock where the worst possible loss will be within the tolerance limit.

Although the objective of this study is not to propose a mathematical model proving this distrust which is created by unavailability of information about the Value at Risk (worst possible loss) still this aspect of the information about Value at Risk is important and that’s why highlighted.

If we want to understand the financial markets, we need to keep in mind that these are driven by how accurate and timely the buyers and sellers have information that varies from buyer to buyer and seller to seller. The information could be about the firm, the industry, the market or any macroeconomic variable. After all this information translates into change in the expected cash flows or the discount rate which are the two most important components of prices.

2.5 Value at Risk in Stock, Metal and Commodity Markets

Highlighting the potential of economic variables for financial risk management as an open field for research and studying the role of market capitalization during crises and non-crises period separately in the estimation of Value at Risk, Dias (2013) concluded that the Value at Risk methodologies perform differently for portfolios with different market capitalization. This conclusion has importance for the practitioner involved in forecasting of Value at Risk because in the literature most of the studies have used large market capitalization stocks or indexes in analyzing different methodologies of Value at Risk.

One of the most important applications of conditional volatility modeling and forecasting is Value at Risk forecasting. Under the absence of a universal model of Value at Risk that could be feasible in all conditions (as mentioned earlier), the Basel Accord's tolerance towards financial institutions to build internal models for Value at Risk forecasts could be supported.

The financial institutions are faced with investments in different markets (Developed, Developing, Emerging, Frontier) and have to forecast Value at Risk by different methods because there is evidence of long memory in developed markets leading to FIGARCH being the favorite model of risk manager for these markets and to cater the asymmetry in either emerging or frontier markets the risk manager would have to favor models like GJR (Slim et al., 2016).

Furthermore. the choice of best method is not only different for different period studied or kind of instrument but also varies in terms of choice of model specification used, number of models evaluated and on the evaluation criteria applied. Yao et al. (2016) has compared realized volatility approach with GARCH type models among others, for three market indices namely S&P500, FTSE100 and DAX30. Total of 13 various risk models were used. The authors concluded that for volatility forecast the realized volatility models were better than GARCH models but when it comes to Value at Risk forecasts, even a simple EGARCH model was considered to be the best.

Volatility spillover is a reality which has been documented in various studies. The reasons are attributed to market players who have invested in more than one market or firms in different markets which are involved in the business with each other or simply a temptation for day traders to score profits whenever opportunity arises. Berger and Missong (2014), to account for the return interdependencies, dynamic conditional correlations and volatility spillovers while forecasting Value at Risk for financial portfolios, have used daily data distributed over both turbulent and calm periods and concluded that 99% Value at Risk forecasts obtained from EVT-GARCH-Copula model are the most appropriate compared to alternative models. Total of four portfolios were investigated of which two comprised of national stock indices, one currency portfolio and one portfolio of individual German stocks.

The study of worst possible loss, the comparison of different models for forecasting volatility which is to be used in generating Value at Risk forecast and even the comparison of different methodologies of forecasting Value at Risk is not limited to the stocks whether individual or indices. There are number of studies which analyze the adequate model for Value at Risk forecast in the metal markets as well (Huang et al., 2015, Chkili et al., 2014, Chaithep et al., 2012, Tully and Lucey, 2007, Hammoudeh and Yuan, 2008).

One key reason for this could be the willingness of investors around the world to invest in gold and other precious metals because these are considered a hedge against inflation.

Again, if there are investors who want to invest in gold the whole mechanism of price determination follows leading to variation in the market price which ultimately ends with market risk.

That's why accounting for the market risk in the metals market is important. Analyzing metals market for the worst possible loss from January 2000 to September 2016 by a two stage approach (GARCH-EVT approach), Zhang and Zhang (2016) conclude that gold has the steadiest and the highest worst possible loss estimate. Whereas the estimate of worst possible loss for palladium was most volatile. The back-testing results give indication of their methodology being adequate.

The price in commodity market changes in response to the changes in demand and supply. The change in price translates in to market risk. The imbalance in demand and supply could be attributed to business cycle in case of energy products and to unexpected weather patterns in case of agricultural commodities. Giot and Laurent (2003a) in order to account for the market risk in commodity market concluded that the skewed student APARCH model performs the best. This conclusion is based on 5 years out of sample forecasts for daily cash prices. Other studies include (Kroner et al., 1995), which concluded that the forecasts which combine market expectations and time series methods performed better than forecasts using only market expectations or time series methods.

2.6 Conclusion

The best methodology for forecasting Value at Risk depends upon number of factors. The factors include the kind of instrument (stock, bond, futures, commodity, currency among others), the time period being volatile or non-volatile, number of models being evaluated, number of evaluation criteria being used, the parametric method used for volatility forecast, which is to be used as input in Value at Risk forecast, the assumption about distribution of returns, market capitalization being large or small, the market being developed, emerging or frontier.

For this reason, the fact that Basel Committee has allowed different financial institutions to use internal models for generating Value at Risk forecast makes sense.

In Pakistan reporting of Value at Risk forecast is not being enforced by SECP or PSX and is not being practiced, the investor faces the problem of adverse selection due to information asymmetry about the Value at Risk and this study will highlight the importance for the regulator.

CHAPTER III

METHODOLOGY AND DATA

For comparison of the Value at Risk forecasts generated by Historical Simulation, Monte Carlo Simulation and Variance-Covariance Method, we have selected energy firms from four sectors which include Oil and Gas Exploration, Oil and Gas Marketing, Power Generation and Distribution and Refinery.

The energy firms in Pakistan include well-established firms which normally enjoy stable cash flows and are considered blue chip companies like Oil and Gas Development Company Limited (OGDCL), Sui Southern Gas Company Limited (SSGC) among others and some growth companies which don't enjoy stable cash flows and there is a lot of uncertainty about their future prospects and are in their initial phase of the life cycle like companies in the Power Generation and Distribution Sector. So, a potential bias due to low volatility in the returns of well-established firms in favor of Historical Simulation could be addressed because energy firms include well established firms along with growth firms and the best methodology should perform better for both groups. In the recent past Pakistan has been going through severe energy crises and China Pakistan Economic Corridor (CPEC) has a substantial share of investments dedicated to the energy sector. This increases the interest of potential investors in energy firms and a study highlighting the need for a framework of forecasting and reporting Value at Risk (worst possible loss).

The share price data for these firms have been obtained from business recorder. The data span ranges from 3rd January 2011 to 28th April 2017. Data for some of the firms was not available from Jan 2011. So starting date of the data for such firms was different. 84 rolling windows were created for all the firms, by dropping the oldest value and adding the next value. The one step ahead Value at Risk forecasts were generated from first trading day of January 2017 to last trading day of April 2017. This adds up to a total of 84 forecasts for each firm. List of firms selected from four sectors for this study is provided in the Appendix A.

A good methodology for forecasting Value at Risk should perform better for both groups of energy firms. So, energy firms are going to be a good test sample for comparison of Historical Simulation, Monte Carlo Simulation and Variance-Covariance Method in Pakistan.

The whole analysis is based on the return series which is constructed by the following equation for each firm.

$$r_t = Ln(P_t) - Ln(P_{t-1}) \tag{1}$$

Where r_t represents the return, Ln represents the natural logarithm, P_t and P_{t-1} represent the share price of current and previous period respectively.

3.1 Historical Simulation

Historical Simulation is one of the most basic methodology for forecasting Value at Risk. This is the most widely used methodology in risk management industry (Danielsson et al., 2016). The assumption of this methodology is that the future will replicate the past. For this reason, there is a lot of criticism on Historical Simulation for not incorporating the time varying nature of stock returns (Hung et al., 2008, Giot and Laurent, 2004).

This study is about forecasting the dynamic Value at Risk. So, in this study rolling window of stock returns will be used to somewhat account for the time varying nature of financial time series. The sole reason for using this methodology to forecast dynamic Value at Risk despite a lot of criticism, is presence of well-established firms in our sample of energy firms. Volatility in stock return for these firms is generally low. The Value at Risk forecast obtained by parametric methodology using the forecast of volatility may not give true picture because of well-established firms. For this sample bias Historical Simulation is also applied for obtaining dynamic Value at Risk forecast and compared with other two methodologies to get the best methodology.

The idea of Historical Simulation is to construct the return series. The 5th percentile or 1st percentile of actual returns will be obtained depending on the confidence interval being 95% or 99% respectively as the one-step ahead Value at Risk forecast.

$$\text{VaR at 5\%} = \int_{-\infty}^{-VaR} f_{r_t} d_{r_t} = F_{rt}(-VaR) \qquad (2)$$

Where the Value at Risk obtained by eq. (2) is going to be the one step ahead forecast by Historical Simulation with a confidence interval of 95%.

The 5th percentile of actual return has been obtained for each firm, as the one-step ahead Value at Risk forecast, with the confidence interval of 95%. A total of 84 one step ahead Value at Risk forecasts have been obtained by dropping the oldest value and adding the new value from 1st trading day of January 2017 onwards.

3.2 Monte Carlo Simulation

Since stock prices follow a random process the forecasting of Value at Risk should be based on some method which accounts for randomness and here Monte Carlo Simulation is a great example which is semi parametric kind of technique for forecasting the Value at Risk.

The idea is to get the mean and standard deviation of stock prices, simulate the random stock prices, construct return series from simulated prices and then the 5th percentile of the simulated return series is the one step ahead Value at Risk forecast if the confidence interval is 95%.

The simulated price for a given stock is given by the following equation:

$$S_{t+i} = S_{t+i-1} + S_{t+i-1}(\mu + \sigma\varepsilon_i) \tag{3}$$

Where S_{t+i} represents the one step ahead simulated stock price, μ is the mean of actual returns of the underlying period in the rolling window, σ is the standard deviation of actual returns of the underlying period in the rolling window and $\varepsilon_i$is the standard normal random variable with mean zero and unit variance. Using equation (3) we get the simulated stock price for the whole period covered under one rolling window. Similarly, simulated prices are obtained for each of 84 rolling windows for one firm under analysis.

In the next step, return series is constructed from the simulated prices and 5th percentile of the simulated returns is considered to be the one step ahead Value at Risk forecast given by following equation.

$$\text{VaR at 5\%} = \int_{-\infty}^{-VaR} f_{r_t} d_{r_t} = F_{rt}(-VaR) \tag{4}$$

Where the Value at Risk obtained by equation (4) is going to be the one step ahead forecast by Monte Carlo Simulation.

3.3 Variance-Covariance Method

Some studies have used the dollar loss relative to the mean (Relative-Value at Risk) in forecasting daily Value at Risk but since the expected value of return is almost zero there is not much difference between relative Value at Risk and zero Value at Risk (Jorion, 2007). The one step ahead zero Value at Risk forecast is given by:

$$VaR_{t+1} = Z_{1-c}\widehat{\sigma_t} + \mu \tag{5}$$

Where in equation (5), Z_{1-c} denotes the left percentile at ''1-c'' for either standard normal distribution or standard student t distribution or any other assumed distribution if the confidence interval is ''c''. The volatility estimate $\widehat{\sigma_t}$ can be obtained by static formula, rolling window standard deviation or by GARCH type model.

For this study the left percentile at 1-c for standard normal distribution has been used, if a valid GARCH type model with student t distribution has not been obtained for a specific rolling window. Similarly, if there is a valid GARCH type model for a rolling window then the left percentile at 1-c for the student t distribution with degree of freedom obtained by that particular GARCH type model has been used. The forecast of conditional standard deviation obtained by a valid GARCH type model has been used for $\widehat{\sigma_t}$.

3.3.1 GARCH (p, q)

Bollerslev (1986) introduced generalized ARCH models to overcome the problems of long lag length (q) which are increased number of parameters to estimate and increased number of non-negative conditions on parameters.

The conditional mean and conditional variance equation of GARCH (p, q) model can be written as follows:

$$r_t = \mu + \sum_{i=1}^{m} \theta_i r_{t-i} + \sum_{i=1}^{n} \varphi_i \varepsilon_{t-i} + \varepsilon_t \tag{6}$$

Where $\varepsilon_t = z_t \sigma_t$, $z_t \sim N(0,1)$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-\mathrm{i}}^2 + \sum_{i=1}^{p} \beta_i\, \sigma_{t-\mathrm{i}}^2 \tag{7}$$

In eq. (6) r_t denotes the estimated return which is linear function of some Autoregressive (AR) process and Moving Average (MA) process. Empirically it is found that r_t follows ARMA (m, n) structure.

In eq. (7) $\omega > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$ and $\sum \alpha_i + \sum \beta_i < 1$ are the necessary conditions for the model to be Variance Covariance stationary. Sum of ARCH and GARCH terms represents the persistence of shock to volatility.

3.3.2 GARCH-t

Empirically it is found that the financial return series is a very special type of return series which exhibits leptokurtosis and have heavy tails suggesting that the distribution is not normal and the assumption of conditional normality for standardized innovations needed to be relaxed. Bollerslev (1987) relaxed this assumption and proposed GARCH-t model where $\varepsilon_t = z_t \sigma_t$, $z_t \sim t(0,1, v)$. With this model there is one more parameter to estimate that is v the degree of freedom of student's t distribution. This same parameter is used to obtain the value of left percentile at 1-c for the student t distribution in equation (5).

3.3.3 TARCH (Threshold ARCH) Models

Empirically it is observed that the negative shock to volatility persists for a longer period of time than a positive shock of same magnitude and the reason for that is presence of mediocre players in the market who panic due to the negative shock and start selling which further decreases the prices. What happens is that the decrease in share price (negative return) causes a decrease in market based equity value. Market based equity value is in the denominator for debt to equity ratio, which increases due to the decrease in share price. As shareholder have residual claim on the assets of company this increase in the debt to equity ratio creates panic and results in mediocre players selling their stocks. This is known as the leverage effect in the literature.

Since there is asymmetric effect of negative and positive shock on volatility, the effect of negative shock being more than the positive shock, a model should account for this phenomenon in the conditional variance equation.

Glosten et al. (1993) proposed a model to account for the asymmetric effect of negative and positive shock to volatility. The conditional variance equation is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-\mathrm{i}}^2 + \sum_{i=1}^{q} \gamma \, \varepsilon_{t-\mathrm{i}}^2 D_{t-i} + \sum_{j=1}^{p} \beta_j \, \sigma_{t-\mathrm{j}}^2 \qquad (8)$$

In eq. (8) $\omega > 0,\ \alpha_i \geq 0,\ \beta_j \geq 0,\ \forall\, i, j\, , and\ 0 \leq \gamma \leq 1$

Where $\varepsilon_t = z_t \sigma_t\, , z_t \sim N(0,1)$ and D is binary dummy which equals 1 for negative shock or bad news and equals 0 for positive shock or good news. Persistence of shock to volatility is given by $\alpha_i + \beta_j + \gamma/2$. A little modification to this original model is made by changing the assumption about distribution of return series from normal to student t. In this case $\varepsilon_t = z_t \sigma_t\, , z_t \sim t(0,1,v)$.

3.3.4 GARCH-M

Investors are present in the market to obtain return for the risk that they are exposed to. A proxy for risk being used in the literature is the volatility of underlying stock. High volatility translates into high risk. Investor will demand high return for investing in a stock with high volatility. This phenomenon is named as risk premium.

To account for the risk premium, (Engle et al., 1987) for the first time proposed an ARCH-M specification. The idea was to incorporate the conditional variance of return into the conditional mean equation. Since GARCH type models are more common than ARCH models nowadays, its common practice to estimate GARCH-M model. The conditional mean equation is given by:

$$r_t = \mu + \sum_{i=1}^{m} \theta_i r_{t-i} + \sum_{i=1}^{n} \varphi_i \varepsilon_{t-i} + \delta\sigma_{t-1}^2 + \varepsilon_t \tag{9}$$

Where $\varepsilon_t = z_t \sigma_t \, , z_t \sim N(0,1)$ or $\varepsilon_t = z_t \sigma_t \, , z_t \sim t(0,1,v)$ depending upon the assumption about the distribution, being standard normal or student t. The positive and significant value of δ will mean that there exists risk premium in the return series. It is not necessarily a requirement to use conditional variance. In some of the cases conditional standard deviation can also be used in the conditional mean equation. Conditional variance equation is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-\mathrm{i}}^2 + \sum_{i=1}^{p} \beta_i \, \sigma_{t-\mathrm{i}}^2 \tag{10}$$

The restriction on parameters in equation (10) is same as in equation (7).

3.4 Evaluation Methods for Value at Risk Forecasts

The three methodologies used for forecasting dynamic Value at Risk have been evaluated using the two evaluation criteria (Binary Loss Function and Quadratic Loss Function). Quadratic Loss Function has been used only if the results of Binary Loss Function are same for two or more methodologies. Quadratic Loss Function although being only marginally different than Binary Loss Function, penalizes the magnitude of exception.

3.4.1 Binary Loss Function

If Value at Risk forecast doesn't cover the actual return on a given day, then this is considered as an exception. If a model is truly giving the forecasts aligned with the assigned confidence interval of suppose ''c'' then the number of exceptions should not increase ''1-c''.

$$BL_{t+1} = \begin{Bmatrix} 1, & if\ r_{t+1} < VaR_{t+1} \\ 0, & if\ r_{t+1} > VaR_{t+1} \end{Bmatrix} \tag{11}$$

This evaluation method has a limitation. Suppose the number of exceptions for any two methodologies equals one, then under this evaluation method, both methodologies will be correct and considered to be the best. We cannot name one methodology better than other in this situation. But if the magnitude of exception for one methodology is large compared to the other then methodology with the smaller magnitude of exception should be considered better compared to other. Binary loss function doesn't take into account the magnitude of exception. Although empirically it is very difficult to encounter this situation, still we need to have a more robust evaluation method accounting for this phenomenon.

In this study the Sum of Binary Loss Function (SBLF) has been used in order to decide the best methodology for forecasting dynamic Value at Risk.

3.4.2 Quadratic Loss Function

This is even more powerful evaluation method than binary loss function because it takes in to account not only the number of exceptions rather the magnitude of them as well. It is possible for the Sum of Binary Loss Function to be the same for more than one methodology. In this case one cannot decide about the best methodology. So Quadratic Loss Function is a better option in that case.

The quadratic loss function is given by:

$$QL_{t+1} = \begin{cases} 1 + (r_{t+1} - VaR_{t+1})^2 & if\ r_{t+1} < VaR_{t+1} \\ 0, & if\ r_{t+1} > VaR_{t+1} \end{cases} \tag{12}$$

The quadratic loss function penalizes the exceptions with huge magnitude more than the exceptions with low magnitude. Empirically it is difficult to find a huge difference in the magnitude of exception among different methodologies. Still this situation may arise and one must have an evaluation method to account for it.

In this study the Sum of Quadratic Loss Function (SQLF) has been used in order to decide upon the best methodology for forecasting dynamic Value at Risk.

CHAPTER IV

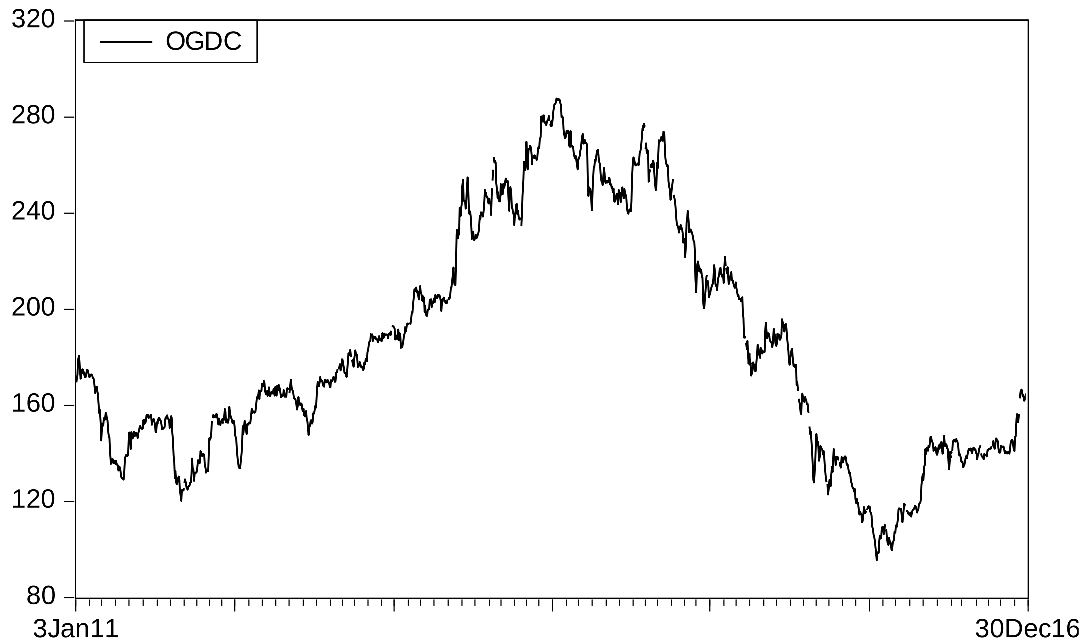
RESULTS AND DISCUSSION

4.1 Visual Inspection

Visual inspection gives a tentative idea about the structure of financial time series. First of all, we plot the series at level to observe if the series follows a trend. Then we plot the return series to observe mean reversion behavior. This also gives us tentative idea about ARCH (Autoregressive Conditional Heteroskedastic) effect if there are clusters of high and low volatility. Then we observe the distribution of return series for the presence of leptokurtosis and heavy tails. Then we plot the PACF (Partial Autocorrelation Function) and ACF (Autocorrelation Function) to get the tentative idea about the ARMA (Autoregressive & Moving Average) structure of the return series.

4.1.1 Stock Price at Level

Figure 4.1-Stock Price at Level



One can observe in the Figure 4.1 that the stock price at level follows trend. If series has a trend, then it doesn't revert back to a specific mean and violates the condition of stationarity. In time series if the objective is forecasting then series must be stationary. The series must have constant mean and variance overtime in order to be stationary. It is evident from the line graph of stock price in Figure 4.1 and from line graph of stock prices for the remaining firms in Appendix B that stock prices at level follow trend. So, stock prices at level cannot be used for forecasting. The observations of only the first rolling window have been plotted in the line graph.[9] The line graphs of remaining 19 firms are available in Appendix B.

4.1.2 Return Series

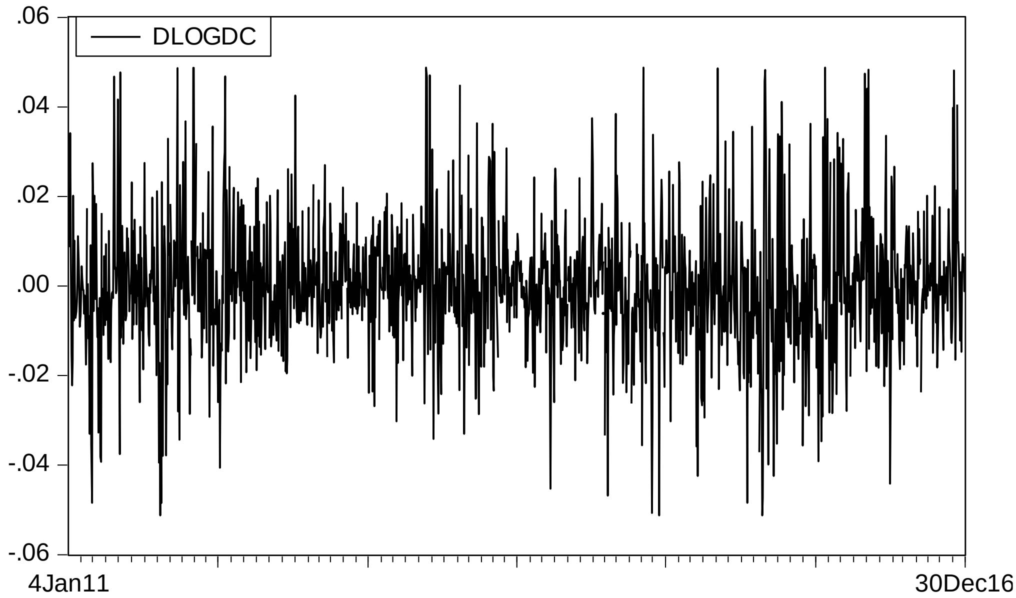
A series with trend cannot be used in the analysis involving forecasting. The series needs to be stationary. Under the assumption of return being continuously compounded, the return series has been constructed by Eq. (1) for each firm. It is found empirically that the stock return series is almost always stationary. The existence of a financial time series integrated of order two is almost impossible. That's why in most cases the stock return series tends to be stationary.

In Figure 4.2, the return series of OGDC (Oil and Gas Development Company Limited) is plotted as an example. The plots for the stock return series of remaining selected firms are available in Appendix C.

One can observe that the stock return series reverts back to its mean of around zero. The stock return series also gives tentative idea about the presence of ARCH effect because one can observe clusters of low and high volatility.

[9] Results for remaining 83 rolling windows of each firm are available but have not been reported here to save space. The line graph of return series, density plot, ACF and PACF plots for OGDC and remaining firms (in Appendices) are also for the first rolling window only.

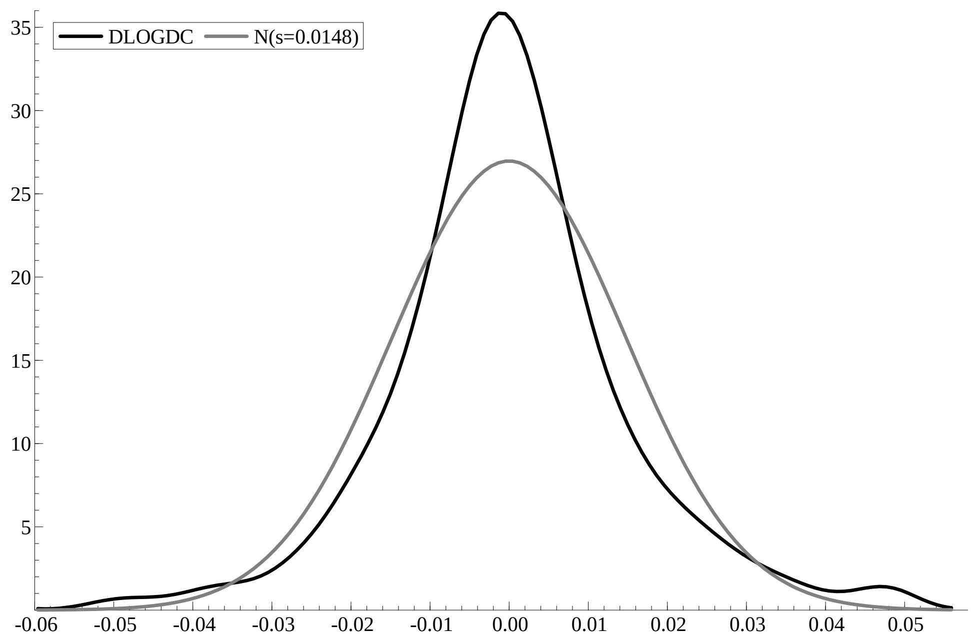
Figure 4.2-Stock Return Series



4.1.3 Density Plot of Return Series

Empirically it is found that the return series is leptokurtic and has heavy tails. The return series also tends to be multi modal. In Figure 4.3, density plot of OGDC is provided as an example and density plots of remaining firms are provided in Appendix D.

Figure 4.3-Density Plot for Return Series



In Figure 4.3, the dark line represents the density of return series and the grey line represents the normal reference. One can observe that the peak of the dark line is higher than the normal reference signifying the series being leptokurtic. The heavy tails are also quite evident. In Appendix D, the dark line has more than one peak for some of the density plots, which supports the claim of return series being some time multi modal. One can observe in the density plots that the mean of each return series is around zero.

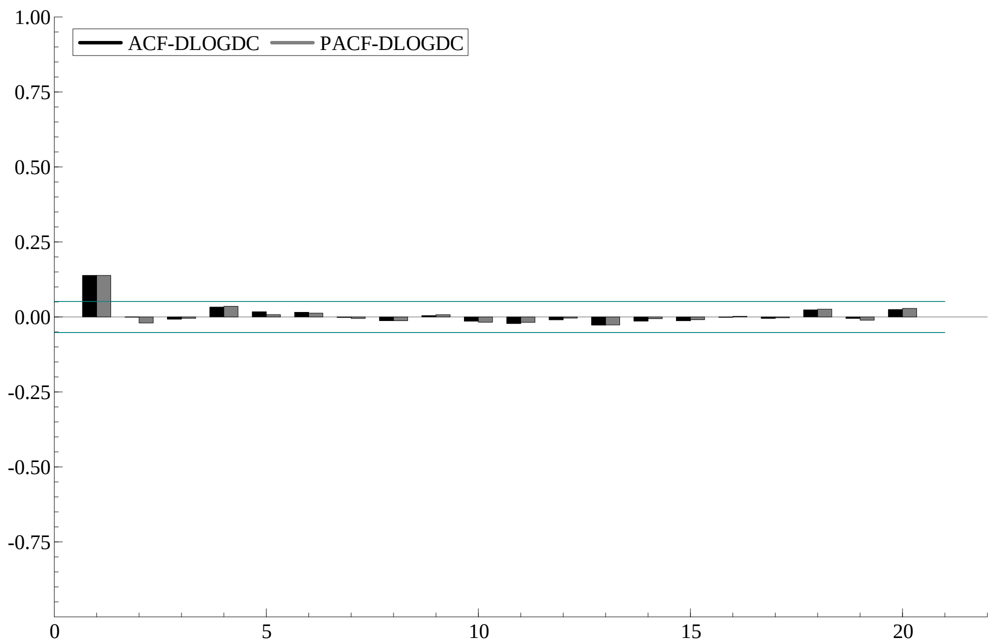
4.1.4 PACF and ACF Plots for Identifying ARMA (m,n) Structure

Specifying the structure of conditional mean equation is important for applying GARCH type model. The Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) plot gives a tentative idea about the Autoregressive (AR) and Moving Average (MA) process respectively. In Figure 4.4, the PACF and ACF plots of the return series of OGDC are given. The PACF and ACF plots for all other selected firms are provided in the Appendix E.

The grey spikes represent the PACF and dark spikes represent the ACF. PACF and ACF plots include up to 20 lags. If the spike of PACF and ACF is out of the upper bound represented by the blue line, this will signify the lag of AR and MA process respectively. For lower bound the grey spike will represent ACF.

One can observe that the spikes are out of the upper bound for the 1st lag only. This gives us the tentative idea about the structure of conditional mean equation in GARCH type model being ARMA (1,1).

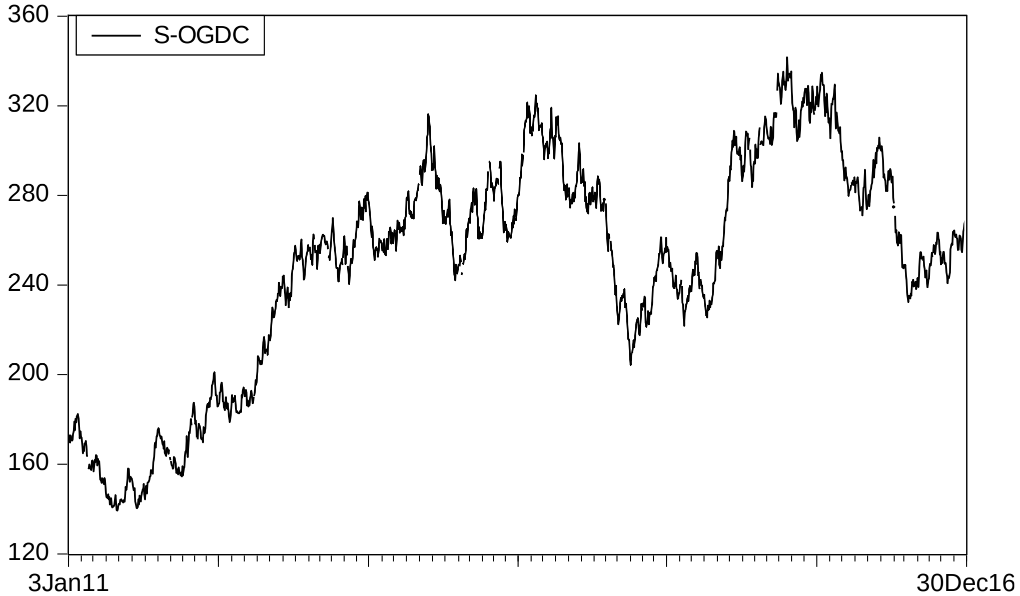
Figure 4.4- PACF and ACF Plot for Return Series



4.1.5 Simulated Stock Price at Level

The line graph of simulated prices for only the first rolling window of OGDC and remaining selected firms has been provided in Figure 4.5 and Appendix F respectively. It is evident that simulated prices follow trend. In the next step, conclusions of visual inspection are calibrated with descriptive statistics.

Figure 4.5-Simulated Price at Level



4.2 Descriptive Statistics

Visual inspection is supposed to provide a tentative idea about the structure of financial time series. The tentative idea we got was that the return series was stationary, leptokurtic, with heavy tails and there was volatility clustering as well. Now same observations need to be calibrated with the help of statistics.

Table 4.1 provides the descriptive statistics for the return series of each selected firm. The mean is around zero and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test shows that the return series of all the firms are stationary because the calculated statistic doesn't cross asymptotic critical values [1% (0.739), 5% (0.463), 10% (0.347)]. The null hypothesis, "series is stationary" cannot be rejected for all the firms.

Skewness is positive for some of the firms which means that most of the return observations lie below mean and negative for some firms meaning that most of the return observations lie above mean, as noted in the density plots. The excess kurtosis for return series of all the firms is positive signifying the series being leptokurtic. Ljung-Box–Pierce Q-Statistics and Q^2-Statistics provide evidence for autocorrelation and presence of possible ARCH effect. The possibility of ARCH effect is further calibrated by the LM-ARCH test. The Variance-Covariance Method uses volatility forecast as an input which is to be obtained by a valid GARCH type model in this study in order to account for the ARCH effect.

P-values are given in parentheses. The null hypothesis of skewness being zero is rejected for most of the firms' return series. The null hypothesis of excess Kurtosis being zero is rejected for all the firms' return series. The null hypothesis of Jarque-Bera test "return series being normally distributed" is rejected for all the firms and it justifies the use of student t distribution.

Table 4.1- Descriptive Statistics

Series	Mean	Standard Deviation	Skewness	Excess Kurtosis	Jarque-Bera	Q-Stat (5)	Q^2-Stat (5)	ARCH 1-2	KPSS
DLOGDC	0.0000	0.0148	0.196 (0.001)	1.635 (0.000)	175.09 (0.000)	30.786 (0.000)	114.220 (0.000)	31.654 (0.000)	0.187
DLMARI	0.0016	0.0240	-0.299 (0.000)	3.199 (0.000)	656.24 (0.000)	135.133 (0.000)	118.335 (0.000)	29.242 (0.000)	0.308
DLPOL	0.0004	0.0154	-0.400 (0.000)	3.848 (0.000)	956.55 (0.000)	30.462 (0.000)	88.211 (0.000)	20.891 (0.000)	0.189
DLBPL	0.0005	0.0240	0.1439 (0.023)	0.215 (0.089)	7.99 (0.018)	98.594 (0.000)	440.320 (0.000)	121.79 (0.000)	0.085
DLSHEL	0.0006	0.0205	-1.094 (0.000)	13.785 (0.000)	12062 (0.000)	29.730 (0.000)	14.204 (0.014)	5.369 (0.004)	0.333
DLSNGP	0.0008	0.0227	-0.391 (0.000)	5.307 (0.000)	1782.4 (0.000)	33.863 (0.003)	15.295 (0.001)	6.836 (0.001)	0.514
DLSSGC	0.0004	0.0217	-0.108 (0.088)	2.780 (0.000)	481.51 (0.000)	25.477 (0.000)	28.119 (0.000)	9.095 (0.000)	0.045
DLHASCOL	0.0027	0.0232	-0.295 (0.002)	3.464 (0.000)	334.59 (0.000)	38.039 (0.000)	32.633 (0.000)	7.421 (0.000)	0.068
DLBYCO	0.0005	0.0267	0.871 (0.000)	3.952 (0.000)	505.48 (0.000)	19.563 (0.001)	49.815 (0.000)	11.315 (0.000)	0.117
DLNRL	0.0005	0.0177	-0.008 (0.929)	1.450 (0.000)	56.97 (0.000)	19.880 (0.001)	59.704 (0.000)	3.952 (0.000)	0.136
DLATRL	0.0009	0.0196	0.134 (0.160)	0.707 (0.000)	15.51 (0.000)	23.313 (0.000)	74.556 (0.000)	26.874 (0.000)	0.249
DLHUBC	0.0008	0.0139	-0.528 (0.000)	4.706 (0.000)	1440.5 (0.000)	13.429 (0.019)	12.503 (0.028)	5.477 (0.004)	0.059
DLNPL	0.0009	0.0168	0.093 (0.139)	2.543 (0.000)	402.86 (0.000)	7.846 (0.164)	40.298 (0.000)	14.325 (0.000)	0.109
DLKOHE	0.0005	0.0208	-0.691 (0.000)	4.699 (0.000)	1485.8 (0.000)	9.782 (0.081)	45.322 (0.000)	14.798 (0.000)	0.079
DLJPGL	0.0008	0.0508	1.525 (0.000)	8.589 (0.000)	5144.2 (0.000)	11.659 (0.039)	83.126 (0.000)	19.088 (0.000)	0.048
DLTSPL	0.0016	0.0779	0.746 (0.000)	8.074 (0.000)	4174.4 (0.000)	49.357 (0.000)	76.062 (0.000)	22.476 (0.000)	0.093
DLKOHP	0.0005	0.0589	0.384 (0.000)	7.506 (0.000)	3525.9 (0.000)	36.337 (0.000)	74.592 (0.000)	35.695 (0.000)	0.135
DLAEL	0.0002	0.0461	0.529 (0.000)	4.291 (0.000)	1209.7 (0.000)	19.463 (0.001)	385.233 (0.000)	120.73 (0.000)	0.137
DLSPWL	0.0002	0.0140	0.056 (0.604)	4.633 (0.000)	454.73 (0.000)	6.051 (0.301)	38.355 (0.000)	5.5978 (0.003)	0.188
DLLPL	0.0001	0.0200	0.118 (0.162)	1.040 (0.000)	39.42 (0.000)	0.931 (0.967)	46.691 (0.000)	18.303 (0.000)	0.298

P-values are in parenthesis.
KPSS test statistic asymptotic critical values are [1% (0.739), 5% (0.463), 10% (0.347)].

4.3 Valid GARCH Type Models for Selected Firms

Valid volatility models and respective residual analysis is given for the 20 selected firms in Table 4.2a, 4.2b, and 4.2c below.

Table 4.2a- Volatility Models

Parameters	**DLOGDC ARMA (1,0) GJR (1,1)**	**DLMARI ARMA (1,0) GARCH (1,1)**	**DLPOL ARMA (1,0) GARCH (1,1)**	**DLBPL ARMA (2,0) GARCH (1,1)**	**DLSHEL ARMA (1,0) GARCH (1,1)**	**DLSNGP ARMA (1,0) GARCH (1,1)**	**DLSSGC ARMA (1,0) GARCH (1,1)**
Conditional Mean Equation							
Constant μ	-0.00041 (0.2108)	0.00101 (0.1289)	0.00048 (0.1118)	-0.00113 (0.0309)	0.00007 (0.8915)	-0.00026 (0.6467)	0.00051 (0.3501)
AR (1) θ_1	0.07729 (0.0054)	0.23865 (0.0000)	0.07197 (0.0104)	0.08719 (0.0079)	0.07540 (0.0714)	0.07666 (0.0100)	0.08094 (0.0072)
AR (2) θ_2				0.04111 (0.1336)			
Conditional Variance Equation							
Constant ω	0.00002 (0.0543)	0.00008 (0.0523)	0.00001 (0.1319)	0.00001 (0.0000)	0.00002 (0.0734)	0.00007 (0.0486)	0.00011 (0.0001)
ARCH (1) α_1	0.08844 (0.0423)	0.08380 (0.0000)	0.12692 (0.0167)	0.37645 (0.0000)	0.08137 (0.0011)	0.20506 (0.0000)	0.16333 (0.0000)
GARCH (1) β_1	0.76705 (0.0000)	0.90444 (0.0000)	0.84884 (0.0000)	0.47379 (0.0000)	0.88763 (0.0000)	0.67421 (0.0000)	0.59250 (0.0000)
GJR (1) γ	0.16062 (0.0016)						
Student (DF)	4.15637 (0.0000)		3.59935 (0.0000)	5.45536 (0.0000)		5.89107 (0.0000)	
Persistence of Shock	0.93581	0.98826	0.97577	0.85043	0.96901	0.87928	0.75584
Residual Analysis							
Q-Stat (5)	9.0671 (0.0594)	4.9844 (0.2889)	8.2346 (0.0833)	4.1450 (0.2462)	1.8863 (0.7566)	7.6161 (0.1066)	7.9591 (0.0930)
Q-Stat (10)	10.6581 (0.2998)	5.7934 (0.7604)	10.4344 (0.3164)	8.4079 (0.3946)	5.0216 (0.8324)	13.0903 (0.1585)	15.2980 (0.0830)
Q2-Stat (5)	1.8680 (0.6002)	2.3766 (0.4979)	2.6790 (0.4437)	9.6850 (0.0214)	0.4505 (0.9296)	1.1238 (0.7713)	0.9749 (0.8073)
Q2-Stat (10)	5.2028 (0.7356)	3.7962 (0.8750)	2.9015 (0.9403)	12.5165 (0.1296)	1.2849 (0.9957)	2.0722 (0.9787)	2.0554 (0.9792)
LM-ARCH (1-2)	0.0507 (0.9505)	1.0123 (0.3636)	0.6564 (0.5188)	4.2796 (0.0140)	0.0098 (0.9902)	0.2164 (0.8054)	0.1494 (0.8612)
LM-ARCH (1-5)	0.3734 (0.8671)	0.4774 (0.7933)	0.5320 (0.7521)	2.2456 (0.0476)	0.0886 (0.9940)	0.2306 (0.9492)	0.1947 (0.9646)

P-values are in parenthesis.

Table 4.2b- Volatility Models (Cont.)

Parameters	DLHASCOL ARMA (1,0) GARCH (1,1)	DLBYCO ARMA (1,1) GARCH (1,1)	DLNRL ARMA (1,0) GARCH (1,1)	DLATRL ARMA (0,1) GARCH (1,2)	DLHUBC ARMA (0,0) GARCH (1,1)	DLNPL ARMA (0,0) GARCH (1,1)
Conditional Mean Equation						
Constant μ	0.00060 (0.4594)	-0.00165 (0.0014)	-0.00046 (0.1974)	-0.00008 (0.8344)	0.0007 (0.0126)	0.00031 (0.3179)
AR (1) θ_1	0.13019 (0.0092)	-0.30610 (0.0100)	0.07731 (0.0061)			
MA (1) φ_1		0.37217 (0.0010)		0.07366 (0.0268)		
Conditional Variance Equation						
Constant ω	0.00005 (0.2654)	0.00006 (0.0166)	0.00003 (0.1735)	0.00001 (0.0218)	0.00004 (0.1805)	0.00001 (0.1341)
ARCH (1) α_1	0.26946 (0.0389)	0.21963 (0.0002)	0.22281 (0.0014)	0.24775 (0.0000)	0.18056 (0.0264)	0.10571 (0.0047)
ARCH (2) α_2				-0.11691 (0.0323)		
GARCH (1) β_1	0.67574 (0.0001)	0.73796 (0.0000)	0.75112 (0.0000)	0.84783 (0.0000)	0.61032 (0.0066)	0.88538 (0.0000)
Student (DF)	4.61496 (0.0000)	3.80599 (0.0000)	3.39473 (0.0000)	4.41846 (0.0000)	3.68593 (0.0000)	3.49625 (0.0000)
Persistence of Shock	0.94521	0.9576	0.97394	0.97867	0.79089	0.9911
Residual Analysis						
Q-Stat (5)	7.6081 (0.1070)	6.5198 (0.0888)	7.2828 (0.1216)	8.1231 (0.0871)	11.8041 (0.0375)	3.6439 (0.6017)
Q-Stat (10)	13.8895 (0.1263)	18.6702 (0.0167)	10.4439 (0.3157)	14.5136 (0.1051)	15.5946 (0.1118)	5.2933 (0.8707)
Q2-Stat (5)	8.7458 (0.0328)	2.6875 (0.4423)	7.0516 (0.0702)	4.8619 (0.0879)	1.6855 (0.6401)	4.0673 (0.2542)
Q2-Stat (10)	12.2393 (0.1408)	6.3168 (0.6117)	11.9844 (0.1519)	6.7983 (0.4501)	6.1097 (0.6349)	16.6251 (0.0342)
LM-ARCH (1-2)	1.0422 (0.3533)	1.1237 (0.3254)	2.2054 (0.1106)	0.5814 (0.5592)	0.3531 (0.7025)	0.8476 (0.4286)
LM-ARCH (1-5)	1.5504 (0.1722)	0.5814 (0.7143)	1.4633 (0.1989)	1.0215 (0.4034)	0.3361 (0.8912)	0.7869 (0.5590)

P-values are in parenthesis.

Table 4.2c- Volatility Models (Cont.)

Parameters	DLKOHE ARMA (1,1) GARCH (1,1)	DLJPGL ARMA (1,1) GARCH-M (1,1)	DLTSPL ARMA (1,1) GARCH-M (1,1)	DLKOHP ARMA (1,1) GARCH (1,1)	DLAEL ARMA (0,0) GARCH (1,1)	DLSPWL ARMA (0,0) GARCH (1,1)	DLLPL ARMA (0,0) GARCH (1,1)
Conditional Mean Equation							
Constant μ	-0.00015 (0.6806)	-0.00667 (0.0000)	-0.00543 (0.0168)	-0.00026 (0.7646)	-0.00001 (0.0010)	-0.00039 (0.3264)	-0.00021 (0.7438)
AR (1) θ_1	0.82194 (0.0000)		0.47738 (0.0003)	0.47389 (0.0000)			
MA (1) φ_1	-0.89151 (0.0000)	0.53952 (0.0000)	-0.69049 (0.0000)	-0.68121 (0.0000)			
ARCH-in-mean (var.) δ		1.26424 (0.0139)	1.05982 (0.0264)				
Conditional Variance Equation							
Constant ω	0.00001 (0.4944)	0.00017 (0.0024)	0.00039 (0.0942)	0.00129 (0.0048)	0.00000 (0.0000)	0.00002 (0.1277)	0.00003 (0.1029)
ARCH (1) α_1	0.10411 (0.3546)	0.16664 (0.0002)	0.16117 (0.0018)	0.14972 (0.0003)	0.26496 (0.0000)	0.19761 (0.0511)	0.08821 (0.0003)
GARCH (1) β_1	0.87235 (0.0000)	0.82064 (0.0000)	0.78596 (0.0000)	0.46214 (0.0009)	0.66985 (0.0000)	0.73204 (0.0000)	0.84111 (0.0000)
Student (DF)		2.92536 (0.0000)			5.66671 (0.0000)	2.98461 (0.0000)	
Persistence of Shock	0.97646	0.98729	0.94714	0.61187	0.93481	0.92966	0.92933
Residual Analysis							
Q-Stat (5)	5.4054 (0.1444)	3.6081 (0.3070)	3.0886 (0.3781)	6.1335 (0.1052)	0.0252 (0.9999)	6.9192 (0.2267)	1.0531 (0.9581)
Q-Stat (10)	9.0415 (0.3387)	8.4842 (0.3876)	8.0906 (0.4246)	7.3161 (0.5029)	0.1438 (1.0000)	7.5051 (0.6770)	2.1878 (0.9946)
Q2-Stat (5)	4.7820 (0.1884)	9.8356 (0.0200)	1.3804 (0.7101)	4.1182 (0.2489)	0.0399 (0.9979)	1.1202 (0.7721)	6.1581 (0.1041)
Q2-Stat (10)	8.8915 (0.3515)	12.8345 (0.1176)	3.5995 (0.8913)	5.1288 (0.7437)	0.0785 (0.9999)	2.0756 (0.9786)	13.9224 (0.0838)
LM-ARCH (1-2)	0.8246 (0.4386)	0.5352 (0.5856)	0.4423 (0.6426)	0.9958 (0.3697)	0.0079 (0.9921)	0.2096 (0.8109)	1.3920 (0.2492)
LM-ARCH (1-5)	0.8396 (0.5215)	1.8902 (0.0931)	0.2849 (0.9215)	0.7956 (0.5527)	0.0080 (1.0000)	0.2220 (0.9530)	1.1351 (0.3401)

P-values are in parenthesis.

In the Table 4.2a, 4.2b and 4.2c, the coefficients of various GARCH type volatility models have been obtained by the Maximum Likelihood. The p-values are given in parentheses. Most of the models have been estimated with the assumption of student t distribution and the student t degree of freedom is significant as well. The persistence of shock for each GARCH type model is less than 1. In the residual analysis Q-stat (on standardized residuals), Q2-stat (on squared standardized residuals) and LM-ARCH test (on standardized residuals) have been conducted. The results of Q-stat show that there is no evidence of autocorrelation at 5^{th} and 10^{th} lag for all the models. Q2- stat show that there is no evidence of autocorrelation in the squared standardized residuals and this same result is calibrated by LM-ARCH test on the standardized residuals. On the basis of Q2-stat and LM-ARCH test, this study concludes that there is no ARCH effect left in the standardized residuals and the models are valid. The results are based on the significance level of either 1%, 5% or 10%.

In Table 4.2a, the parameter of γ in the GJR model for DLOGDC series is significant. This parameter captures the asymmetric response of volatility to positive and negative news. In Table 4.2c, the parameter of δ for the GARCH-M model estimated for two return series DLJPGL and DLTSPL respectively represents the risk premium.

One of the crucial aspect to modeling volatility to be used as input in forecasting Value at Risk by Variance-Covariance Method, is the risk of change in model specification overtime. If we have a series where the model specification is changing overtime and volatility forecast is obtained by only one specific model specification, then the Value at Risk forecast might not be accurate. As this study has used rolling windows created by dropping the oldest value in the series and adding the next value, and fitting a valid GARCH type model on the new set of observation, the risk of change in the valid model specification overtime as identified by (Chiu and Chuang, 2016) has been accounted for as well.

4.4 Results of Evaluation Methods for Value at Risk Forecasts

In Table 4.3 below, the Sum of Binary Loss Function (SBLF) and Sum of Quadratic Loss Function (SQLF) for each methodology of forecasting dynamic Value at Risk have been provided. The best Methodology has been identified for each selected firm. If SBLF is same for two or more methodologies, then the best methodology is identified on the basis of SQLF. This study concludes that the Variance-Covariance Method using the volatility forecasts by a valid GARCH type model (with assumption of normal distribution or student t distribution and in some cases, a more general model like GJR or GARCH-M) is the best in forecasting Value at Risk. Monte Carlo Simulation is also best methodology for some of the firms in Oil and Gas Exploration, Power Generation and Distribution and Refinery.

Table 4.3- Sum of Binary and Quadratic Loss Functions

Firm	**Historical Simulation**		**Monte Carlo Simulation**		**Variance-Covariance Method**		**Best Method**
	SBLF	*SQLF*	*SBLF*	*SQLF*	*SBLF*	*SQLF*	
Oil and Gas Exploration Sector							
OGDC	7	7.00089	5	5.00081	3	3.00068	Variance-Covariance Method
MARI	5	5.00039	5	5.00037	6	6.00091	Monte Carlo Simulation
POL	3	3.00037	3	3.00024	3	3.00005	Variance-Covariance Method
Oil and Gas Marketing							
BPL	4	4.00014	5	5.00021	2	2.00000	Variance-Covariance Method
SHEL	5	5.00200	5	5.00171	4	4.00127	Variance-Covariance Method
SNGP	6	6.00061	5	5.00045	1	1.00000	Variance-Covariance Method
SSGC	8	8.00088	6	6.00065	6	6.00045	Variance-Covariance Method
HASCOL	3	3.00023	3	3.00010	0	0	Variance-Covariance Method
Refinery							
BYCO	1	1.00001	0	0	0	0	Variance-Covariance Method
NRL	1	1.00057	1	1.00064	0	0	Variance-Covariance Method
ATRL	8	8.00170	1	1.00045	4	4.00014	Monte Carlo Simulation
Power Generation and Distribution							
HUBC	5	5.00014	2	2.00006	0	0	Variance-Covariance Method
NPL	7	7.00241	5	5.00203	3	3.00074	Variance-Covariance Method
KOHE	2	2.00001	2	2.00002	3	3.00028	Historical Simulation
JPGL	1	1.00709	1	1.00392	0	0	Variance-Covariance Method
TSPL	1	1.00073	0	0	1	1.00251	Monte Carlo Simulation
KOHP	0	0	0	0	0	0	All
AEL	0	0	0	0	10	10.00281	Monte Carlo Simulation and Historical Simulation
SPWL	3	3.00233	2	2.00198	1	1.00076	Variance-Covariance Method
LPL	2	2.00065	2	2.00054	3	3.00100	Monte Carlo Simulation

CHAPTER V

SUMMARY, CONCLUSION AND POLICY IMPLICATION

5.1 Summary

This study employed Historical Simulation, Monte Carlo Simulation and Variance-Covariance Method for forecasting one day ahead Value at Risk at 95% confidence interval. Binary Loss Function and Quadratic Loss Function were used to evaluate the Value at Risk forecasts obtained by three methodologies. One day ahead Value at Risk forecasts were obtained for 20 selected energy firms. Firms were selected from four sectors (Oil and Gas Exploration, Oil and Gas Marketing, Refinery, Power Generation and Distribution). The daily data covered the period from first trading day of January 2011 to last trading day of April 2017. 84 rolling windows were created by dropping the oldest value and adding the new value from January 2017 onwards for each firm. This way 84 Value at Risk forecasts were obtained for each firm.

5.2 Conclusion

This study concludes that Variance-Covariance Method using the volatility forecast obtained by a valid GARCH type model (GARCH, GARCH-M, GJR) is the best compared to Historical Simulation and Monte Carlo Simulation for most of the firms.

Furthermore, this conclusion accounts for the model specification risk by allowing for the model specification to change overtime. The assumption about the distribution of return series in most cases is that of student t distribution instead of normal distribution because the return series exhibited leptokurtosis and heavy tails.

Assumption of normal distribution has only been used in cases where convergence was not being achieved or standardized residuals were not independent and identically distributed or in some cases if the persistence was greater than one. Monte Carlo Simulation is the best methodology for four out of 20 selected firms.

5.3 Policy Implication

Firms don't report the Value at Risk measure. There is no law forcing the firms to report Value at Risk measure. This study highlights the importance of Value at Risk forecast for the regulator, so that, a framework of forecasting and reporting the Value at Risk measure by a valid model could be made for the listed firms and mutual funds. It will contribute to increased information disclosure on the part of listed firms and mutual funds. This information disclosure has the potential to solve the problem of adverse selection due to asymmetric information about the worst possible loss (Value at Risk), which investors with commitments (of certain payments in future) are facing. By developing such a framework, a number of potential investors with commitments (of certain payments in future) could be encouraged to participate in the market.

REFERENCES

ABAD, P. & BENITO, S. 2013. A detailed comparison of value at risk estimates. *Mathematics and Computers in Simulation,* 94**,** 258-276.

AHMAD, H., FIDA, B. A. & ZAKARIA, M. 2013. The co-determinants of capital structure and stock returns: evidence from the Karachi stock exchange. *The Lahore Journal of Economics,* 18**,** 81.

ALOUI, C. & MABROUK, S. 2010. Value-at-risk estimations of energy commodities via long-memory, asymmetry and fat-tailed GARCH models. *Energy Policy,* 38**,** 2326-2339.

ANGELIDIS, T., BENOS, A. & DEGIANNAKIS, S. 2004. The use of GARCH models in VaR estimation. *Statistical methodology,* 1**,** 105-128.

APERGIS, N., ARTIKIS, G. & ELEFTHERIOU, S. 2011. The Role of Macroeconomic Factors for Excess Returns: Evidence from a Group of Emerging Economies. *Journal of Accounting, Finance and Economics,* 1**,** 1-12.

BANZ, R. W. 1981. The relationship between return and market value of common stocks. *Journal of financial economics,* 9**,** 3-18.

BAO, Y., LEE, T. H. & SALTOGLU, B. 2006. Evaluating predictive performance of value-at-risk models in emerging markets: a reality check. *Journal of Forecasting,* 25**,** 101-128.

BASU, S. 1983. The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. *Journal of financial economics,* 12**,** 129-156.

BERGER, T. & MISSONG, M. 2014. Financial crisis, Value-at-Risk forecasts and the puzzle of dependency modeling. *International Review of Financial Analysis,* 33**,** 33-38.

BOLLERSLEV, T. 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics,* 31**,** 307-327.

BOLLERSLEV, T. 1987. A conditionally heteroskedastic time series model for speculative prices and rates of return. *The review of economics and statistics***,** 542-547.

BRENNAN, M. J. 1970. Taxes, market valuation and corporate financial policy. *National tax journal,* 23**,** 417-427.

BROOKS, C. & PERSAND, G. 2002. Model choice and value-at-risk performance. *Financial Analysts Journal,* 58**,** 87-97.

CARHART, M. M. 1997. On persistence in mutual fund performance. *The Journal of finance,* 52**,** 57-82.

CHAITHEP, K., SRIBOONCHITTA, S., CHAIBOONSRI, C. & PASTPIPATKUL, P. 2012. Value at risk analysis of gold price returns using extreme value theory. *The Empirical Econometrics and Quantitative Economics Letters,* 1**,** 151-168.

CHENG, W.-H. & HUNG, J.-C. 2011. Skewness and leptokurtosis in GARCH-typed VaR estimation of petroleum and metal asset returns. *Journal of Empirical Finance,* 18**,** 160-173.

CHIU, Y.-C. & CHUANG, I.-Y. 2016. The performance of the switching forecast model of value-at-risk in the Asian stock markets. *Finance Research Letters,* 18**,** 43-51.

CHKILI, W., HAMMOUDEH, S. & NGUYEN, D. K. 2014. Volatility forecasting and risk management for commodity markets in the presence of asymmetry and long memory. *Energy Economics,* 41**,** 1-18.

DANIELSSON, J., JAMES, K. R., VALENZUELA, M. & ZER, I. 2016. Model risk of risk models. *Journal of Financial Stability,* 23**,** 79-91.

DIAS, A. 2013. Market capitalization and Value-at-Risk. *Journal of Banking & Finance,* 37**,** 5248-5260.

ENGLE, R. F., LILIEN, D. M. & ROBINS, R. P. 1987. Estimating time varying risk premia in the term structure: the ARCH-M model. *Econometrica: Journal of the Econometric Society***,** 391-407.

FAMA, E. F. & FRENCH, K. R. 1996. Multifactor explanations of asset pricing anomalies. *The journal of finance,* 51**,** 55-84.

FAMA, E. F. & FRENCH, K. R. 2016. Dissecting anomalies with a five-factor model. *Review of Financial Studies,* 29**,** 69-103.

FAN, Y., ZHANG, Y.-J., TSAI, H.-T. & WEI, Y.-M. 2008. Estimating 'Value at Risk'of crude oil price and its spillover effect using the GED-GARCH approach. *Energy Economics,* 30**,** 3156-3171.

GIOT, P. & LAURENT, S. 2003a. Market risk in commodity markets: a VaR approach. *Energy Economics,* 25**,** 435-457.

GIOT, P. & LAURENT, S. 2003b. Value-at-risk for long and short trading positions. *Journal of Applied Econometrics,* 18**,** 641-663.

GIOT, P. & LAURENT, S. 2004. Modelling daily value-at-risk using realized volatility and ARCH type models. *journal of Empirical Finance,* 11**,** 379-398.

GLOSTEN, L. R., JAGANNATHAN, R. & RUNKLE, D. E. 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance,* 48**,** 1779-1801.

HAMMOUDEH, S. & YUAN, Y. 2008. Metal volatility in presence of oil and interest rate shocks. *Energy Economics,* 30**,** 606-620.

HENDRICKS, D. 1996. Evaluation of value-at-risk models using historical data (digest summary). *Economic Policy Review Federal Reserve Bank of New York,* 2**,** 39-67.

HUANG, C.-K., HUANG, C.-S. & CHIKOBVU, D. 2015. Extreme risk, value-at-risk and expected shortfall in the gold market. *The International Business & Economics Research Journal (Online),* 14**,** 107.

HUNG, J.-C., LEE, M.-C. & LIU, H.-C. 2008. Estimation of value-at-risk for energy commodities via fat-tailed GARCH models. *Energy Economics,* 30**,** 1173-1191.

JENSEN, M. C., BLACK, F. & SCHOLES, M. S. 1972. The capital asset pricing model: Some empirical tests.

JORION, P. 2007. *Value at Risk The New Benchmark for Managing Financial Risk,* The McGraw-Hill Companies.

KHINDANOVA, I., RACHEV, S. & SCHWARTZ, E. 2001. Stable modeling of value at risk. *Mathematical and Computer Modelling,* 34**,** 1223-1259.

KRONER, K. F., KNEAFSEY, K. P. & CLAESSENS, S. 1995. Forecasting volatility in commodity markets. *Journal of Forecasting,* 14**,** 77-95.

KUESTER, K., MITTNIK, S. & PAOLELLA, M. S. 2006. Value-at-risk prediction: A comparison of alternative strategies. *Journal of Financial Econometrics,* 4**,** 53-89.

LINSMEIER, T. J. & PEARSON, N. D. 2000. Value at risk. *Financial Analysts Journal,* 56**,** 47-67.

LINTNER, J. 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The review of economics and statistics***,** 13-37.

MARKOWITZ, H. 1952. Portfolio selection. *The journal of finance,* 7**,** 77-91.

MAYERS, D. 1972. Nonmarketable assets and capital market equilibrium under uncertainty. *Studies in the theory of capital markets,* 1**,** 223-48.

MERTON, R. C. 1973. An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society***,** 867-887.

MOSSIN, J. 1966. Equilibrium in a capital asset market. *Econometrica: Journal of the econometric society***,** 768-783.

PIOTROSKI, J. D. & BARREN, T. R. 2004. The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices. *The Accounting Review,* 79**,** 1119-1151.

PRITSKER, M. 1997. Evaluating value at risk methodologies: accuracy versus computational time. *Journal of Financial Services Research,* 12**,** 201-242.

ROSS, S. A. 1976. The arbitrage theory of capital asset pricing. *Journal of economic theory,* 13**,** 341-360.

SARMA, M., THOMAS, S. & SHAH, A. 2003. Selection of Value-at-Risk models. *Journal of Forecasting,* 22**,** 337-358.

SHARPE, W. F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance,* 19**,** 425-442.

SLIM, S., KOUBAA, Y. & BENSAÏDA, A. 2016. Value-at-Risk under Lévy GARCH models: Evidence from global stock markets. *Journal of International Financial Markets, Institutions and Money*.

TULLY, E. & LUCEY, B. M. 2007. A power GARCH examination of the gold market. *Research in International Business and Finance,* 21**,** 316-325.

WILLIAMS, J. B. 1938. *The theory of investment value*, JSTOR.

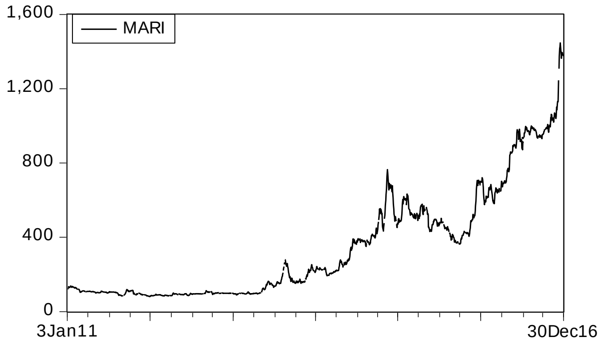
YAO, W. Z., CHEONG, C. W. & HOOI, T. S. 2016. Daily value-at-risk modeling and forecast evaluation: the realized volatility approach. *The Journal of Finance and Data Science*.

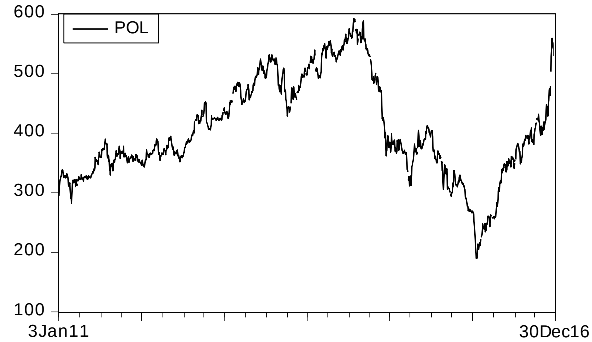
ZHANG, Z. & ZHANG, H.-K. 2016. The dynamics of precious metal markets VaR: A GARCHEVT approach. *Journal of Commodity Markets,* 4**,** 14-27.

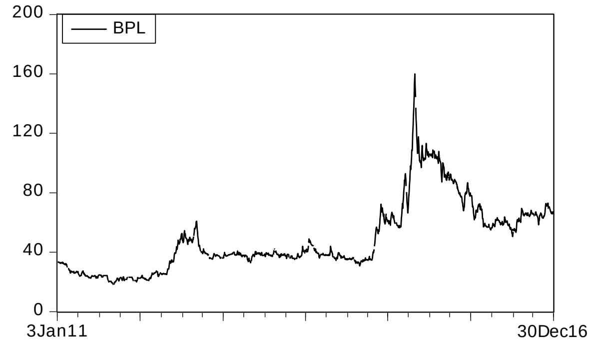
APPENDIX A: LIST OF SELECTED FIRMS

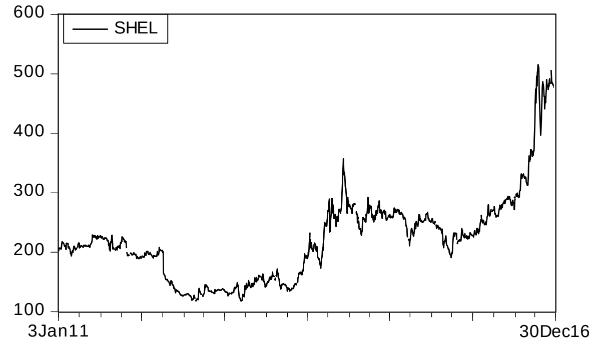
Sr. No.	Name	Symbol	Stock Return Series
	Oil & Gas Exploration Companies		
1	Oil & Gas Development Company Limited	OGDC	DLOGDC
2	Mari Petroleum Company Limited	MARI	DLMARI
3	Pakistan Oilfields Limited	POL	DLPOL
	Oil & Gas Marketing Companies		
4	Burshane LPG (Pakistan) Limited	BPL	DLBPL
5	Shell Pakistan Limited	SHEL	DLSHEL
6	Sui Northern Gas Pipelines Limited	SNGP	DLSNGP
7	Sui Southern Gas Company Limited	SSGC	DLSSGC
8	Hascol Petroleum Limited	HASCOL	DLHASCOL
	Refinery		
9	Byco Petroleum Pakistan Limited	BYCO	DLBYCO
10	National Refinery Limited	NRL	DLNRL
11	Attock Refinery Limited	ATRL	DLATRL
	Power Generation & Distribution		
12	The Hub Power Company Limited	HUBC	DLHUBC
13	Nishat Power Limited	NPL	DLNPL
14	Kohinoor Energy Limited	KOHE	DLKOHE
15	Japan Power Generation Limited	JPGL	DLJPGL
16	Tri-Star Power Limited	TSPL	DLTSPL
17	Kohinoor Power Company Limited	KOHP	DLKOHP
18	Arshad Energy Limited	AEL	DLAEL
19	Saif Power Limited	SPWL	DLSPWL
20	Lalpir Power Limited	LPL	DLLPL

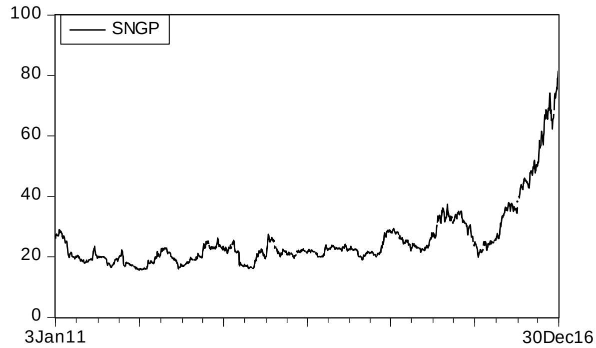
APPENDIX B: STOCK PRICES AT LEVEL

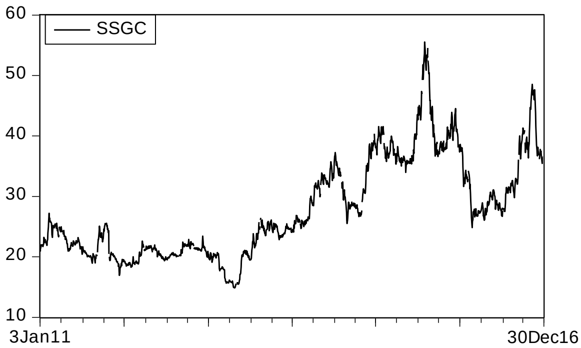


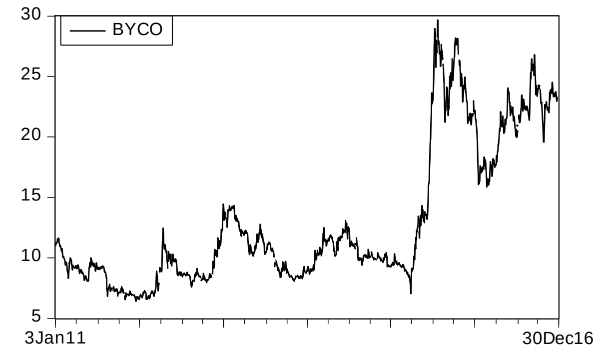


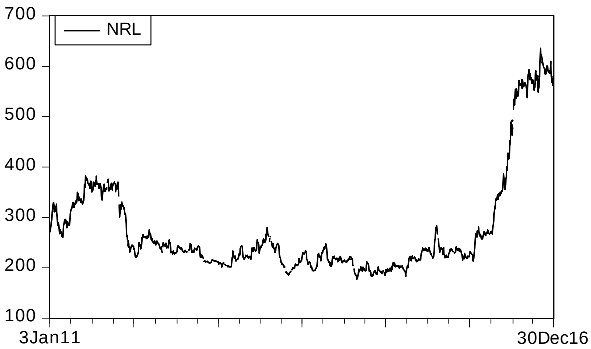


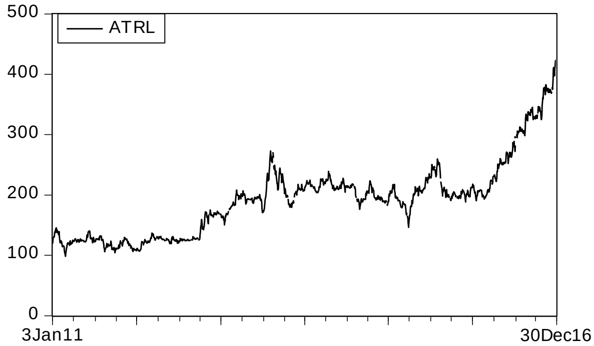


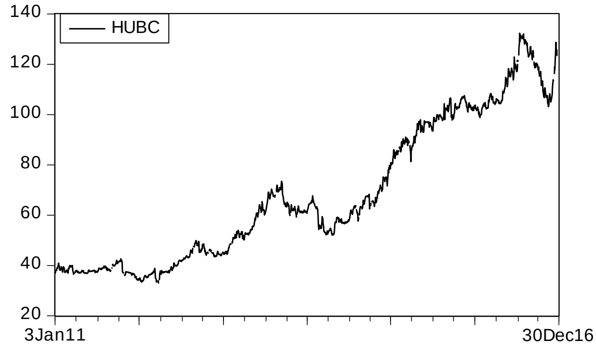


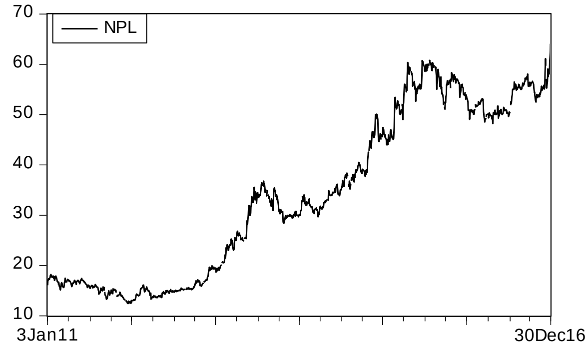


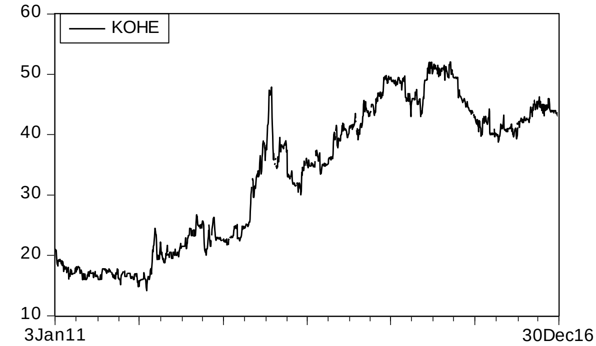


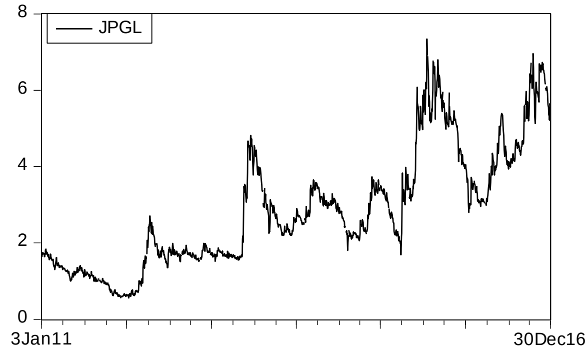


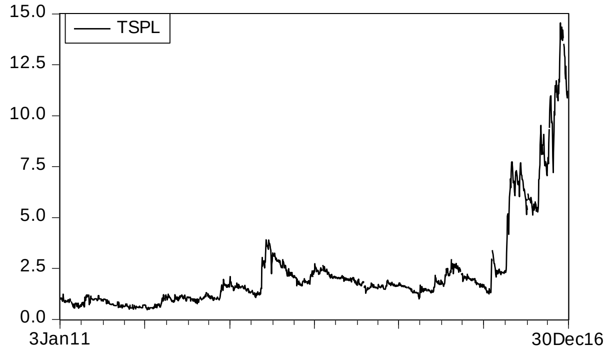

ATRL
500
400
300
200
100
0
3Jan11
30Dec16

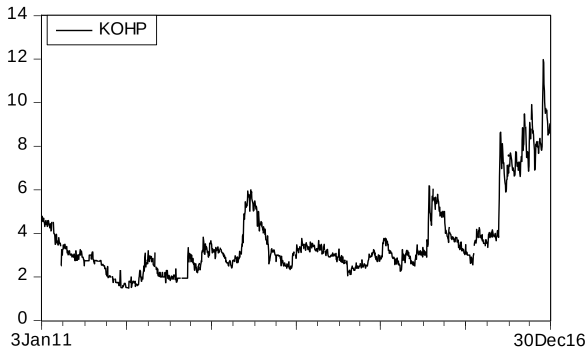

HUBC
140
120
100
80
60
40
20
3Jan11
30Dec16

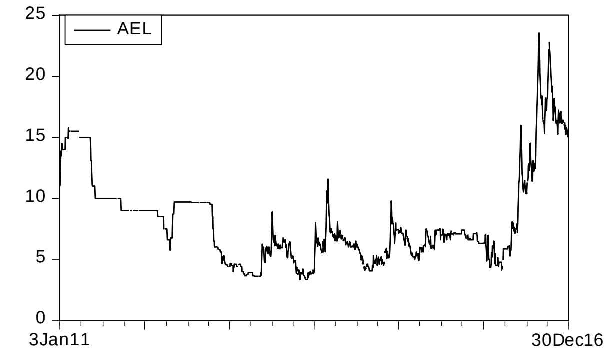

NPL
70
60
50
40
30
20
10
3Jan11
30Dec16

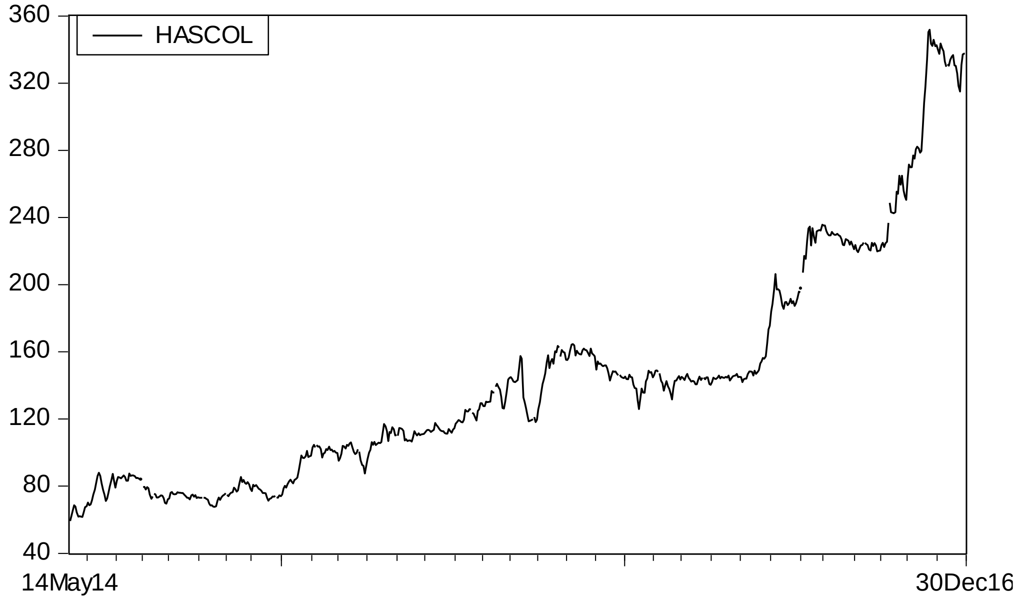

KOHE
60
50
40
30
20
10
3Jan11
30Dec16

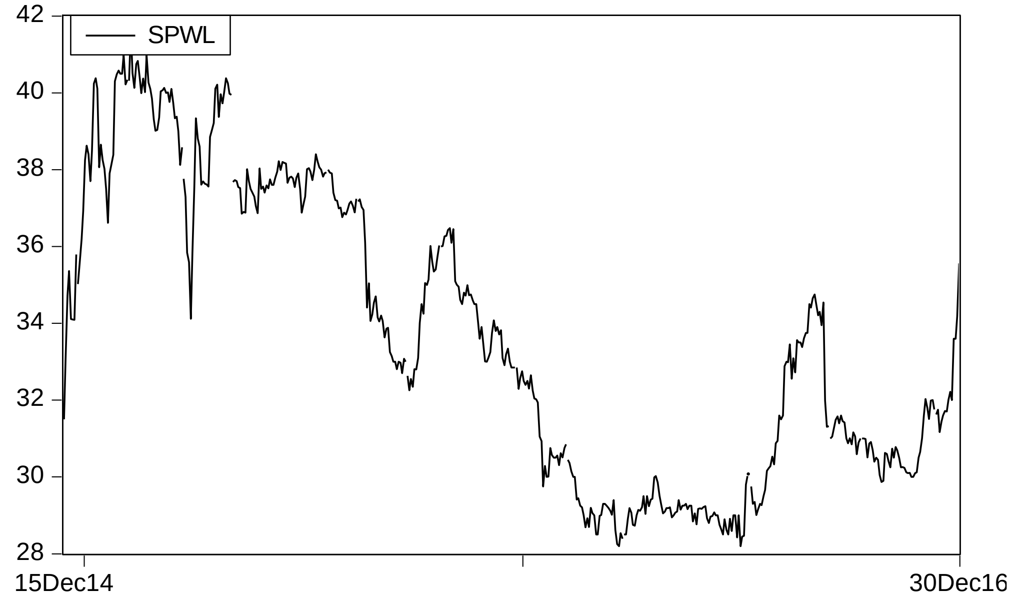

JPGL
8
6
4
2
0
3Jan11
30Dec16

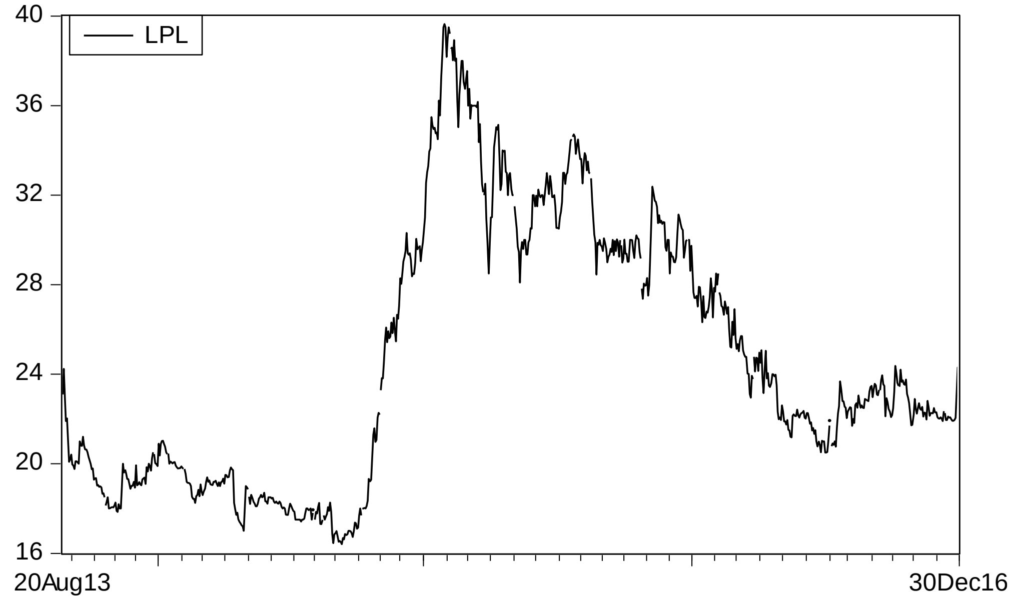

TSPL
15.0
12.5
10.0
7.5
5.0
2.5
0.0
3Jan11
30Dec16


KOHP
14
12
10
8
6
4
2
0
3Jan11
30Dec16

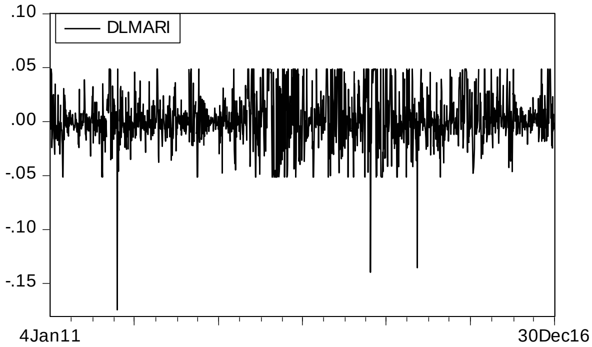

AEL
25
20
15
10
5
0
3Jan11
30Dec16

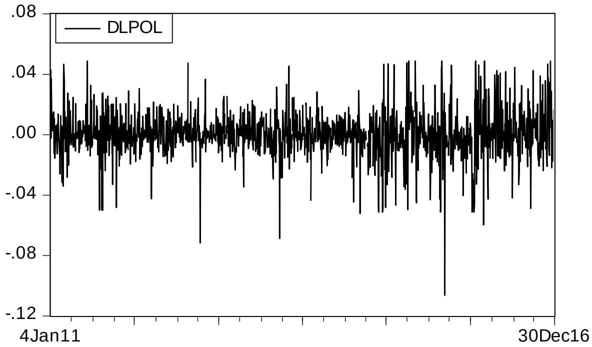

HASCOL
360
320
280
240
200
160
120
80
40
14May14
30Dec16

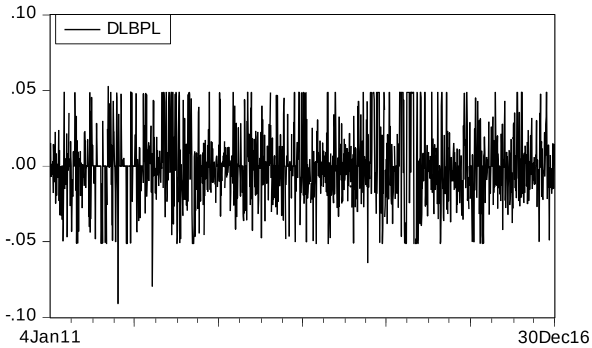

SPWL
42
40
38
36
34
32
30
28
15Dec14
30Dec16

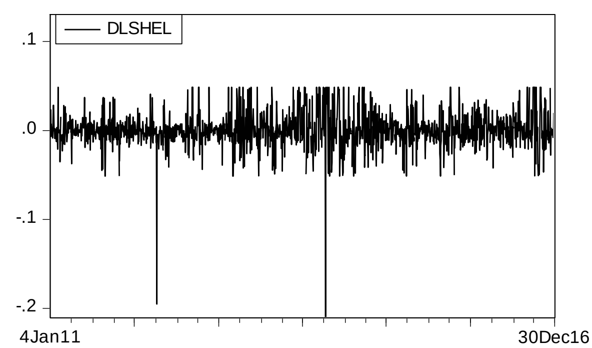

LPL
40
36
32
28
24
20
16
20Aug13
30Dec16

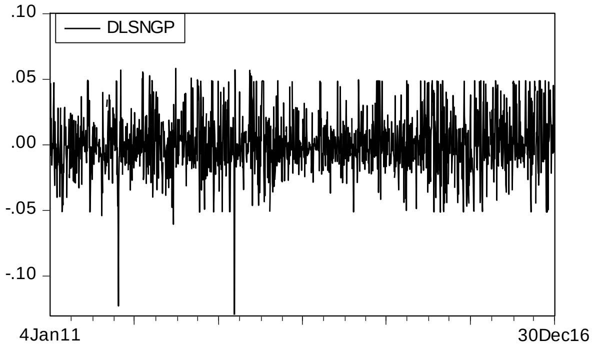
APPENDIX C: RETURN SERIES

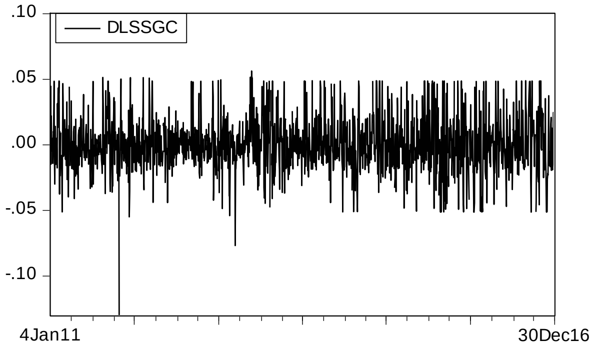


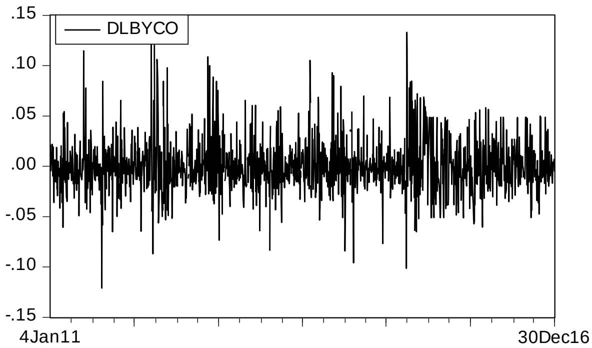


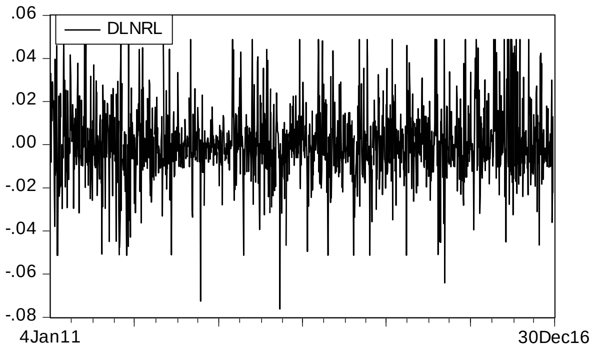


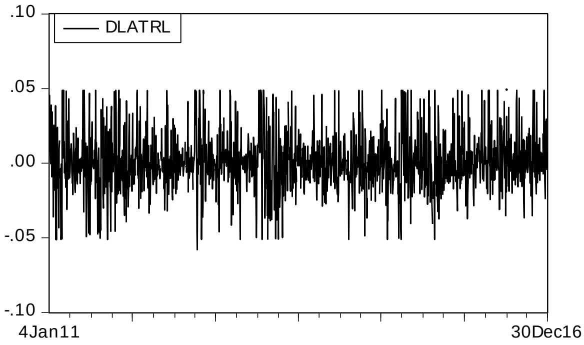


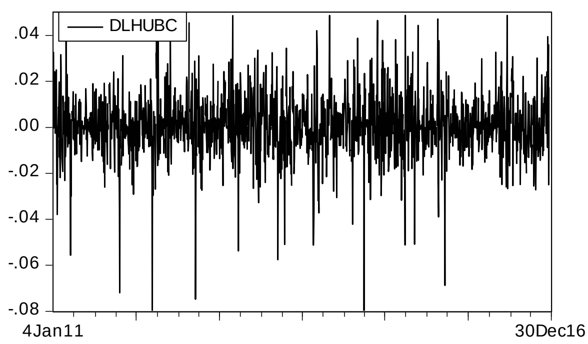


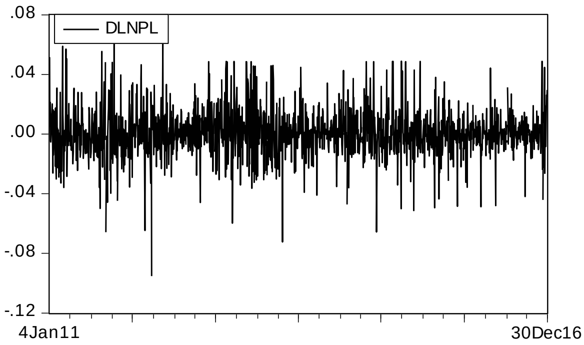


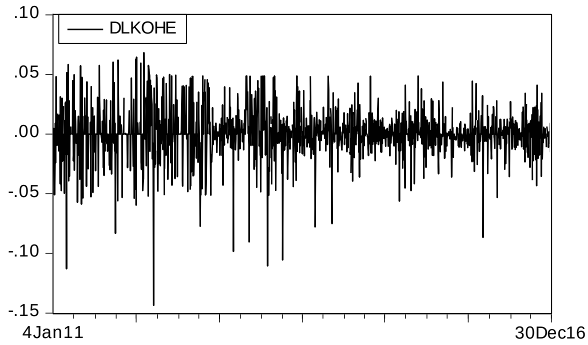


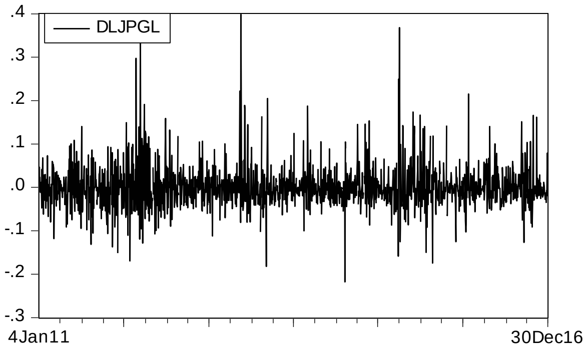


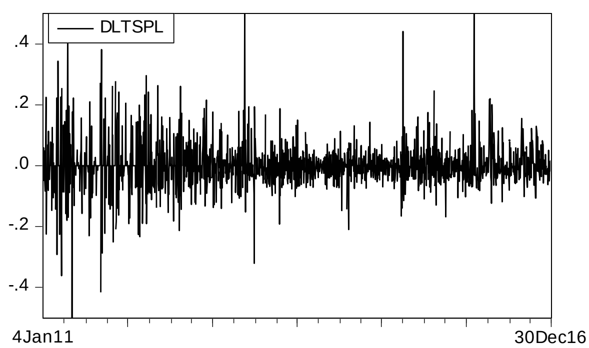

DLATRL
.10
.05
.00
-.05
-.10
4Jan11
30Dec16

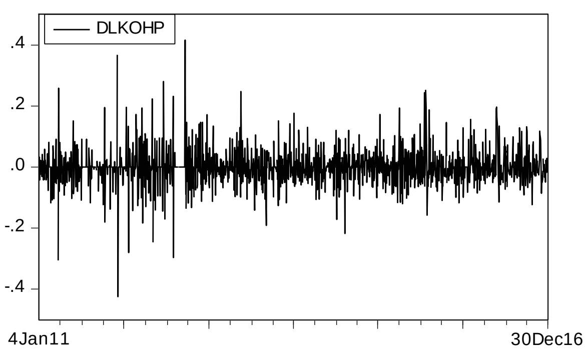

DLHUBC
.04
.02
.00
-.02
-.04
-.06
-.08
4Jan11
30Dec16

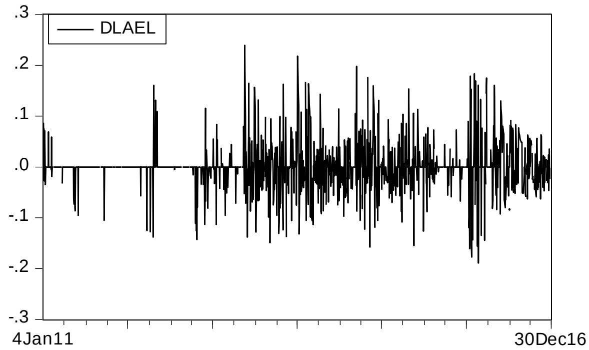

DLNPL
.08
.04
.00
-.04
-.08
-.12
4Jan11
30Dec16

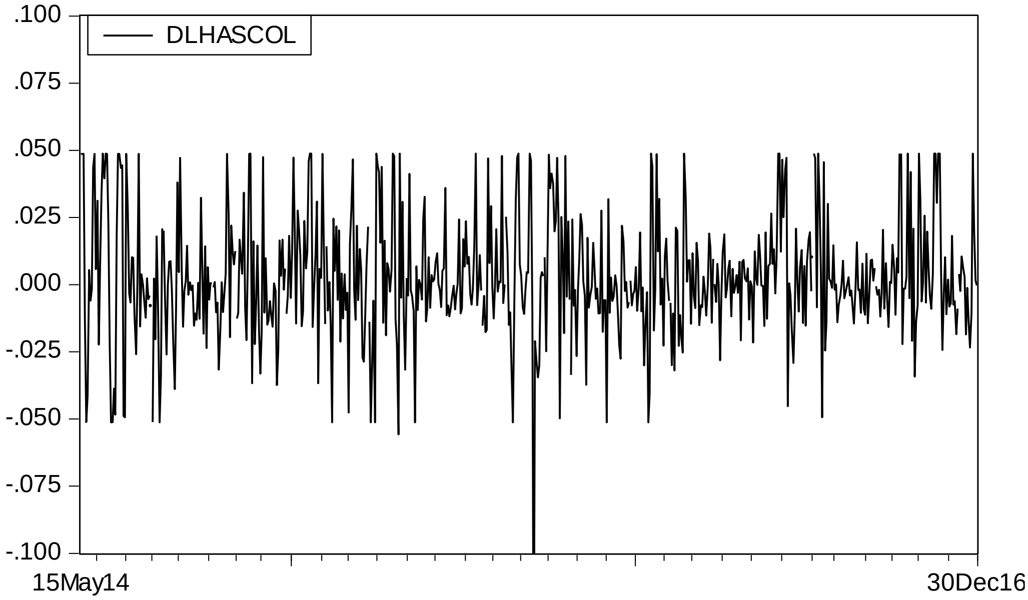

DLKOHE
.10
.05
.00
-.05
-.10
-.15
4Jan11
30Dec16


DLJPGL
.4
.3
.2
.1
.0
-.1
-.2
-.3
4Jan11
30Dec16

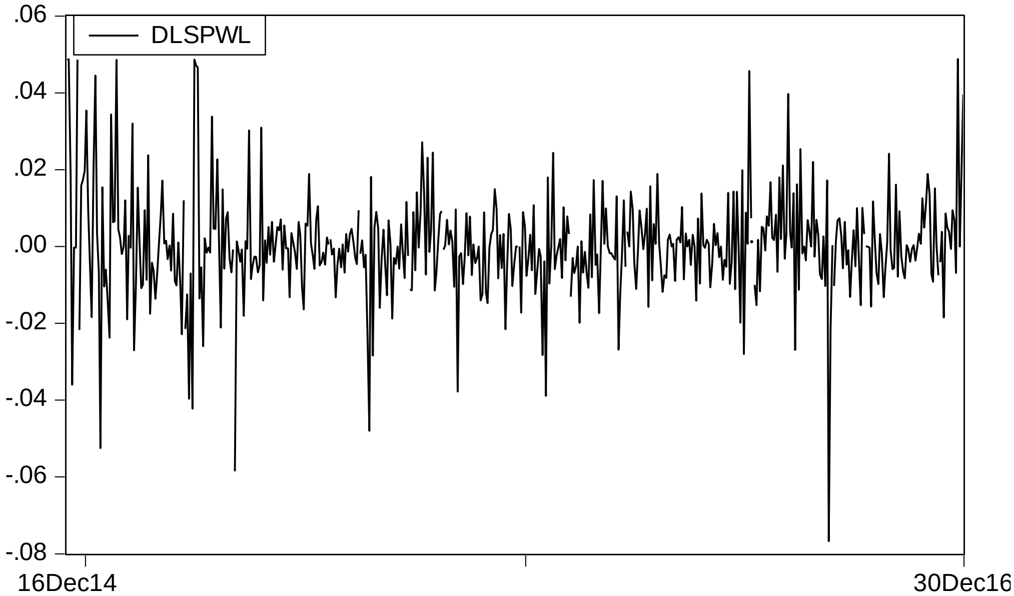

DLTSPL
.4
.2
.0
-.2
-.4
4Jan11
30Dec16


DLKOHP
.4
.2
.0
-.2
-.4
4Jan11
30Dec16

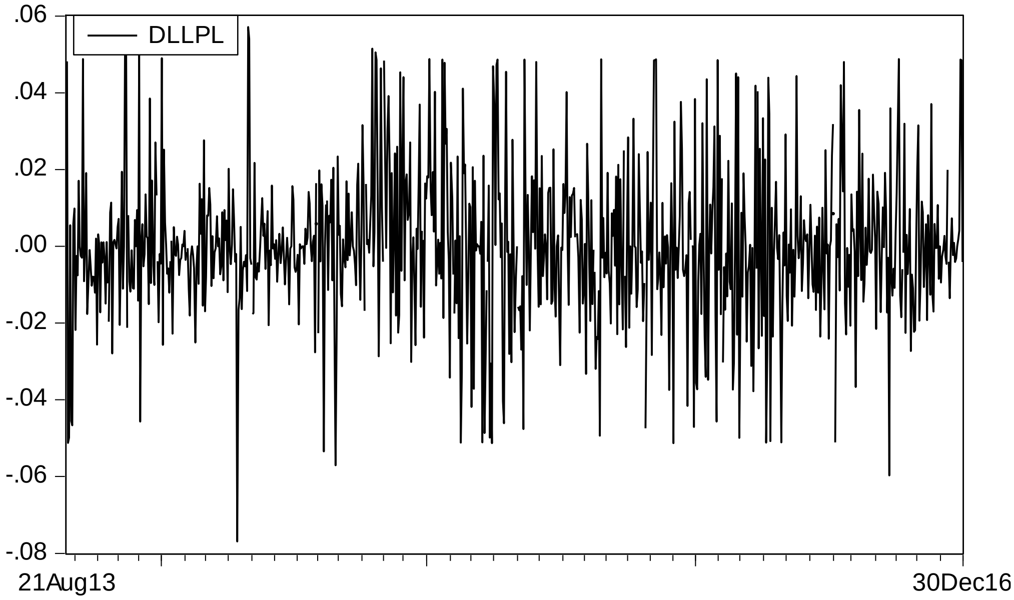

DLAEL
.3
.2
.1
.0
-.1
-.2
-.3
4Jan11
30Dec16



.100
.075
.050
.025
.000
-.025
-.050
-.075
-.100
DLHASCOL
15May14
30Dec16

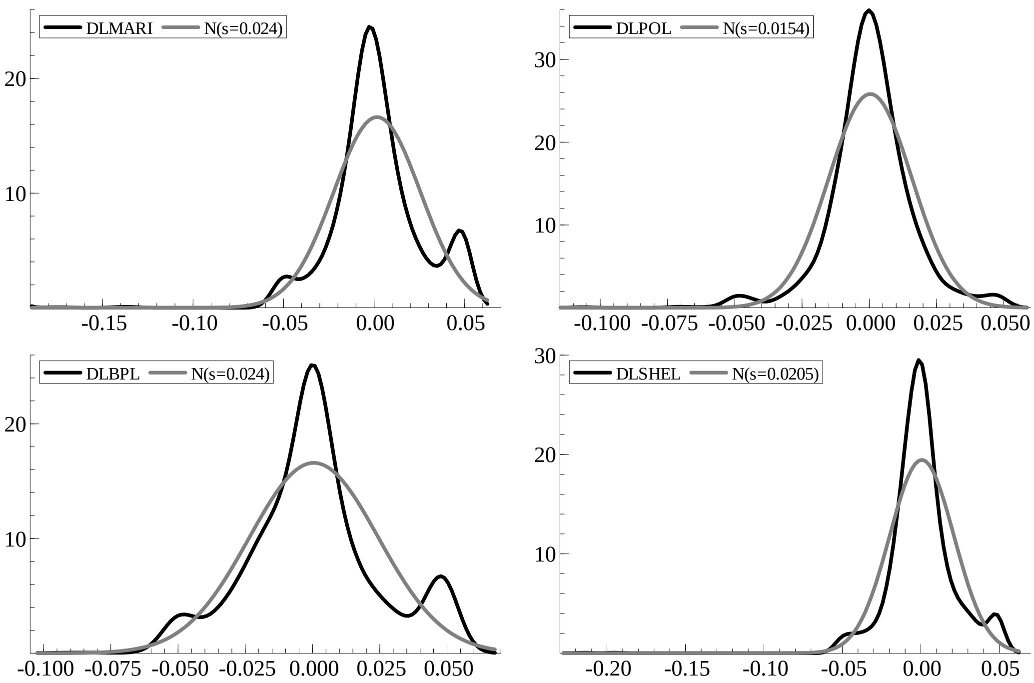


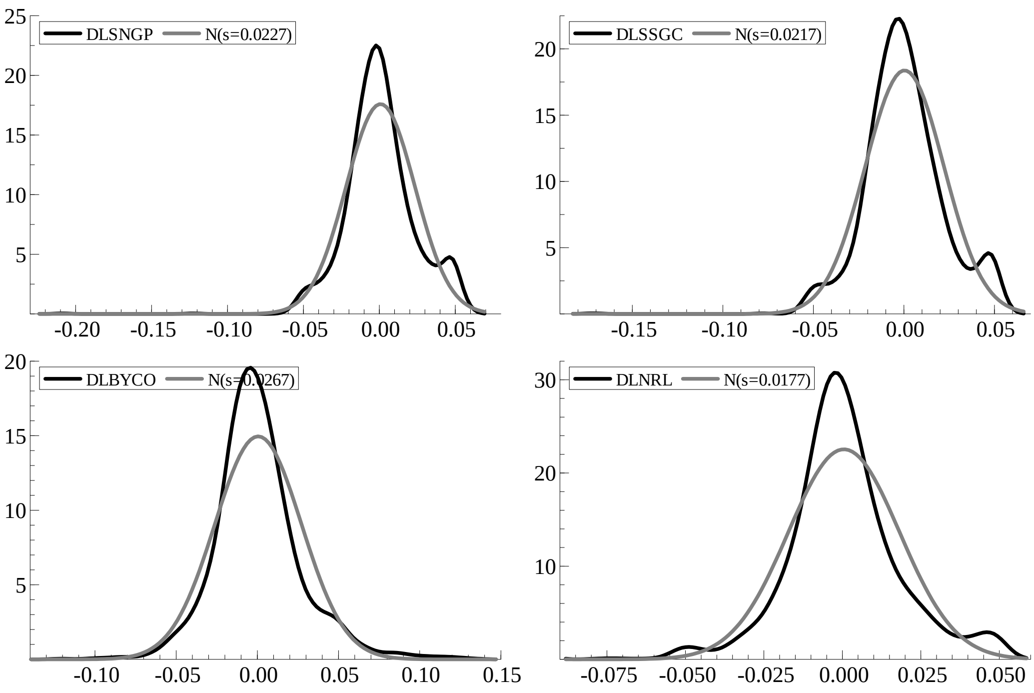
.06
.04
.02
.00
-.02
-.04
-.06
-.08
DLSPWL
16Dec14
30Dec16

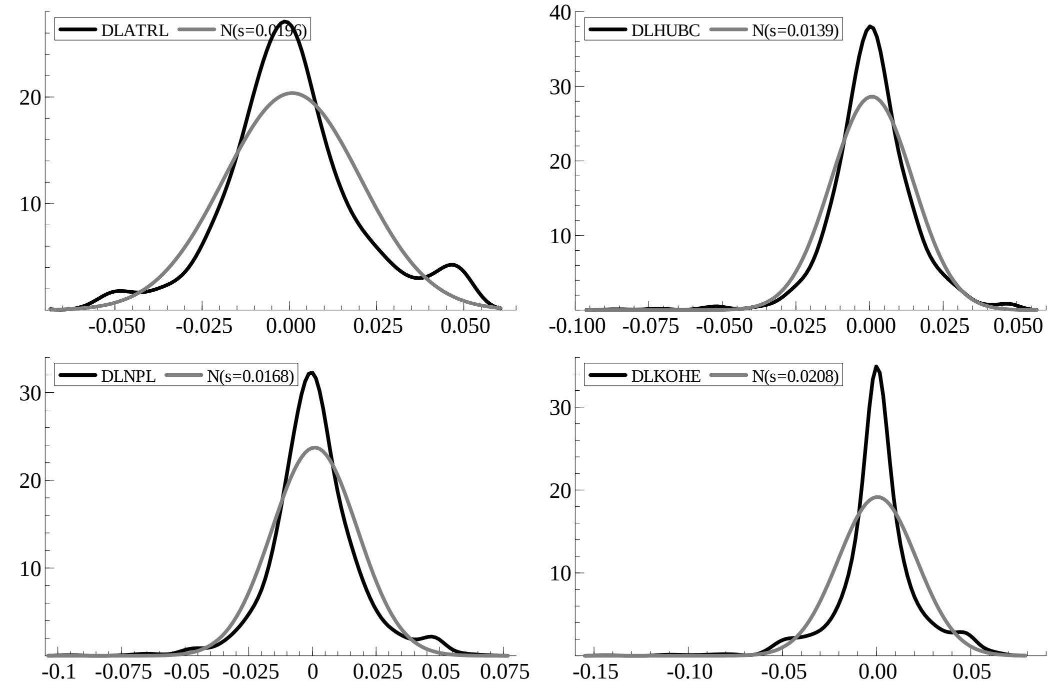


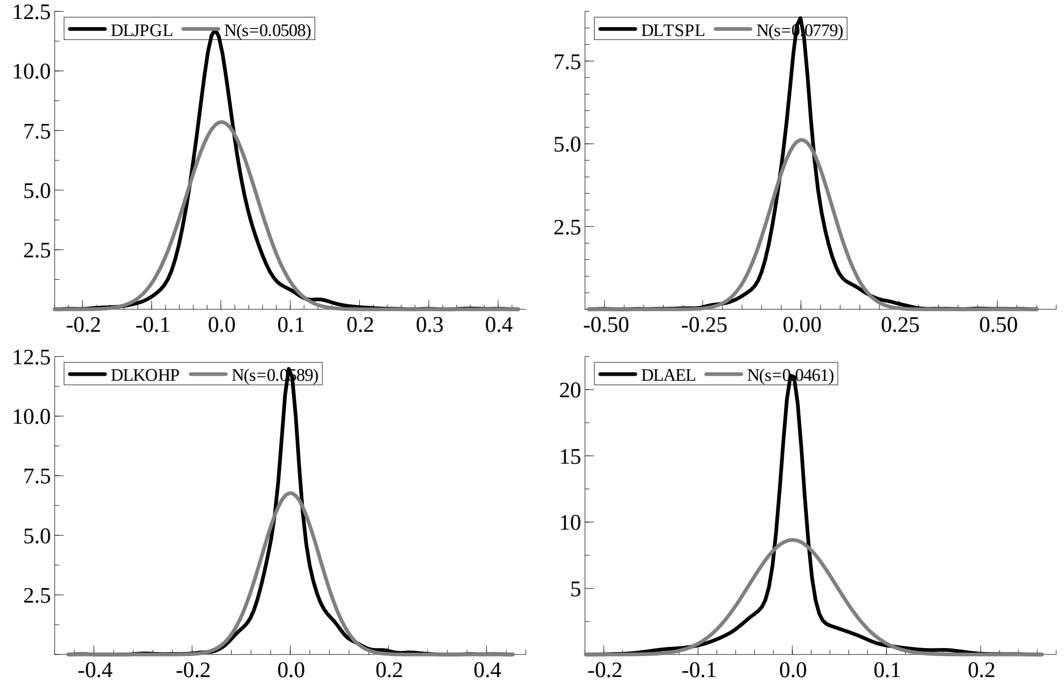
.06
.04
.02
.00
-.02
-.04
-.06
-.08
DLLPL
21Aug13
30Dec16

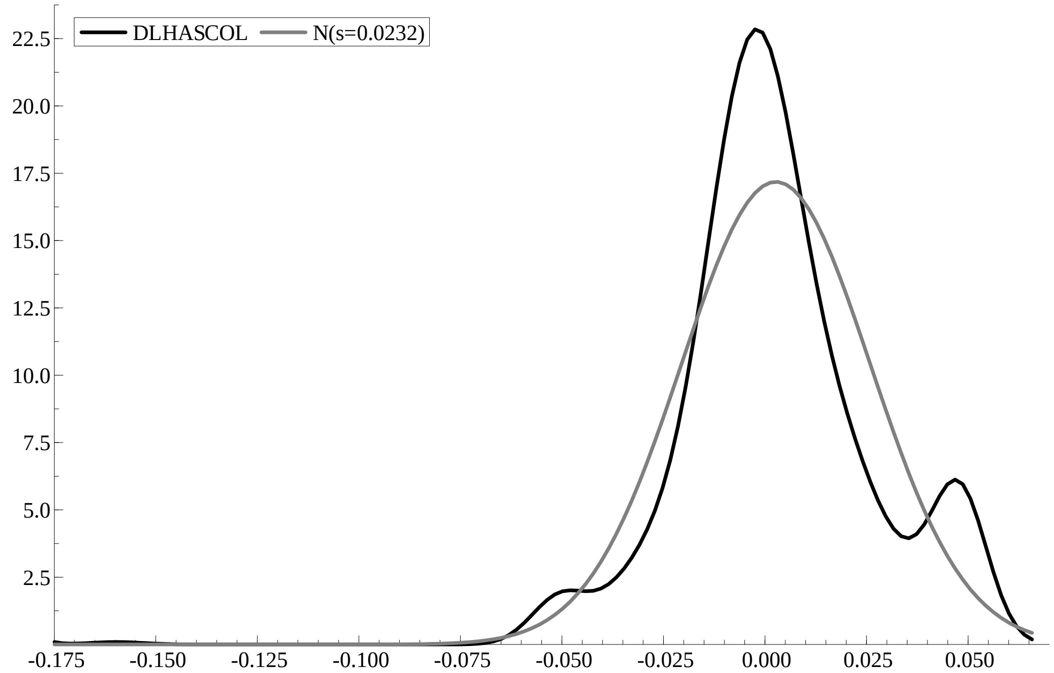
APPENDIX D: DENSITY PLOTS

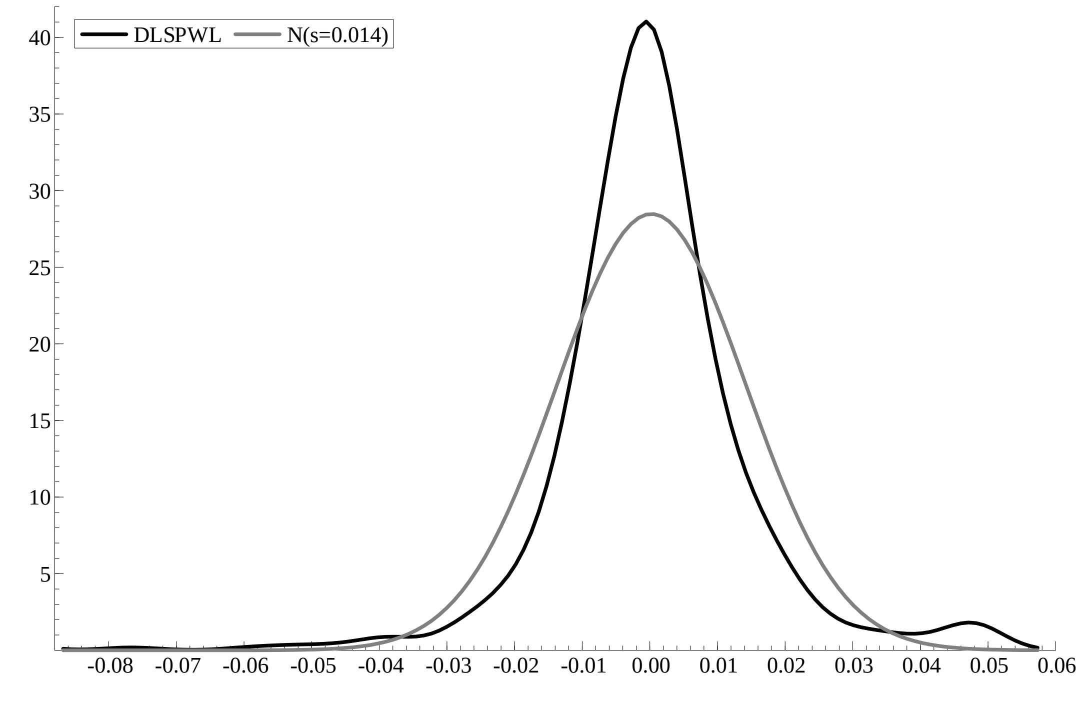


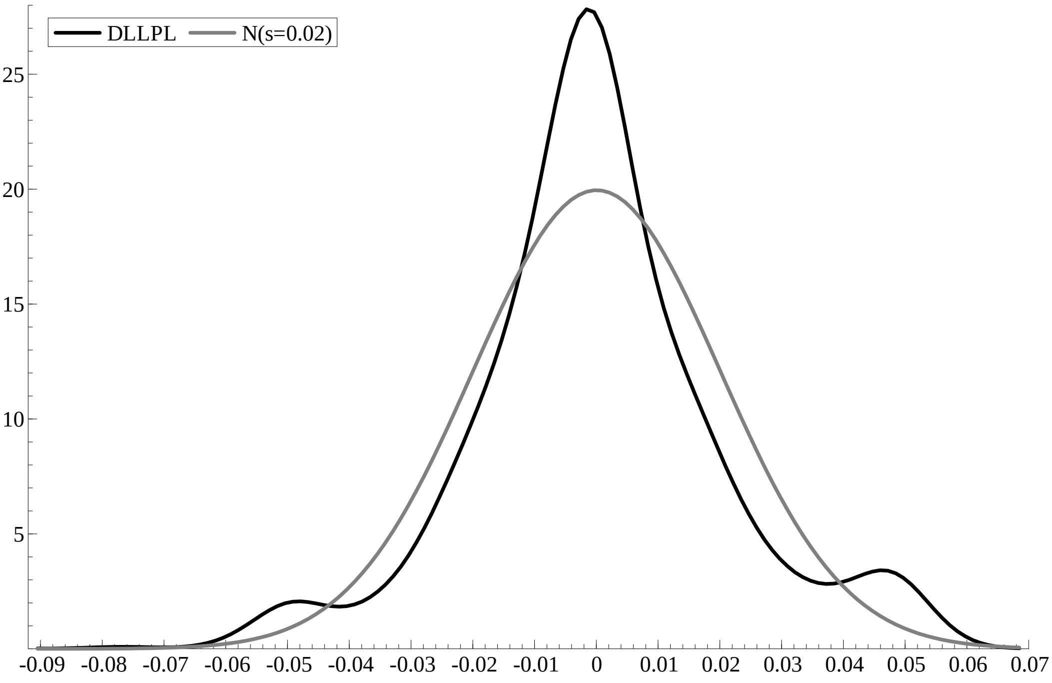



DLATRL N(s=0.0196)
DLHUBC N(s=0.0139)
DLNPL N(s=0.0168)
DLKOHE N(s=0.0208)

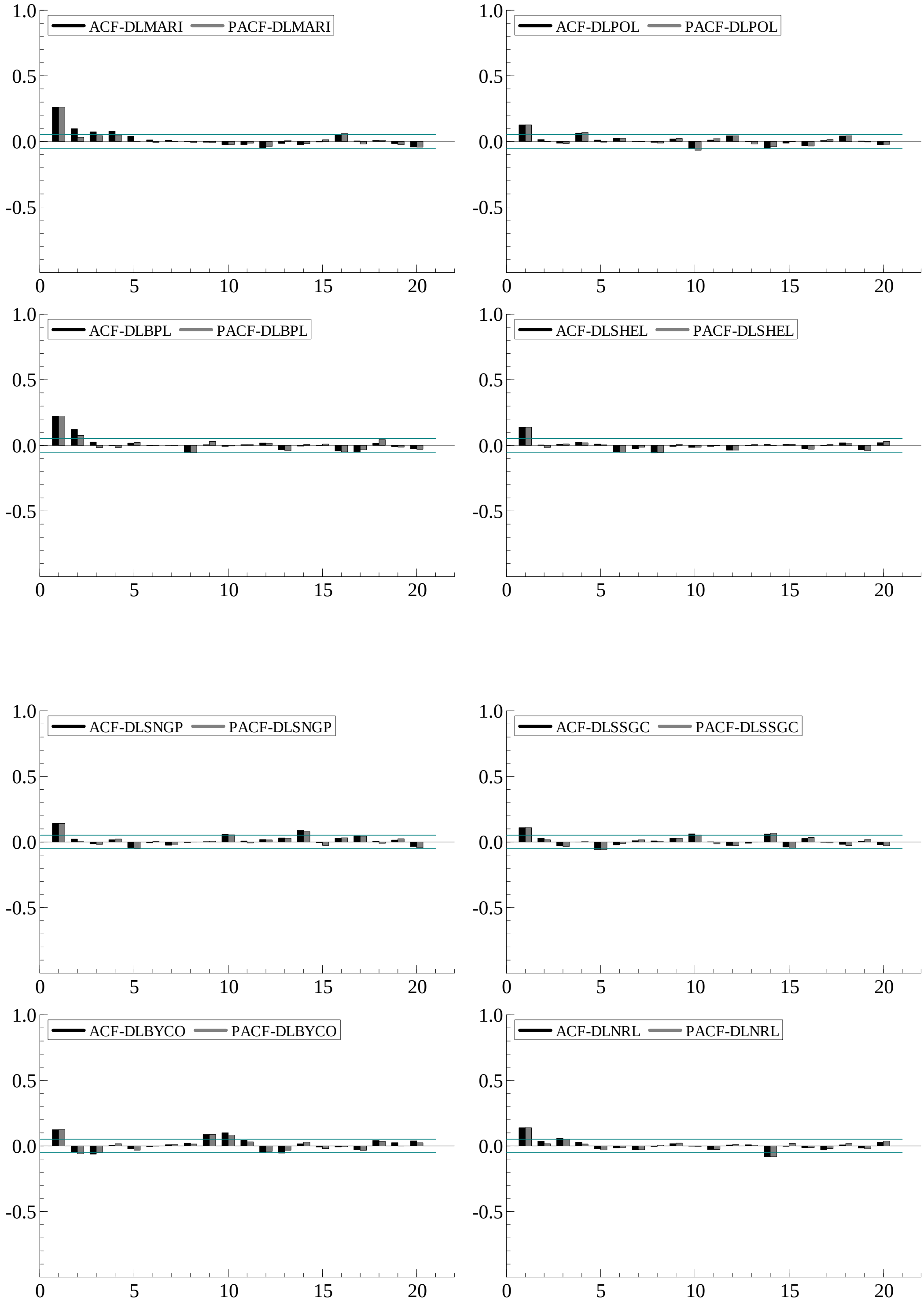

DLJPGL N(s=0.0508)
DLTSPL N(s=0.0779)
DLKOHP N(s=0.0589)
DLAEL N(s=0.0461)

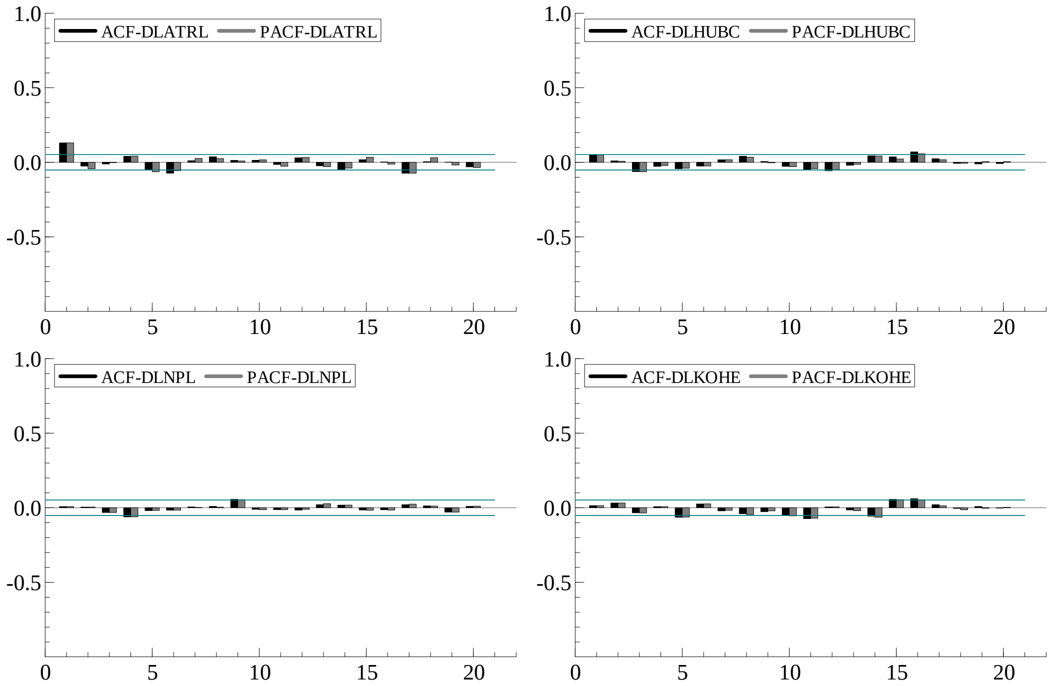

DLHASCOL
N(s=0.0232)
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
-0.175
-0.150
-0.125
-0.100
-0.075
-0.050
-0.025
0.000
0.025
0.050

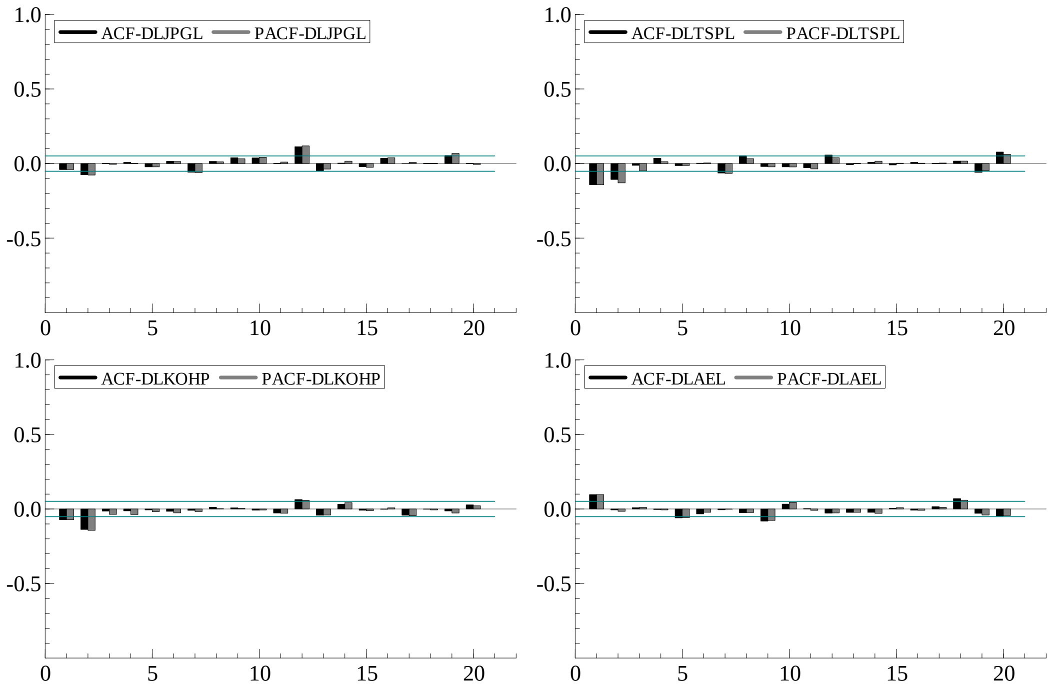

DLSPWL
N(s=0.014)
40
35
30
25
20
15
10
5
-0.08
-0.07
-0.06
-0.05
-0.04
-0.03
-0.02
-0.01
0.00
0.01
0.02
0.03
0.04
0.05
0.06

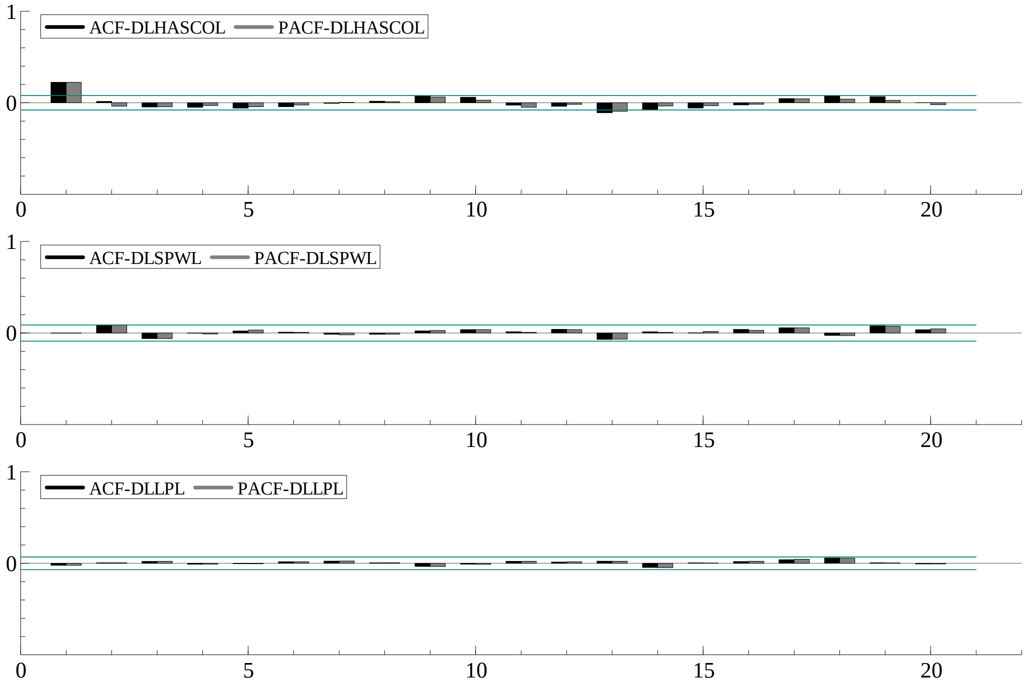

DLLPL
N(s=0.02)
25
20
15
10
5
-0.09
-0.08
-0.07
-0.06
-0.05
-0.04
-0.03
-0.02
-0.01
0
0.01
0.02
0.03
0.04
0.05
0.06
0.07

APPENDIX E: PACF AND ACF PLOTS

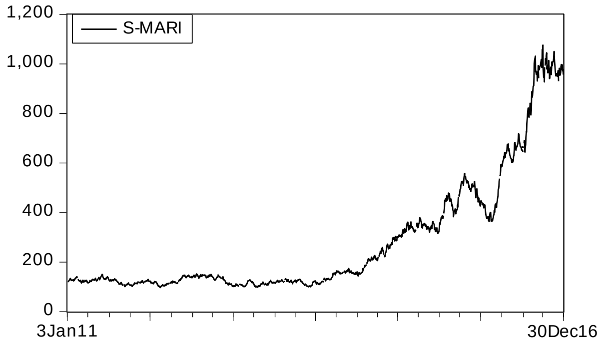


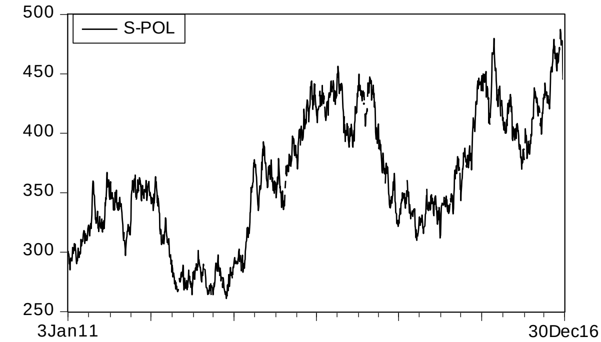

ACF-DLATRL
PACF-DLATRL
ACF-DLHUBC
PACF-DLHUBC
ACF-DLNPL
PACF-DLNPL
ACF-DLKOHE
PACF-DLKOHE
1.0
0.5
0.0
-0.5
0
5
10
15
20

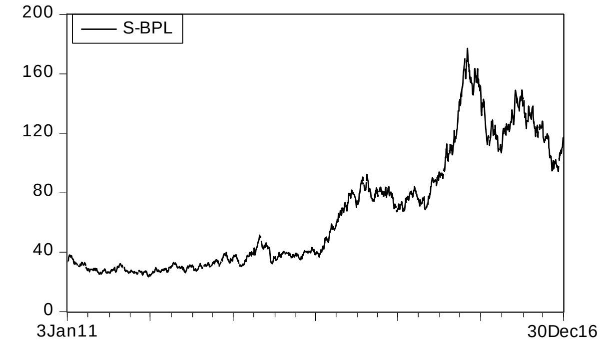

ACF-DLJPGL
PACF-DLJPGL
ACF-DLTSPL
PACF-DLTSPL
ACF-DLKOHP
PACF-DLKOHP
ACF-DLAEL
PACF-DLAEL
1.0
0.5
0.0
-0.5
0
5
10
15
20

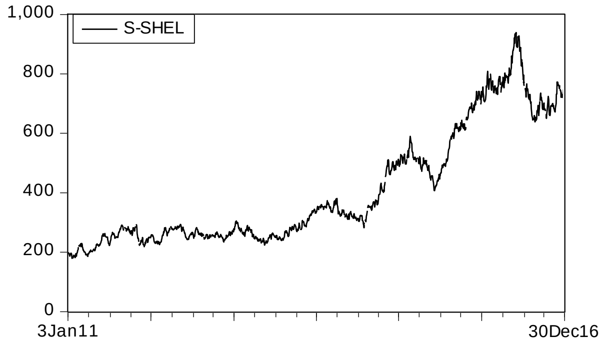

ACF-DLHASCOL
PACF-DLHASCOL
ACF-DLSPWL
PACF-DLSPWL
ACF-DLLPL
PACF-DLLPL
1
0
0
5
10
15
20

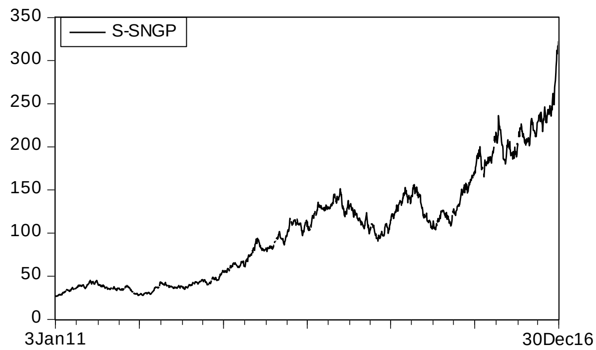
APPENDIX F: SIMULATED STOCK PRICES AT LEVEL

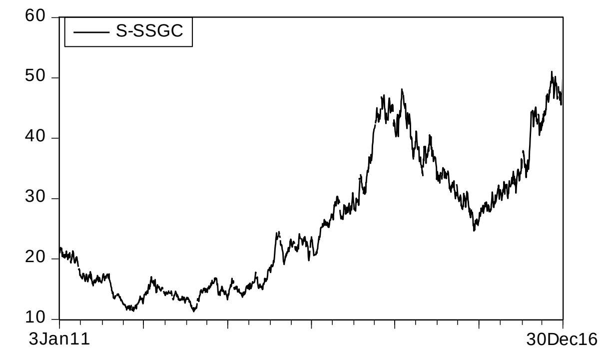


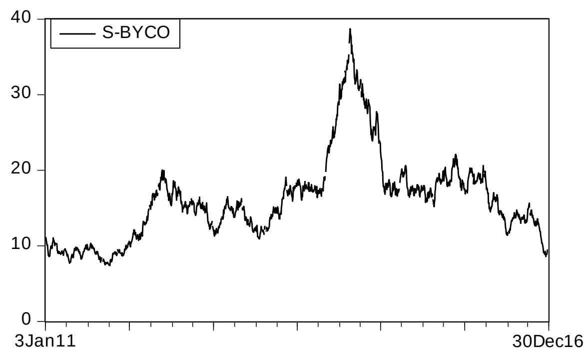


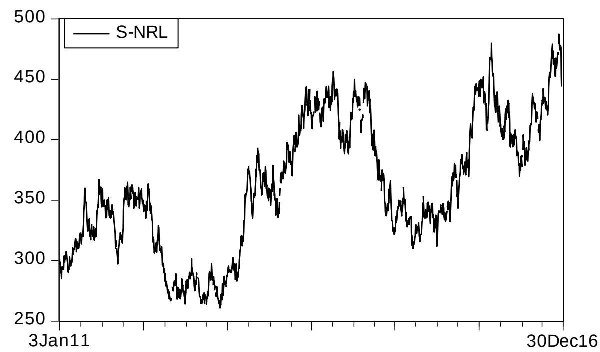


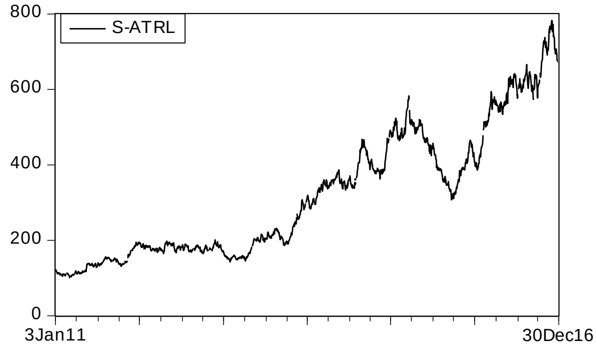


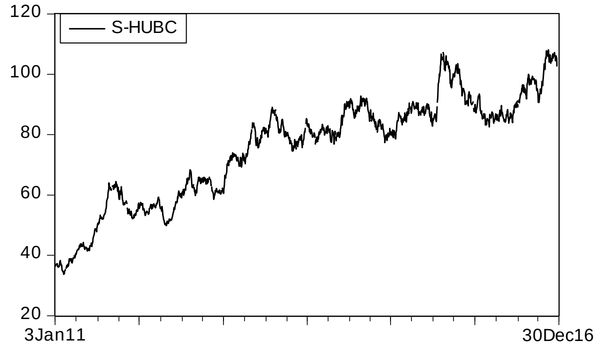


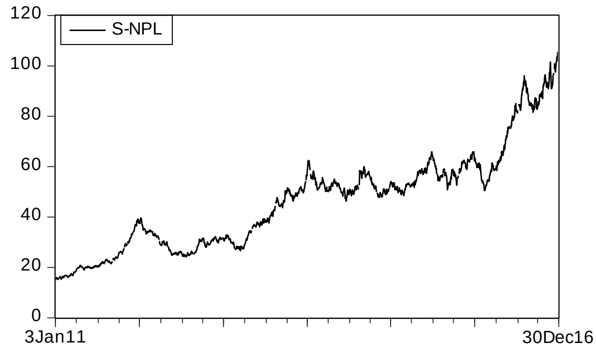


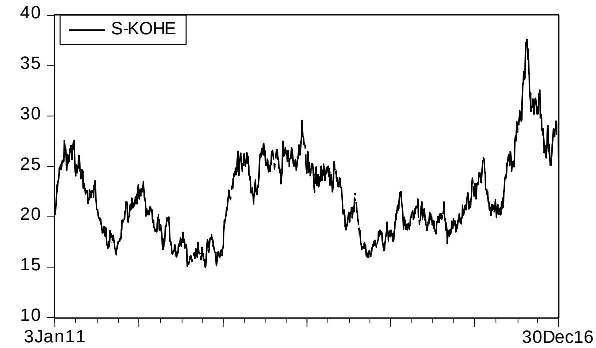


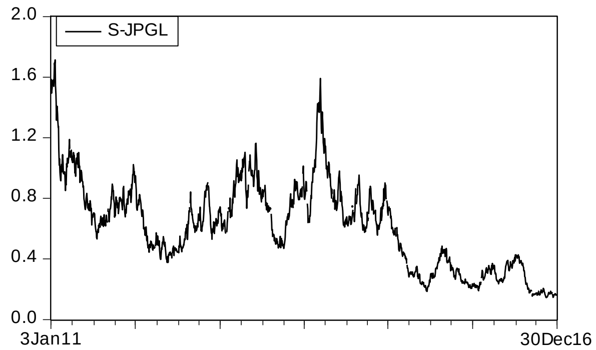


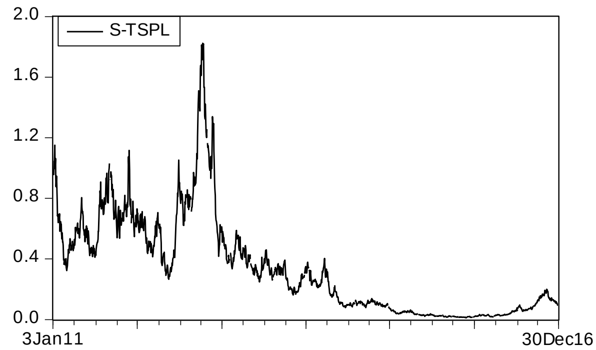

S-ATRL
800
600
400
200
0
3Jan11
30Dec16

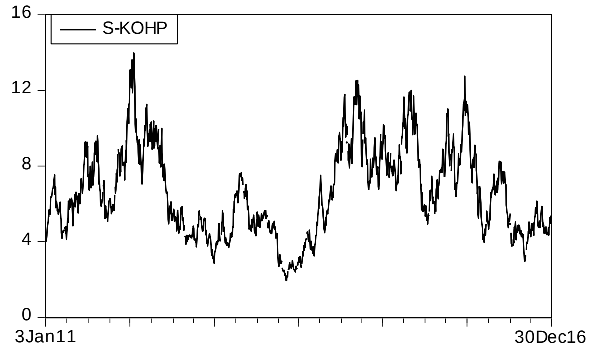

S-HUBC
120
100
80
60
40
20
3Jan11
30Dec16

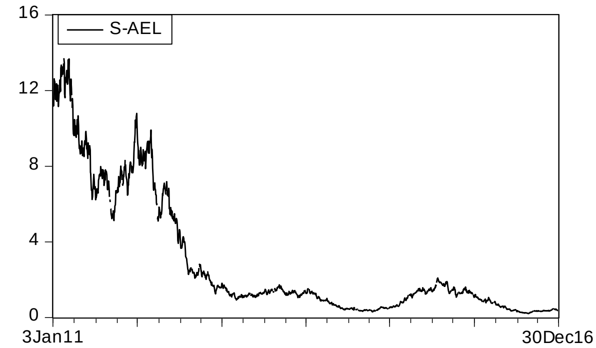

S-NPL
120
100
80
60
40
20
0
3Jan11
30Dec16

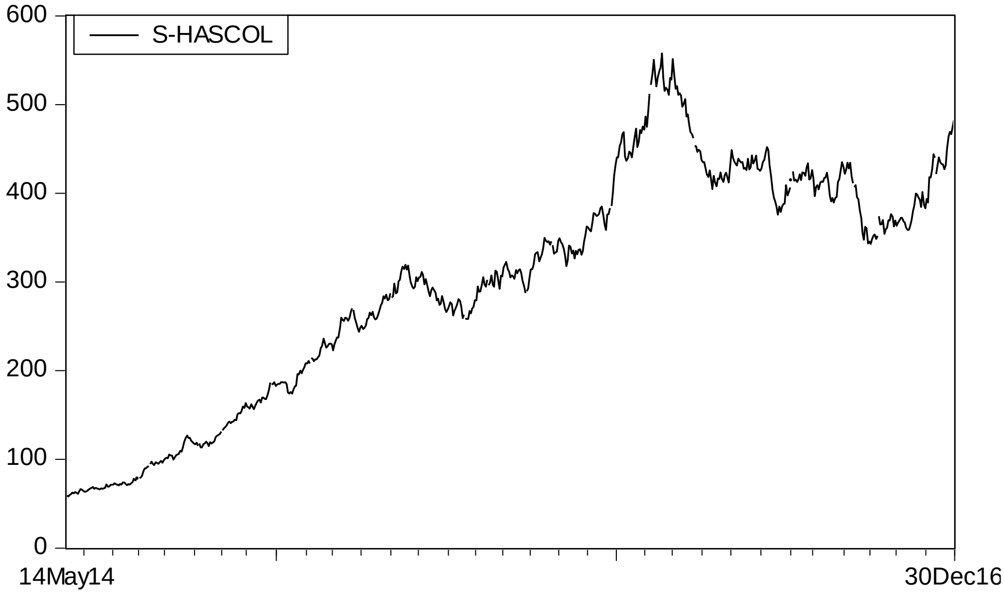

S-KOHE
40
35
30
25
20
15
10
3Jan11
30Dec16

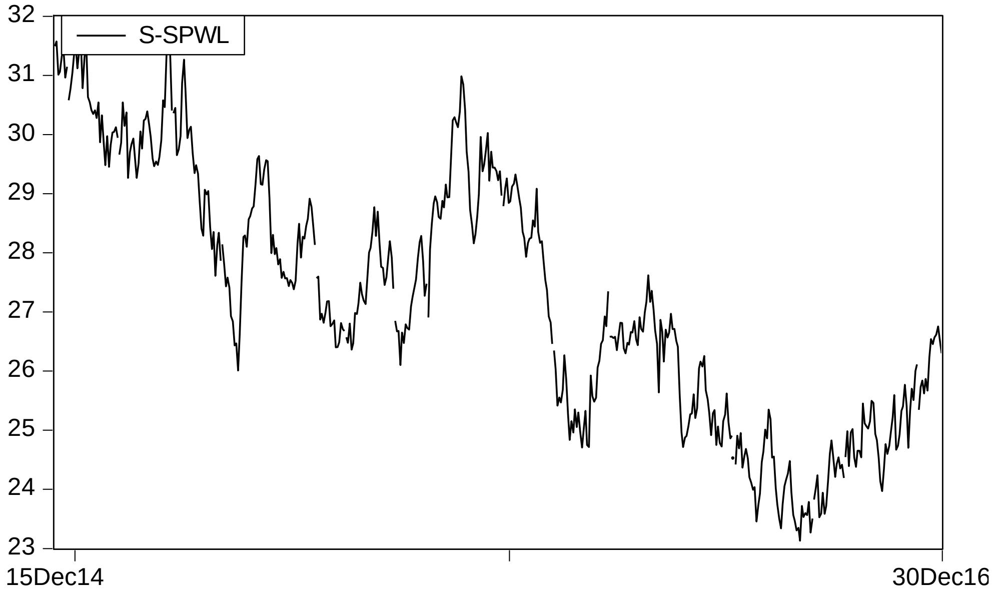

S-JPGL
2.0
1.6
1.2
0.8
0.4
0.0
3Jan11
30Dec16

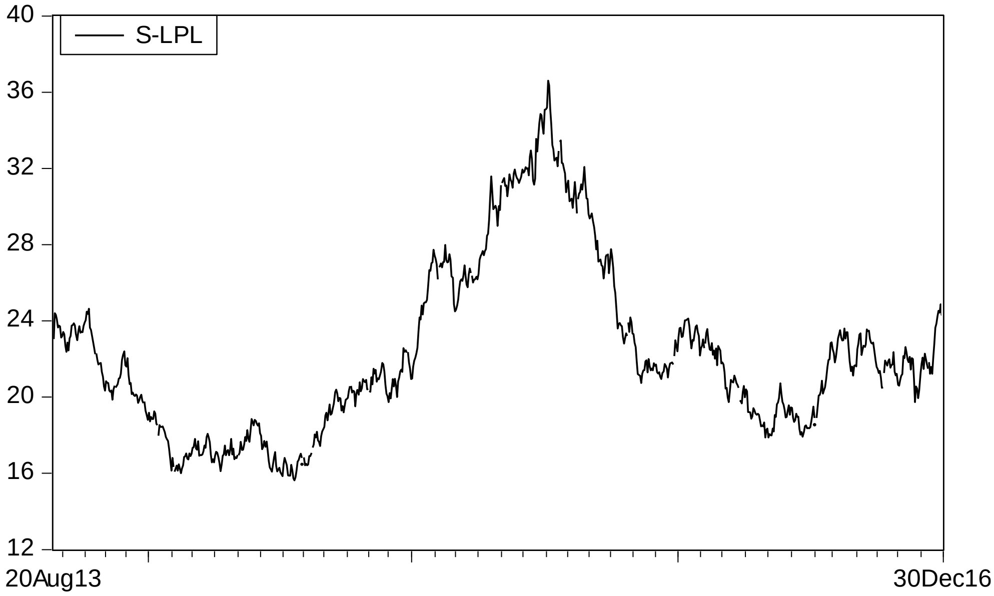

S-TSPL
2.0
1.6
1.2
0.8
0.4
0.0
3Jan11
30Dec16


S-KOHP
16
12
8
4
0
3Jan11
30Dec16


S-AEL
16
12
8
4
0
3Jan11
30Dec16


600
500
400
300
200
100
0
S-HASCOL
14May14
30Dec16


32
31
30
29
28
27
26
25
24
23
S-SPWL
15Dec14
30Dec16


40
36
32
28
24
20
16
12
S-LPL
20Aug13
30Dec16