Predicting Sectoral Stock Volatility in Amman Stock Exchange Using Various Approaches

Mansour Al-Khaza'leh

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Assoc. Prof. Dr. Ali Hakan Ulusoy
Acting Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Doctor of Philosophy in Finance.

Assoc. Prof. Dr. Nesrin Özataç
Chair, Department of Banking and Finance

We certify that we have read this thesis and that in our opinion it is fully adequate in scope and quality as a thesis for the degree of Doctor of Philosophy in Finance.

Prof. Dr. Salih Katırcıoğlu
Supervisor

Examining Committee

1. Prof. Dr. Murat Donduran
2. Prof. Dr. Fazıl Gökgöz
3. Prof. Dr. Salih Katırcıoğlu
4. Prof. Dr. Vedat Yorucu
5. Assoc. Prof. Dr. Korhan Gökmenoğlu

ABSTRACT

There are a numerous number of methods that can be used in financial markets to forecast in the literature; the prominence of predicting is to give the investment community the ability to build their prospect vision decisions about the future expectations, assets allocation, portfolio management, assets pricing and other benefits. This study presents the Autoregressive Moving Average model, Generalized Autoregressive Conditional Hetroscedasticity models, and Vector Autoregressive model which are from the most important forecasting mechanisms that we can use, in financial time series data. The main aim of this study is to predict the volatility of Amman Stock Exchange as one of the emerging markets for the banking sector index volatility using ARIMA model, insurance sector using GARCH models, and the role of oil price in financial sectors performances in ASE by using VAR model. Firstly, we check the stationarity by using unit root test which indicates that there is a stationarity at level for all sectors banking, insurance, and financial sectors. Secondly, the resulted models for this study for banking sector volatility is: ARIMA (0, 0, 1), CGARCH model is the best for insurance sector volatility. Finally, there is no interaction between international oil prices and financial sectors in ASE according to VAR model.

Keywords: Financial Markets, Volatility, ARIMA, GARCH, VAR

ÖZ

Finansal piyasalara yönelik tahminler için literatürde birtakım yöntemler mevcuttur; bu tahmin yöntemlerinin amacı, yatırımcılara, geleceğe yönelik beklentilerle ilgili, varlık dağıtımlarında, portföy yönetiminde, varlık fiyatlandırmasında, ve diğer benzeri faydalar konusundaki kararlarında yardımcı olmak ve ışık tutmaktır. Bu çalışma, otoregresif hareketli ortalamalar modeli, otoregresif değişen varyans modeli, ve vektör otoregresif model yöntemlerini, ki bunlar sahada bilinen en popüler yöntemlerdir, kullanarak finansal serilerle ilgili tahmin yürütmektir. Bu bağlamda, bu çalışmanın temel amacı, gelişmekte olan piyasalardan biri olan Amman Borsası'nda (ASE), ARIMA ve GARCH yöntemlerini kullanarak bankacılık ve sigortacılık sektörleri indekslerindeki dalgalanmaları tahmin etmek ve VAR yöntemlerini de kullanarak petrol fiyatlarının finansal dalgalanmalarla olan ilişkisini ortaya çıkarmaktır. İlk etapta, serilerin durağanlık testleri yapılmıştır ve Ürdün bankacılık ve finans piyasalarındaki bankacılık, sigortacılık, ve finans sektörü indeks serilerinin durağan olduğu sonucuna varılmıştır. İkinci olarak, bu çalışmada, bankacılık sektörü için ARIMA (0, 0, 1) yönteminin ve sigortacılık sektörü için CGARCH yönteminin en uygun yöntem olduğu sonucuna varılmıştır. Son olarak, bu çalışmada, VAR yöntemleri sonucunda, uluslararası petrol fiyatları ile ASE'de işlem gören bankacılık ve finans sektörlerinin indekslerindeki dalgalanmaları arasında anlamlı bir ilişki tespit edilememiştir.

Anahtar Kelimeler: Finansal Piyasalar; Dalgalanma; ARIMA; GARCH; VAR.

DEDICATION

To My Father Spirit Who Is In Allah Bless, My Great Comfort

Spring Compassion To My Great Mother

To My Older Brother Hammad

To My Brother, Ahmad, Who I Can't Respond To A Famous Forever

To Great Sisters Dear Maisoon, Hanan, Nihad, And Fatima

To My Wife That Encouraged Me And Stood By My Side Always, Thekrayat

To My Daughter Bisan

To my son, Nasir Al-Dean

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ACF	Autocorrelation Function
ACT	Algorithmic Complexity Theory
ADR	American Depository Receipts
AMEX	American Stock Exchange
AMH	Adaptive Market Hypothesis
ARCH	Autoregressive Conditional Heteroskedasticity
ARIMAX	Auto-Regressive Integrated Moving Average with eXtra / eXternal
ARIMA	Autoregressive Integrated Moving Average
ASE	Amman Stock Exchange
BFT	Behavioral Finance Theory
CRSP	Center for Research in Security Prices
CGARCH	Component Genaralized Autoregressive Conditional Heteroskedasticity
ECM	Error Correction Model
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
EMH	Efficient Market Hypothesis
EQMM	Econophysics and Quantum Mechanics Method
FEAS	Federation of Euro-Asian Stock Exchange
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
IFC	International Finance Corporation
IOSCO	International Organization for Securities Commissions

JSC	Jordan Securities Center
KLCI	Kuala Lumpur Composite Index
MSE	Mean Square Error
NAGARCH	Non-Linear AsymmrtricGeneralized Autoregressive Conditional Heteroskedasticity
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
PACF	Partial Autocorrelation Function
PARCH	Power Autoregressive Conditional Heteroskedasticity
QML	Quasi-Maximum Likelihood
RWM	Random Walk Model
SEM	Standard Error Mean
STD	Standard Deviation
TARCH	Threshold Autoregressive Conditional Heteroskedasticity
UBJ	Univariate Box Jenkins
UJFTA	USA-Jordan Free Trade Agreement
VWRETD	Value Weighted Return
VAR	Vector Autoregressive
WFE	World Federation of Exchange SDC

Chapter 1

INTRODUCTION

1.1 Introduction

One of the most important financial markets' missions is to support countries' economies over new decades; this significance role can be applied by creating a connection between those sectors that have extra funds with those who need funds (businessmen and governments), leading and contributing these economies to achieve sustainable growth and development in various fields (Jeff, 2006).

Volatility has an impressive mission in the financial market. The term is primarily correlated with risk; it indicates that the process of pricing securities is not accurate, and the mechanism employed in capital market is not effective in its job as it must be. As a result, dealing with derivatives, estimating the volatility, and predicting it strictly is a very important target for all the members related to investment community, so, managing the possibility of exposure for their investment portfolios to its belongings is critical (Stephen, 2004).

Volatility remains fundamental to recent financial markets and hypothetical investigation. The relationship among instability and risk is not clear, but then again volatility in financial markets is not certainly a terrible issue. Actually, acutely truthful volatility is able to shape the foundation for effective charge finding, which is welcomed by traders and investors too. On the other hand, investors will pay less attention to fundamentals than they formerly did, trusting in policy to rescue them if only they eat the magic risk pill in order to get the magic return. Financial markets know how to make an alteration for to a certain degree remarkably, and the prices of securities might remain changed, excessively instable, to stay realistic through variations in essentials. Such obvious proofs taken in consideration during investigation in excess of the years, also are quiet being intentional powerfully. Volatility predicting in financial markets is very imperative information in hedging, asset valuing, asset portion and portfolio administration (Elena & Storis, 2009).

In guessing trials that may happen in the forthcoming, a person who forecast has should depend on information dealing with actions that have happened in the past. Anyway, in order to format the foundation of a forecast process, the forecaster should make an analysis according to past data and must support the forecast on the results of the analysis. The forecaster analyses the data in order to classify a pattern that can be employed to illustrate it (Bruce & Richard, 2003). Volatility models and their forecasting routine paying attention the awareness of many economic activity dealers, principally for area concern with financial risk management. The role of economic dealers is to decide in which one will be able to find the finest model for volatility predicting issue (Srinivasan, 2010).

Forecasting volatility in financial markets is very important information in pricing financial securities, portfolio allocation, evaluation of assets, and derivatives trading (Andersen & Bollerslev, 1998). Expectedness of volatility is vital in scheming the best possible dynamic hedging policies for options and futures (Baillie & Myers, 1991). Most researchers have the same opinion about the predictability of volatility in many asset markets, but they vary on how to model it. In latest years, there are many different techniques, some of which are theoretical, while others are empirical

(Engle & Victor, 1993). Widespread effort has been completed on the financial time series as a process of modeling, together as a theory and empirical either on developed or emerging markets like Europe, Asia, Middle East, and United States. There exists a huge amount of literature on volatility modeling. However, due to inaccurate information flow before the conception of ‘’Globalization’’ many speedily rising emerging markets could not be a magnet for the awareness of financial researchers (Kashif, 2007), such as Amman Stock Exchange (ASE) as example of emerging market.

In this study, we choose ASE because there is less number of studies that search and concern about forecasting volatility by using ARIMA, GARCH models, and VAR model to know the reaction of financial sectors when oil shocks occurred on the ASE sectors as an emerging market, thus, this study is expected to fill the gap in the literature for the case of the ASE by evaluating the effect of oil prices’ variations on the Jordanian stock markets. To the best knowledge of us, such investigation has not been addressed previously in the relevant literature for the case of Jordan.

ARIMA (Auto Regressive Integrated Moving Average) simulations are specifically well-matched to a short-run predicting. Alan (1983) considered a short-run predicting since furthermost ARIMA simulations residence weighty importance on the latest past relatively than the distant past. An ARIMA model is an algebraic testimonial showing in what way observations on a variable are statistically associated to a procedure for accomplishing model past values of the time series variable and past values of the error terms (Alan, 1983).

High frequency data employed to reflect more accurate forecasting and make it better to take in consideration all of the dynamic features of volatility, in which it is very important for forecasting. Recognized measures are precious predictors of future volatility in the models of reduced forms. Additionally, those measures allowed the enlargement of new volatility models that offer more precise predictions. As a result, an improvement in the valuation of volatility predictions in vital methods is available to whom it may concern in the investment community. Moreover, high frequency data have improved our understanding of the forces that drive volatility and their relative significance. For example, high frequency data have allowed an analysis in details of news declarations and their impact on the financial markets.

However, the effects of numerous declarations like yield predictions, variations in interest rates, variations in oil expenses, assertion of war, etc. might cause diverse influences on investor's manners in developed markets. As a result, we expect that these factors also will affect similarly the emerging markets, hence, using a daily stock markets data is very important in emerging markets, so that we have used a daily data for Amman Stock Exchange (Veiga & Mcaleer, 2003).

Oil is a considered product employed as a feedback in all economic actions. For that reason, shocks in the oil market is able to influence stock yields as well as stock market associations due to the universal energy reliance (Hamilton, 1983). Evaluating the influence of financial shocks on trade flows is essential to realize fluctuations in the world oil market, and to discover what are occurring in the countries that produce and consume oil. As a result, financial stock volatility represents the foundation stone in assessing the impact of oil price shocks on the countries' economies over the world, especially in the emerging countries' economies.

There is a large literature focused on the relation between oil price shocks and stock market volatility, for example, Baumeister (2012), Basher et al. (2012), Kilian and Lewis (2011), Filis et al. (2011), Lippi and Nobili (2009) demonstrated the significance of taking into consideration the roots of the association between oil price shocks and stock market volatility in returns. On the other hand, Arouri and Rault (2011) showed that, the countries that export oil have a positive relationship. Many studies concerned with European stock exchanges expose that positive oil price variations tend to negatively influence stock yields. (See Jammazi & Aloui, 2010; Cong et al., 2008). Particularly, oil- interrelated stock market sectors have a tendency to raise the value of in the event of a progressive oil price change, while the opposite embrace for serious sectors (see Scholtens & Yurtsever, 2012).

Burton G. M, (2012) suggested that, it was normally assumed that the market securities were enormously efficient to reflect information about financial securities held by individuals and about the stock exchange as an entire. The believed interpretation was that, at the moment, information rises, the broadcast extents very speedily and is merged into the securities prices devoid of delay. Therefore, neither technical analysis, nor even fundamental would allow an investor to attain returns larger than those that could be gained by holding a randomly designated portfolio of individual stocks, at least not with equivalent hazard. George. F (2014) proposed that supply-side shocks and oil specific demand shocks do not influence volatility, while, oil price fluctuations according to aggregate demand shocks imply to a drop in the volatility of stock market.

The establishment of Amman Stock Exchange (ASE) was in March 1999 as an organization that didn't aim to profit with directorial and financial independence. It is certified to survive as an exchange for the securities trading. The exchange is administrated by a board of directors. The ASE membership in Jordan is composed of 62 brokerage firms. To fulfill with principles and best practices that were known internationally, the ASE works intimately with the Jordan Securities Commission JSC on supervision matters and preserves burly relationships with other exchanges, relatives, and international organizations. The exchange is an energetic member of the Arab Federation of Exchanges, Federation of Euro-Asian Stock Exchanges (FEAS) and a full member of the World Federation of Exchanges (WFE).

In this study, the data recorded daily by using historical indices of the banking sector, insurance sector, and financial sectors. We have used the E-VIEWS, MINITAB, and EXCEL, programs to analyze the data. The economic importance of ASE sectors is reflected by its huge contribution in GDP (Gross Domestic Product). Moreover, the sectors are considered as one of the biggest employers within the private sector, as well as the insurance sector having the largest market capitalization in ASE and it contains 20 listed firms. On the other hand, the data employed in studying the role of oil price shocks on financial sector's performances and stock volatility in ASE are daily stock market indices of financial firms (lnFIN), banks (lnBANK), insurance firms (lnINS), financial services (lnFS), and real estate firms (lnRE) listed in the Amman stock Exchange (ASE) of Jordan and has been gathered from the ASE website for the period ranging from July 3^{rd}, 2006 to April 12^{th}, 2018 and comprising 2,916 daily observations. The crude oil prices of Brent-Europe, in Dollars per barrel are compiled daily from the Federal Reserve Bank of St. Louis for the same period.

1.2 Aim of the Study

Volatility regarded as one of the major dynamic and fruitful fields of research in the modern econometrics and economic predicting in latest current days (Andersen, Andersen, Francis & Peter, 2005). Practically and theoretically financial market volatility is a very important field that can help investors to: price the assets, allocate it, and manage it (Hussein, 2009). The objectives of this study are;

1) Determining characteristics of Amman Stock Exchange returns as a financial data. Amman Stock Exchange is the wildest increasing stock market in the area (Anastassios, 2007). A modern revise available by the International Monetary Fund points that the ASE weighs against favorably with several other Arab markets with respect to the investment limitations, clearness, and the authoritarian surroundings, and has had comparatively low-down price volatility.

2) Nowadays ASE is functioning on increasing a policy criteria for the upcoming period (2016-2018) which contain a numerous number main objectives namely as: intensification of the investment situation in the ASE, intensification of the lawmaking and methodological settings of the ASE, motivating the existence of the ASE at the local and global affairs, encouraging the investment consciousness by financial securities, and developing the mechanisms and technique of working management of the ASE. ASE will afford for more flexibility and assist in the diversification process of introducing services and products. A few years ago, ASE was affected by exterior state of affairs and local and global crises like any other stock exchanges in the region and in the world. The whole economic position of the Kingdom is exaggerated. The performance of the ASE is affected, in particular, by these conditions. In spite of these conditions in the region, ASE is considered as an attractive direction for Arab and foreign investors.

3) Modeling volatility of returns on Amman Stock Exchange using ARIMA model for banking sector.

4) Proposing forecasting techniques for volatility in order to achieve a more accurate forecast.

5) We can effectively predict volatility and classify a convenient method to attain this target. In this study, modelling and predicting will be done by employing a set of real data.

6) The main problem of this paper is to estimate and quantify the volatility of returns on ASE by using GARCH models for the insurance sector volatility.

7) Discussing the role of oil price shocks on financial sectors performances using VAR model.

Predictions that will happen in the prospective future, require from the analyst to depend on information dealing with these actions that have been arisen in the earlier period. As a result, to get ready a predicting output, the predictor should investigate precedent data and should rely the forecasting process on the outcomes of this investigation. So, that the predictors employ data available about the past in the following way. Analyzing the data so as to recognize a model that be able to employ to illustrate it. Then this model is generalized, addicted to the future to arrange a prediction. This basic approach is used in most predicting methods and reposes on the hypothesis that the shape has been recognized as willpower remain in the forthcoming. A predicting practice cannot be anticipated to provide worthy forecasts unless this assumption is effective. If the identified data configuration neither does nor persists in the future, this designates that the predicting practice being used is expected to create imprecise forecasts.

According to all of the above, the main problem offered in this research is to quantify the instability of yields on ASE by means of ARIMA, GARCH techniques for the sectors volatilities: banks, and insurance. Then, it applies the model on emerging stock market (ASE) by using a high-frequency data for empirical analysis. Finally, we can effectively predict volatility and recognize a convenient technique to achieve the appropriate goals. On the other hand, the main contribution of this study is dealing with high frequency data to get the best tentative models that can be employed in forecasting future volatilities of these sectors: as a result, enabling the investment community represented by different types of investors to take the necessary buying and selling decisions that make them happy when they achieve their goals of the underlying investments. Furthermore, deciding whether oil prices have effect on financial sector performances or not.

1.3 Structure of the Study

The remainder of this study is organized as follows: Chapter 2 explains the definition, importance of volatility, measuring volatility, and forecasting volatility according to high frequency data for a stationary time series. Chapter 3 presents the relevant literature that includes many studies concerned with ARIMA, GARCH and other models either in Amman Stock Exchange as an emerging market or in different industries among distinct countries. Chapter 4 investigates the analysis of banking sector volatility. The good ARIMA model is derived for banking sector regarding to the mean square error (MSE). The Box-Jenkins stages are defined and stated, and the characteristics of good ARIMA model are also introduced. Chapter 5 investigates insurance sector volatility according to GARCH model, a deep theoretical setting is showed, and the results then are shown. While Chapter 6 discusses the role of oil price shocks on financial sectors performances, and stock volatility in ASE. Chapter 7 provides conclusion, summary of the finding, policy implications and directions for future researches.

Chapter 2

VOLATILITY IN FINANCE

2.1 Introduction

In this chapter, some of the financial markets' definitions are stated, literature reviews that concern with these definitions are mentioned, Also, the importance of volatility in general, and in particular in the financial markets is emphasized. In addition, the main volatility measures are reflected. Finally, a brief introduction for volatility in emerging markets is provided.

A financial market can be defined as a purchasing or selling mechanism for the financial securities (stocks and bonds). The major role for financial markets is to make easy the inrush of reserves to permit funding and exploiting by households, corporations, and government supports. However, financial markets operate as mediator or a connection instrument between those who have funds more than they need and those who need these funds. There are many benefits of facilitating, such as helping students in universities to get loans, families to obtain mortgages, businesses to finance their expenditures and give money to others. Furthermore; investors and financial institutions invested securities through financial markets and institutions, this operation is called an investment management, in which it can be done by corporations which invest in many securities, at this moment the stage will corporate financing of existing operations and expansion (Jeff, 2003).

2.2 Definition of Volatility

Nowadays volatility forming and predicting have concerned much consideration, mainly driven by its significance in financial markets (John & Stephen, 2007). Volatility becomes very significant to everyone worried in the financial markets. Publicly the term is basically indistinguishable with risk: a large value of volatility is supposed as an indication of market distraction. Volatility denotes that securities are not being valued reasonably and the functions of the capital market are not as well as it must to be. Nevertheless, for individuals who are covenant with derivatives, considering volatility, predicting it correctly, and organization the disclosure of their stock portfolios to its possessions are essential. In an attempt to account for different stylized essentials, numerous kinds of models have been expanded. But the expression was used in some of the earliest research on the topic and being more colorful than the more precise it has stuck in popular practical Stephen (2004). The most two broadly employed ways are time-series models and option ISD (implied standard deviation). A tremendous analysis of volatility predicting is shown in Poon and Granger (2003). Option ISD makes available a better prediction of the performance among assets because it includes well-off evidence nearby forthcoming volatility. On the other hand, so far there is miniature investigation on forecast assessment, or on mixing the predictions of diverse techniques. Forthcoming investigation possibly will afford more outcomes on this area (Poon & Granger, 2003).

2.3 Importance of Volatility

Stock market volatility is a foundation in recent practical financial analysis in a broad series of actions. Producing better predictions requires a well-defined model in dealing with a different type of available information like a conditional heteroscedastic model and throughout the precedent two decades a huge literature has emerged examining and expanding them. For the emerging markets, however, the models have been less strictly examined although predicting risk may perhaps be particularly needed for these highly volatile markets (Kim, 2007).

Volatility is differing from risk, they are not equivalent. When it understands as uncertainty, it turned into an answer contribution to a lot of investment choices and portfolio formations. Investors and portfolio administrators can accept a definite level of risk. A superior prediction of the instability of the charges of assets over the investment holding dated is a worthy benchmark theme for evaluating investment risk. Nowadays volatility is one of the majority dynamic and fruitful areas of research in econometrics and financial predicting. In practice and theory, financial market volatility is an essential topic that can assist in; asset valuing, asset portion and risk managing. A volatility model must have the ability to predict the volatility. Almost all the financial practices of volatility models bring about predicting that deals with future yields. In general, a volatility technique is employed to predict the absolute amount of returns. According to Stephen and John (2007), such forecasts play an important role in risk administration, derivative assessing and prevaricating, market making, portfolio choosing. At the present time, a person has the ability to purchase derivatives that are made on volatility itself, as a result the meaning and quantifying of volatility will be obviously classified in the agreements of the derivative (Poon & Granger, 2003).

Furthermore, volatility in the financial markets has a broad impact on the whole economy. The events reasoned in September 11, 2001 terrorists attack, and the current financial exposure indignity in the United States created a foundation for a huge chaos in financial markets on numerous regions and an unconstructive collusion on the economy of the whole world. As a result, this is an apparent proof of the imperative connection that combined the uncertainty of financial market with public confidence. Because of this motive, policy makers often depend on the assessment of the market guesstimates of instability as indicator for the susceptibility of financial markets and the economy (Poon & Granger, 2003).

The volatility dealer has a diverse perception on the market than the usual stock market investor. The volatility dealer recognizes that periods of declining the stock prices and increasing the volatility are predictable. However, periods of high volatility offer an equal number of trading opportunities as when the stock charges increase (George, Tom, & Richard, 2003).

Therefore, the causes of volatility changes: asset meditation, stock market growth, microstructure properties, and lastly macroeconomic influence. The most obvious cause is the first one, which depends on the degree of diversification. When the economy turns out to be more advanced, it regularly becomes more varied, according to this situation, volatility of the country's component security returns should raise. That is, as stocks are less dependent on one sector, their covariances should decline which should increase the variance. The third is microstructure research; here we say that it is well acknowledged when the heterogeneity of trader's information sets as well as liquidity affects the variance of returns. In industrialized markets, huge variations in charges across stocks propose a larger flow of secretive data being exposed to the market Geert (1997).

2.4 Volatility in Emerging Markets

As emerging markets build up they grew to be attractive investment outlets for investors who seek larger possible returns. So, the investors have a huge willingness to be very effective in the participation of investment community. There are many features for emerging markets: high risk and high profit, extremely understandable and large instability associated with industrialized markets (Geert & Harvey, 1997). Instability in returns is a vital facet of market economies which assures an imperative response for portfolio managing and market regulations (Poon & Granger, 2003). Securities volatilities differ meaningfully through worldwide markets (Geert & Campbell, 1997).

Mollah and Mobarek (2009) also discovered that emerging markets are extremely volatile contrasted to developed markets. When volatility is high in the emerging markets, we can conclude that it can be ascribed to significant macroeconomic reasons exact to emerging markets, for instance, events that related to a political, social and economic affair (Sabur, 2009).

In reality, a considerable sum of dealers in emerging markets can trade on the foundation of undependable information, which implies for the prices of shares to move away from their prices at equilibrium. Furthermore, given that there is an asymmetry property of informational, noise traders may also bend towards response delaying to the new information in order to go after the informed trader’s response, and then do the actions accordingly (Russel & Torbev, 2002).

Andersen et al. (2003) built and investigated long-memory Gaussian vector (VAR) models for a vector of realized variances. A consistent type of reduced-form volatility predictions is the regression that depends on forecasts; while the second approach is the model-based approach for volatility forecasting which is constructed from a model for returns, such as a GARCH type model that identifies the whole distribution of returns. High frequency data have been employed in two distinct methods in this situation; either to improve a presented volatility by including a realized measure into the model or to exploit high-frequency based statistics to improve or make simpler the estimation of the statistical model (Andersen et al., 2003). In their study, Andersen et al. (2003) focused on return volatility where return is defined as:

$$r_t = |\log(x_t) - \log(x_{t-1})| \qquad (1)$$

Where r_t is the yields, x_t is the observation at time t, x_{t-1} is the observation time t-1, log is the logarithm and $|.|$ is the absolute value.

Modern portfolio theory and volatility are not the only means investor use to analyze the risk caused by many different factors in the market. And things like risk tolerance and investment strategy affect how an investor views his exposure to risk. The other measures that can be employed to find volatility are: standard deviation which shows how values are spread out around the average price, it gives traders an idea of how far the price may deviate from the average, beta in which indicates to the volatility of a fund according to the disparity of its returns over a period of time, R-squared which describes the degree to which a fund's volatility is a result of the day to day fluctuations experienced by the overall market. And alpha, which measures how much if any of this extra risk helped the fund outperform its corresponding benchmark.

2.5 Theories of Volatility in Finance

There are many theorems that attempt to explain the relationship between volatility and stock prices (EMH, BFT, ACT, AMH, and AQMM). But in general, each one of them cannot be regarded as best one of them. In other words, no one of them beat the others.

The hypothesis of market efficiency presented firstly in Fama (1965, 1970) besides Samuelson (1965) might remain a very familiar theory related to finance for rational investors. The naturalness according to this theorem headed to new techniques trying to explain the mechanism of how to form a price in the market. Therefore, the price levels in the market depend directly on the existing information, and its updates incoming the market implies to changes in the prices. Since the randomly nature of the coming information implies price variations randomly as well. Thus, stochastic processes are able to model price variations, in which they cause a volatility in prices according to the coming information. On the other hand, as a correlation between stock prices and oil prices exists, the influence of variability will lead to a volatility in oil prices as well. However, the insufficiency of hypothetical background and asymmetrical financial time series have headed to substantial disapproval toward the validity of EMH. Some investigational exploration (Biondo et al., 2013) verified that random processes do not have the ability to explain the financial price series dynamics and similarly, the variations in prices are not consistently stochastic. LeRoy and Porter (1981) and Shiller (1981) presented elevated instabilities in profits by rationalistic attitude of stockholder which cannot clarify instability. However, numerous financial marketplaces anomalies like volatility and clustering were considered by Malkiel (2003) Rubinstein (2001), and Ball (2009) in an EMH harmonious way.

The Behavioral Finance Theory (BFT) presented by Shiller (1990) focused on the intention of analysis for the investors' decision-making restraint -via the methodical investigation ideals Consistent with the BFT, risk aversion, approach improvement, and distribution of resource are affected by knowledge and favorites. On the other side, Barberis and Thaler (2002) claimed the key reasons for non- efficiency in markets: 1) the market price is not thoughtful its standard faces and 2) the biased investors' performance leading to seemingly unbelievable conclusions. De Long et al. (1990) employed a technique of overlapping generations in which illogical noise investors occur to clarify the financial irregularities like volatility clustering, because of the irregularities to poor financially cultured investors. De Bondt and Thaler (1985) explored the tendency of the investor towards making a huge action to modern acquaintance. They confirmed that financial securities having maximum return in the preceding times are typically lesser in the following period and the inversely is true. As Daniel et.al (1998) highlighted, the environment of acquaintance is an additional vital reason. They argued that investors overreact in the direction of private information but make underreacting to public information. Hubermann and Regev (2001) verified that black looks and white looks could be very infectious, initiating a fast rise of price volatility over a short period of time. Whilst BFT offerings techniques clarifying specific anomalies, a chief constraint of like a model is the point related to insufficiency to offer a widespread mechanism that can capture the whole ecosystem aspects related to finance.

Algorithmic Complexity Theory (ACT) was offered by Kolmogorov (1965) and Chaitin (1966), assuming that the time series can be considered unpredictable, if the information capacity is not compressible in a more compacted format. Interactions of efficiency besides returns randomness is that a time series with accumulated nonexcessive information on economy (same as efficiency theory) have similar characteristics as a sequence produced arbitrarily. Volatility in forecasting prices is happening because of the huge amount of data and information and not because of the nonexistence of information. In other words, the efficiency is not perfect in the market when the modern information makes non-random variations in prices, nonetheless, this modification precisely awards us the opportunity to touch the price series extracted by the modern market information. Trading patterns are caused by diverse magnitude heterogeneous investor sets, availability of information and knowledge. Contrary to EMH scheme, in which market integrates the physical charges of information look like to be exceedingly associated with the economic charges. The amount of data adapted by investors is severely restricted by the level of asymmetry in the information and the magnitude of efficient information dealings. Experimental researches related to financial markets, showed that price manners are nearly associated with information treating manners, highlighting the relationship among behavioral finance and information theory. Here are the explanations for those theories:

The hypothesis of adaptive markets Hypothesis framed via Lo (2004), offers a modern resolution in examining the financial bubble by considering the fundamentals of development for instance; the natural picking and opposition for financial interface. In AMH background, BFT together with EMH are exceptional conditions of infinite shade of market predictions. Even though, AMH may not designate the whole financial schemes operating, it offers an extra malleable context that lets implementation of more heterodox performs in the direction of forming the changes within a system of financial time series. Segal and Segal (1998) highlighted that quantum properties can clarify the specific of anomalies in financial securities prices differences occasioned by investors' manifest unreasoning attitude.

Econophysics and Quantum Mechanics Method, in which it is similar to the motorized classifications, the operations of financial market are ruled via instructions persisting not differ terminated periods of time. Econophysicists suggested the approaches on the foundation of statistics concepts in exploring financial structures using mathematics, economics, probability and physics. Quantum mechanics techniques authorize the econophysicists to explore the aggregate actions of financial structure deprived of the prerequisite for the attitude depth revision of the constituent portions earlier. Chakraborti et al. (2011) offered the volatility clustering and availability of fat tails which established experimentally by numerous examinations. Sornette (2003) detailed the main market crashes events happening in emerging and developed countries and decided that these episodes can be forecasted. Exploration of financial phenomena employing the conception of quantum mechanics is an exceptional investigation area within econophysics. Haven (2002) confirmed that, in a financial structure, the Heisenberg's uncertainty rule occurs for the reason that prices are volatile, also, the level of the price does not have the ability to be stately precisely. Khrennikov (2007) highlighted the insufficiency of public disciplines can obtain the mechanism of quantum process through probable philosophical outcomes in the operations of financial markets. Dima et al. (2015) have showed a construction in order to explore the dynamical system volatility in the volatility of dynamical structure along with a pricing process illustrative proceeding the foundation of varied sets of investors. Quantum physics essentials are appropriate if the markets in the financial environment are considered as complex schemes where investors interact each other similar to that of quantum particles interactions.

Chapter 3

LITERATURE REVIEW

3.1 Introduction

Some of the financial markets studies that deal with foreign countries are stated in this chapter. Also, main studies that focused on Amman Stock Exchange are mentioned. There is a large literature that talked about financial markets forecasting, in particular volatility forecasting. Also, there are many studies done as the continuation of previous work in determining the interactions between oil price shocks and financial sector's performances, so we will mention some of these studies briefly.

3.2 Literature Review

Mustafa, Ali and Shalini (2015) introduced a short review about Box-Jenkins model that acknowledged as ARIMA model (Autoregressive Integrated Moving Average). It is an upright technique to anticipate for stationary and non-stationary time series. The data gathered monthly for the sales of Naphtha product (in Azzawiya Oil Refining Company – Libya), they specified a tentative proper model for the monthly sales. The consequences of this study exhibited that the effective model to correspond to the data of the time series according to AIC, and MSE criteria was the ARIMA (1, 1, 1).

Narendra and Eswara (2014) developed a linear mixed model in which it can keep both data trend and preserves a forecasting exactness. This technique is called

ARIMA-GARCH model, moreover it can improve the forecasting precision for TSD (Time Series Data). The model applied on data provided by NSE (Indian stock Exchange) then compared with classical and available existing models. The major finding of this study is that if ARIMA model is used alone is the problem that it just valid for short run predicting, on the other hand, this model cannot be applicable for long run forecasting since the resulted forecasting will not be accurate. The solution of the previous problem in long-run forecasting is to mix ARIMA with other types of models. Finally, accuracy techniques such as MAPE (Mean Absolute Percentage Error), and RMSE (Root Mean Square Error) verify the enhanced forecasting correctness compared to classical techniques ARIMA and GARCH Data drift observed better than others when using hybrid model. Mina and Mohammadreza (2014) studied the Sefidrud River in the North of Iran for industrial sector and agricultural sector; as a result, pollution went up due to the activities exercised. ARIMA model employed in forecasting the trend of variation in TSS, DO, and NO3 parameters in two stations located on the borders of the river.

Nor et al. (2014) used (ARIMA) and (GARCH) models in predicting monthly for the period started from July 1997 until July 2012 data Malaysia stock market. The capacities of these two models afforded by employing Akaike's information criterion (AIC), and Root Mean Squared Error (RMSE). Stationarity achieved at first difference for the data sets, and according to AIC values ARIMA (1, 1, 4) and GARCH (4,1) are the best models for Kuala Lumpur stock exchange series. The deduction of this study is that ARIMA models exceeds GARCH model in the accuracy of the prediction for the market properties and shares.

Patimaporn and Naragain (2014) compared the autoregressive, moving average, autoregressive moving average and Holt’s &winter exponential models. They found ARIMA is the best model for the five sets of data according to distributor of plastic industry in Thailand. Yaziza et al. (2013) applied ARIMA and GARCH models to predict gold price. Although ARIMA model is very suitable in many cases, but it cannot accurately express about volatility and nonlinearity existed in the data series, so meeting this problem requires finding another approach to solve ARIMA limitations. As a result of the problems resulted from using ARIMA model, GARCH models employed to capture the features of volatility and nonlinearity. The plan for this study is to deal with time series data available through ARIMA models which will be either written as a deterministic component without error term or with error component, then investigate whether nonlinearity and heteroskedasticity exist or not, at the last stage writing a merged model that model and predict a gold price. Finally, considering both ARIMA and GARCH models, which is called a hybrid model, the resulted proposed model after transforming the data is ARIMA (1,1,1)-GARCH (0,2).

Sohail, Shahid and Imran (2012) recognized and guesstimated the best fitted non-linear models GARCH (Generalized Autoregressive conditional Hetroscedasticity) and ARCH (Autoregressive conditional Hetroscedasticity) that can predict volatility for the closing stock prices of MCB (Muslim Commercial Bank) by applying ARIMA-GARCH models according to residuals behavior obtained. The best parsimonious model depending on having a minimum value of RMSE (Root Mean Square Error) and also AMAPE (Adjusted Mean Absolute Percentage Error) is ARIMA (1, 1, 0) and ARIMA (0, 1, 1) since they represent the only significant models. Finally, they have shown that GARCH (1, 1) model is the finest model that can fit the predictability of the MCB (Muslim Commercial Bank) closing stock prices as measured up to ARCH models. Hussein Al-Zeaud (2011) employed ARIMA model in forecasting volatility for the (ASE). The result proved that the tentative banking ARIMA model for the banks sector is (2, 0, 2).

Dumitru and Cristiana (2010) exercised U.S. and Romanian daily stock return records and established that EGARCH model reveals commonly lesser predicting error and more truthful than the estimates given by the other asymmetric GARCH models such as TGARCH and PGARCH models outperform superior than the traditional GARCH model. Özden (2008) explored the finest appropriate model for the Istanbul Stock Exchange (ISE) 100 Index return volatility with GARCH models. He has employed daily closing prices among the 2000 and 2008 and concluded that the best model for the mean equation is ARMA (2,2), while TGARCH (1,1) is the more precise model to anticipate stock returns volatility in ISE.

Richard (2007) employed GARCH models proposed for the S&P100 data of a close prices daily stock returns, and the VIX (implied volatility index) covered the period that extended from 6/1/1988 till 5/17/2002. Realized and historical volatility used as proxies of the latent integrated volatility are clearly suffering from clustering over time. The main results of this study imply that, predicting outputs that based on univariate models using concurrently information from share returns and option prices by implied volatility in a GARCH model prove that implied volatility affords important information about future changes in volatility because of many sources. The latter result is that predicting weakness and probable misspecification of volatility models is most excellently specified by the nontrivial enhancements resulted from modifications of the model anticipated.

Andersen and Bollerslev (1998) showed the volatility modeling using ARCH model provide noticeably precise forecasts for the volatility factor that would be of concern in most financial applications. Nelson (1992) explored the characteristics of the conditional variance estimates generated by ARCH model. He employed a GARCH $(1,1)$ to estimate the immediate conditional variance matrix of the diffusion. He concluded the ARCH is success in short term forecasting using high frequency data and construct a good estimate of volatility. In contrast, Hansen and Lunde (2005) found out that there is no confirmation that a GARCH$(1,1)$ did much better than other models by more stylish in exchange rates data. They compared 330 ARCH-type models in terms of their capability to illustrate conditional variance. As a result, the evaluation according to the squared returns might choose an inferior model as the most excellent with a possibility that converge to one as the sample size raises.

Alshiab (2006) studied the autocorrelation function and partial autocorrelation functions analysis tests employed to determine whether the data set was stationary or not stationary. The resulted model studied the predictability of Amman stock exchange (ASE) Performance. He examined the univariate ARIMA predicting model, employing the ASE general daily index in the period 4/1/2004 to 10/8/2008. He found that the forecasting was not reliable with real presentation through the same period of the forecast over the 150 coming days.

Sarıoğlu (2006) in how to oppose “how fluctuations of common stocks dealt in Istanbul Stock Exchange (ISE) can be estimated”, analyzed ISE-100 Index for the time period extended from January 1991 until December 2004. Depending on the regression analysis, conditional models in forecasting and modeling the fluctuations in ISE-100 Index, she found out that GARCH (1, 1) and EGARCH (1, 1) models are the preeminent fitted models for ISE-100 Index. Awartani and Corradi (2005) employed S&P-500 Index to check up the out of sample extrapolative capability of 10 dissimilar GARCH models for six dissimilar forecast horizons. Outcomes display that, there is obvious confirmation that asymmetric GARCH models engage in recreation a central function in volatility forecasts and the Risk Metrics exponential smoothing model appears to be the model with the lowly extrapolative facility.

Reena, Carlo and Ricardo (2005) examined the movements in volatility of emerging stock market returns during the period 1985-1995. The high volatility in emerging markets is noticeable by numerous moves. The outsized variations in the instability appear toward remaining associated to vital state definite party-political and economic events. The grist of fluctuations in variance varies among countries. They also rely on the frequency of the data: the higher the frequency, the higher the volatility.

Andrew and Helen (2004) studied the broadcast of equity returns and volatility between nine Asian equity markets through the period 1988 to 2000. Three of these markets are considered as developed (Hong Kong, Japan and Singapore), whereas the bulk is classified as emerging (namely, Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand). A multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model is employed to classify the foundation and the amount of spillovers. The appraised coefficients from the conditional mean return equations signify, as anticipated, that there is a great integration for all Asian equity markets. Nonetheless, mean spillovers from the developed to the emerging markets are not homogeneous crosswise the emerging markets, signifying that some markets may be more helpful in predicting equity returns in emerging markets than others. This would designate that alterations in volatility in emerging markets from inland conditions are comparatively further imperative than those typically established in developed markets.

Chen and Shen (2004) studied the daily Taiwan's exchange rate according to CGARCH-Jump model for classifying 172 jump dates through the data set, moreover time-varying conditional volatility. The consequences implied that there was a volatility perseverance or long memory declared according to employing the conditional volatility models. That is to say, the CGARCH and FIGARCH models which have long memory are superior outfitted to arrest determination than are the GARCH and IGARCH models. While, a study by Louis (2004) evaluated the capability of the diverse models to predict volatility that covered over multi-day periods, Models employed are historical standard deviation, GARCH (1,1) model, and the exponentially weighted moving average model for a daily data. They match up predicting the capability among different markets: S&P500 index, Japanese Yen/Dollar exchange rate. What concluded in this study is that GARCH (1, 1) puts too much weight on current records comparative to older records. Additionally, they found that the parameters estimated using OLS imply considerably longer memories than GARCH model and also generate better forecasts in sample. Finally, they initiated that models depend on absolute return innovations commonly predict better than otherwise comparable models based on squared deviations.

Olga (2004) presented an econometric revision of office yields resolve in the Helsinki region presented, an undersized European market, over the 30-years for the period that extended from 1971 to 2001. Principally, the research examines the variant in office capital growth, which is the most volatile module of office total return in the Helsinki market using three unconventional models, namely; a regression model, an error correction model (ECM), and ARIMA model with exogenous explanatory variable (i.e. ARIMAX). The outcomes designated that the models, joining earlier values of capital growth and growth in service sector employment and in the gross domestic product, are talented to elect to choose up tremors present in the data, and thus provide the best forecasting tool for office yields in Helsinki.

Poon and Granger (2003) concerned with the significance of volatility in investment decisions, risk administration and monetary strategy making, which can be achieved by constructing a volatility predicting using historical information set and by the time ahead volatility resulted from traded option prices. On the other hand, clustering, asymmetry, and other features of volatility are investigated for the real returns. The models employed in achieving the target of this study are random walk model, moving average, exponential smoothing and exponentially weighted moving average methods. The last two models rely more on contemporary volatility estimates, moreover all of the models above enlarge the number of observations and sampling nearer to time t, in addition to ARCH that fairly used to explain the conditional variance resulted for the data. The results of this study showed that 56% of the studies prove that historical volatility is more preferable than GARCH models. On the other hand, 44% of studies showed the opposite.

Robert Engle (2001) showed that ARCH and GARCH models are widely used and very useful in dealing with a financial data. The process of decisions taken in finance always depend on comparing between risk and return for any set of investments in different securities. Hence, a Value at Risk is an example to measure the risks faced by their portfolios. Consequently, using econometrics provide a tool that may construct a guide in answering a different type of questions, for instance how to make an optimization for a portfolio? How to price an option? And how to make an analysis for the risk management approach. Econometrics tools present a road map for the persons who are professional to take economic decisions. A large extension of ARCH models, and autoregressive and vector autoregressive can be applied usefully for solving limitations concerned with portfolio to analyze a huge number of assets according to their volatilities and correlations analysis, as a result, finding the best framing based on testing the supposed hypothesis.

Foreign energy reliance shows an essential role in economic and financial system (Memis & Kapusuzoglu, 2016). Shaeri and Katircioglu (2018) focused on the link between crude oil prices and performance of financial, oil and transportation companies in the United States (U.S.) and found significant influences of oil price variations on financial performance of these sectors. Furthermore, Shaeri et al. (2016) examined the oil price risk exposure of U.S. financial and non-financial industries and found that financial and non-financial sectors in the U.S. are significantly sensitive to oil price changes and oil price risk exposures. Shaeri et al. (2016) also found that the degree of oil price sensitivity differs significantly across financial and non-financial subsectors and the volume of oil prices' impact on the financial subsectors was significantly lower than the volume of its impact on the non-financial subsectors. Sodeyfi and Katircioglu (2016) also found significant effects of crude oil prices on business environment and business conditions in the economies.

Chapter 4

PREDICTING BANKING SECTOR VOLATILITY IN THE ASE USING ARIMA MODEL

4.1 Introduction

In this chapter, we employed a number of tests to formulate banking sector index in the ASE for predicting by utilizing ARIMA model. Firstly, the volatilities for banking sector is computed by utilizing Equation (2). There are many forecasting techniques that are used in statistics (Autoregressive Conditional Heteroskedastic Model, Exponential Generalized Autoregressive Conditional Heteroscedasticity Model, and Autoregressive Integrated Moving Average Model). The method selected relies on the target and significance of the predicting as well as the cost of the substitute forecasting ways.

Autoregressive Moving Average (ARIMA) models can be used as a modeling and forecasting techniques to achieve the aims of our study. In this chapter, we consider the time series data that can be investigated using the ARIMA technique. We also go over the single-series definition, then we present when the technique used. Moreover, the procedure for forming and constructing a superior ARIMA models, also we mention the features of this type of models compared with others which make it as a good model. Finally, we go more intensely into the keys essential for ARIMA investigation.

4.2 Theoretical Setting and Methodology

4.2.1 Time Series Data

The records employed in time series might be made yearly, monthly, weekly, daily, and so on; in either macro or micro variables. Regardless of the variable type used in time series, the general target is to forecast the value of an entry by studying past actions of that entry over time. Time series data are playing a very important role for today's people. However, one of the first stages in analyzing time series data is to assess it by taking it visually. This is the most easily achieved through a lot of diversified graphical setups. So, we can define time series data as the observations that express about a variable over time as a sequence. With a help of the high decision software graphics programs existing today, it is very easy to sketch graphs of time-series data which are of brilliant type for analyzing time-series data (Patricia & Ricky, 1994).

4.2.2 Univariate Time Series

The most impressive feature of the stationarity in time series is that it does not have a drift, meaning that, it rises and falls nearby a fixed mean. If the premier series does include drift, without the availability of seasonality appearance, it can be altered into a series without trend by picking a first or second differences of the records according to the assessment of the time series requirements for stationarity (i.e. subtracting the values of two adjacent observations in the series or the differencing the first differences respectively) (Patricia & Ricky, 1994). Univariate Box-Jenkins practice is used directly when dealing with a short-term forecasting. It is principally suitable for that type of forecasting, in other words, the ARIMA techniques residence substantial highlighting on the current past but not on the far past**.** The concentration on latest past denotes that long-run predictions from ARIMA techniques are fewer steadfast than short-run predictions. Additionally, Univariate Box Jenkins is flexible for the Data types, since it can be applied for the two types of data discrete data or continuous data. Constructing an ARIMA model necessitates a sufficient size for the sample selected. A huge sample bulk is particularly engaging when seasonality on the data is available. Additionally, stationary series must be achieved when ARIMA model is applied. A stationary time series has a lot of features that enable ARIMA model to be applicable; fundamentally, these are a fixed mean, fixed variance, and fixed autocorrelation function over time.

An autocorrelation function is one of the important ways of determining in what way the observances among a single data series are correlated to each other. The stationary postulation a bridges the theory implicit the Univariate Box Jenkins models and aids to guarantee getting a useful estimate of constraints from a reasonable grist of observations as the mean of a stationary series indicates the general scale of the series. On the other hand, furthermost nonstationary series that ascend in exercise is able to be converted into stationary series by using moderately straightforward procedures. Box-Jenkins model has many features over the other classical single-series models. First one is that, the perceptions related with UBJ models are obtained via traditional likelihood principle and mathematical statistics. The second one is that, ARIMA techniques are a set of techniques, not just only a one model. As a result, you can choose one or more tentative model. Lastly, it can be showed that a proper ARIMA model yields most advantageous UBJ predictions with a lesser mean-squared prediction error Alan (1983).

4.2.3 Advantages of Time Series as a Quantitative Methods

There are many positive features of time series data as a quantitative method that can be employed in the forecasting process; the most important one is that there is a mission to appraise the accurateness of the forecast, also it is very cheaply in time overwhelming in generating forecasts from them, on the other side, once the choice of independent variable(s) is made, the forecasts are based only on their determined values and thus are entirely objective, finally, it has a range of values that rely on a confidence interval (Patricia & Ricky, 1994).

4.2.4 Autocorrelation Function and Partial Autocorrelation Function

We will refer to a very important tool as the first stage of proposing a tentative ARIMA model, identification stage which is basically applied according to autocorrelation and partial autocorrelation functions. The mission of both of them is to quantity the algebraic association among records in a single data series, this is affording a help in determining the stationarity of the series as well as (along with the partial autocorrelation function) a fitted ARIMA model (Patricia & Ricky, 1994).

4.2.5 The Box-Jenkins Modeling

We aim to obtain superior pattern that demonstrate in what way the records in a single time series are interrelated to each other. An ARIMA model is an arithmetical declaration viewing the relationship in a time series such that $y_t$is related to its own past values (y_{t-1}, y_{t-2}, y_{t-3}, …). A tentative model encloses the least grist of predictable constraints wanted to satisfactorily adequate the pattern for the records Alan (1983).

4.2.5.1 The Box-Jenkins Modeling Procedures

There are three-step process for detecting a respectable model. The steps are: Identification, in which two declarative strategies to amount the association among the records inside a series. Those strategies are predictable autocorrelation function and predictable partial autocorrelation function. The simple indication is this: each ARIMA model has a hypothetical acf and pacf related with it. At the first step, we contrast the predictable acf and pacf resulted beginning the available data with numerous hypothetical acfs and pacfs**.** In the second phase, estimation, we acquire accurate guesstimates of the model coefficients selected at the first step. At this moment, some caution signs that make a model highly adequate. If the estimated coefficients do not achieve some of arithmetical circumstances, that model is cannot be acceptable. At the estimation phase, we build a well-organized model of the available data by getting accurate estimates of just a least number of parameters (the mean and some AR and/or MA coefficients).

Box and Jenkins good deed preferring coefficient estimates at the estimation phase according to the maximum likelihood (ML) criterion. Diagnostic checking, there are some suggestions that help in the determination of adequacy of the proposed model. A model that does not pass these diagnostic checks is excluded. Additionally, the outcomes at this step might similarly designate how a pattern could be enhanced. This points us to repeat the sequence of the three steps till finding the finest model that might be employed in the forecast. The supreme public ARIMA model comprised the constraints: p, d, and q where p is the grist of autoregressive constraints, d is the grist of differencing constraints and q is the grist of moving average constraints (Alan, 1983).

4.2.5.2 ARIMA Model Form

The common ARIMA model is given by Bruce et al. (2005), and John and David (2003):

$$z_t = C + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + ... + \varphi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - ... - \theta_p a_{t-q} \tag{2}$$

Where

t : the episodic period

φ_i :for $i = 1, 2, ..., p$ are the AR constraints

θ_j :for $j = 1, 2, ..., q$ are the MA constraints & a_t :is the shock element at time t

The first step of an suitable ARIMA model includes two stages: altering the records if essential into a stationary time series and defining appropriate technique according to the performance of acf's and pacf,s. The model suggests the lag grist not to be greater than the quarter of observations number of autocorrelations, the autocorrelation coefficient measures the correlation among a set of records and a lagged set of observations in a time series. The predictable PACF is employed as an attendant, alongside with the predictable ACF, in picking an ARIMA model to fit the data (Alan, 1983).

Precision of a forecasting model relies on how close the predicted values are to the real values. Practically we identify the disparity among the real and the expected values as the error of predicting. If the model is going on the way that qualify it to do a good profession in predicting the real data, then the forecast error resulted will be comparatively is not big. In fact, if we have acceptably modeled the data, then the resulted volatilities (errors) in a time series that have no pattern that can be defined. Sometimes these fluctuations are resulted because of outside actions that in themselves cannot be predictable. In other words, the error for each period of time is solely random volatility just about the predicted value. As a result, if we were to add them we should get a value very closed to zero (Patricia & Ricky, 1994). Furthermost, vital common features of hypothetical AR and MA are defined as follow (Alan, 1983):

A) Autoregressive procedures have hypothetical ACF's that decline or damp out" headed for zero.

B) Moving-average procedures have hypothetical ACF's that ends at zero next a definite grist of sharp points. The lateness size for the latest ACF sharp point equivalents MA procedure degree and hypothetical PACF's decline headed toward zero.

4.3 Results and Discussion

4.3.1 Descriptive Statistics of the Banking Index

Table 8 (Appendix A) showed the descriptive statistics for banking sector. The minimum value is 4561 and the maximum is the 9587.6, this sector has a large range. Additionally, the standard deviation is very high, which incomes the extent is moreover huge nearby the mean. Whereas, the standard errors mean is 19.251, it affords a guesstimate of how many fluctuations from the population constraint that we be able to anticipate in a sample guesstimate of the mean. Moreover, we noted that the median is larger than the mean which incomes that there is a negative skewness (-0.025818) which means that the left tail is lengthier; the bulk of the distribution is focused on the right side. Furthermore, there is a positive kurtosis in the Figure 4 in Appendix B which incomes that the distribution has a further curved top and longer heavier ends**.**

4.3.2 Volatility Analysis for Banking Sector

The volatility for the banking sector is computed via Formula 1. Figure 5 listed in Appendix B showed the plot of the banking sector volatility. While, the descriptive statistics are showed in Table 8 Appendix A. The great volatility in emerging markets is obvious by numerous moves. As an example, there were a huge number of small significant volatility shifts during 2010-2015 (as can be shown in Figure 5 in Appendix B). The standard deviation was 0.008572.

The huge fluctuations in instability are associated with significant nation detailed governmental, and economic events, wars, refugee's movements' problems and other causes. The number of changes in variance varies among banking sector, because of the economic world, and the results following 2008 financial international crises. The banking sector volatility sector has positive kurtosis, which incomes that the distribution has a severer top, lengthier, heavier ends. The higher kurtosis means more of the variance.

4.3.3 Unit Root Test

These tests determine if a time series variable is non-stationary employing an autoregressive model. One of the furthermost well-known checks is the augmented Dickey- Fuller test. The further negative ADF is the tougher the rejection of existence of a unit root at confidence level. (Said & David, 1984). Table 9 in Appendix A presented the ADF check outcomes for banking sector volatility. Seasonality is a unique feature of time series, but it was ignored in this study, which is implicitly assumed that there is no seasonality in the data. A popular model for seasonal time series is in seasonal ARIMA model. The outcomes of this research, powerfully approve stationarity at levels for banking sectors.

4.3.4 Autocorrelation and Partial Autocorrelation Analysis for Banking Sector Volatility

Table 10 in Appendix A showed the ACF and PACF for the volatility of the stocks indices for banks records, the autocorrelation is calculated for 16 lags by, also, the values of Q-stat and p-value remain also specified, the ACF at the first lateness is (0.485), which is knowingly doesn't equal zero (Q-statistic is 312.49 with p-value less than 5%). The ACF for the indices of banking fluctuations displays big affirmative major sharp point at the first lateness 1. The rest of all other ACF's are inside the confidence interval (see figure 6 in Appendix B). While, the PACF at lag 1 is (0.0485) and it is knowingly diverse from zero (Q-stat is 313.36 with p-value lower than 5%. Also, there is another spike at lags 2, 3, 4 but their behavior is fluctuated around the significant interval limits decaying toward zero. Additionally, Figure 7 in Appendix B displayed that PACF a big positive significant spike at lag 1, similarly we have a positive and negative substantial spike at lags 2,2,4 but fewer than lag 1. All the other partial autocorrelations are not significant.

A volatility model must have the ability to predict the volatility. Almost all the financial usages of volatility models bring about predicting what deals with forthcoming returns (Robert F. Engle & Andrew J. Patton. 2001). Box-Jenkins procedure consists of the implementation or completion of (with the aid of a computer (Eviews) program) several steps as mentioned in the theory of ARIMA model in this chapter. However, at a more general level, in the identification step, a time series must be stationary, and then an appropriate model is recognized.

The identification practice is typically approved out by revising the performance of the autocorrelation and partial autocorrelation function. The second step is the estimation; firstly, calculating primary estimates for the constraints of the appropriate model and then permit the software to generate the finishing guesstimates by an iterative practice. The third step is diagnostic checking which is implemented in checking the acceptability of the model to the data. We do this by running tests on the residuals $(Y_t - \hat{Y}_t)$ and by testing the significance and relationships of the parameters. In this study, the MSE is adopted to determine the fit ARIMA model for the ASE sectors data. Finally, the forecasting is the final step, once the suitable model has been created, it can be combined and future forecasts can be initiated (Alan, 1983).

4.4 Conclusion

According to the outputs of autocorrelation and partial autocorrelation in addition to the minimum mean square error, as a result, it is very easy to suggest the finest ARIMA model. Table 1 exhibited that totally selections of ARIMA models for this sector with difference equal to zero (there is no need for differencing because the stationarity achieved for the volatility data at level). These selections tested built on the minimum MSE include all of the ordered pairs between the (0, 0, 0) (2, 2, 2) at level. The finest model for banking is ARIMA (0, 0, 1) in which it is the moving average of order one (MA (1)). This model provides the minimum mean square error with significance equals to0.0000481665. Hence, we can write the general formulae for the best ARIMA model after checking their significance of coefficients as the following:

$$Z_t = \mu + \theta_1 a_{t-1} \qquad (3)$$

Table 1: Outcomes of the Finest ARIMA Model for Banking Sector Index Volatility in ASE

Model	MSE	Model	MSE
(1,0,0)	0.000056213	(0,0,1)	0.0000481665
(1,0,1)	0.000048203	(0,0,2)	0.000073375
(1,0,2)	0.000048191	(2,0,2)	0.000048218
(2,0,0)	0.000052039	(2,0,1)	0.000048206

The ARIMA (0, 0, 1) was recognized, guesstimates for fixed and the coefficients should be acquired. Employing EViews find out the appraised coefficients as shown in Table 4.5 of the ARIMA (0, 0, 1), that resulted by using reduplicating process. Meanwhile, the t-test for both coefficient and steady are 38.10039, 7.301317 respectively, and their values are larger than 2, thus, we cannot accept null postulate for both of them. That is mean the coefficient and constant are significantly diverse from 0. The parameters of the equation are demonstrated in Table 2. Therefore, the concluding equation the Banking sector volatility is given as:

$$Z_t=0.002399+0.723238a_{t-1} \tag{4}$$

Table 2: Parameters of ARIMA (0, 0, 1) Model for Banking Sector Index Volatility in ASE

Type	Coef	SE Coef	T	P
MA 1	0.723238	0.018982	38.10039	0.0000
Constant	0.002399	0.000329	7.3013	0.0000

Furthermore, predicting with the concluding equation, it is essential to accomplish numerous investigative checks with the aim of authenticate the goodness of fit of the model. A good way to check the adequacy of a Box-Jenkins model is to analyze the residuals $(Y_t - \hat{Y}_t)$. If the residuals are actually random, the autocorrelations and partial autocorrelations computed using the residuals must be statistically equivalent to zero. If they are not, this is a sign that we have not fitted the precise model to the data. The residuals of ACF and PACF of Banking sector volatilities (Figures 8 and 9). Appendix B designates the insignificance in all 36 lags for autocorrelation and partial autocorrelation coefficients. All p-values are less than 5%. Consequently, the residuals are haphazard and the model is a respectable in fitting records.

Figure 10 shows a standard EViews graph of the real values, fitted values, and residuals, while the four-in-one residual plot is showed in Figure 11. The components are: normal probability plot in which it is designated if the residuals are normally scattered or not, former in constants are prompting reaction, or outliers occur in the records. And, the fit reversion line presented how the residuals are fastened to the fit line. The histogram the skewness; the histogram displayed roughly the complete records positioned on the average of records. The last diagram exhibited the residuals against order observations which is daily for banking sector instability. The concluding model for this sector is demonstrated in Equation 4.4. The number of the daily records is 1327. While, Figure 12 presented the scheme of the real and anticipated values designed for this sector.

Finally, the limitations of the ARIMA model can be explained by its need to a time series that is stationary, which means that it has constant mean, constant variance, and constant autocorrelation. Also, it is recommended that there are at least 50 observations in the input data. It is also assumed that the values of estimated parameters are constant throughout the series.

Chapter 5

PREDICTING INSURANCE STOCK VOLATILITY IN THE ASE USING GARCH MODEL

5.1 Introduction

There is a large literature regarding to the process of volatility modeling using Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. In the last decades, economies started to critically model these sequential dependencies. There is a huge number of former revisions relied on the ARCH frame pioneered by Engle (1982). In econometrics, regression plays an essential function both in theoretical and empirical financial economies (Nielsen et.al., 2004).

Numerous studies showed that standard volatility models clarify modicum of the variability in ex-post squared returns; see Cumby et al., (1993), Figlewski (1997), Jorion (1995), and Jeffery (1996). This has implied to a proposition that those models may be of limited realistic value. Consequently, Engle (1982) proposed the ARCH process to permit the conditional variance to alter over time as a function of past errors leaving the unconditional variance invariable.

A classical time series and econometrics models activate under a supposition of fixed variance. Many studies employed both of Autoregressive Integrated Moving Average (ARIMA) and GARCH model to deal with financial time series. Murinde and

Pashakwale (2001) examined the major characteristics of six stock market's fluctuation in the emerging markets of European changeover economies via daily indices. They use ARIMA, BDSL technique and asymmetric GARCH models, they get that in all six markets, volatility shows considerable conditional heteroskedasticity, non- linearity, and volatility appears to be of a permanent nature. Moreover Weiss (1984) suggested Autoregressive Moving Average (ARMA) with ARCH errors as successful models in representing 30 U.S microeconomic time series. Models for this structure with respect to conditional variance as a proxy for the risk premium are given in Engle et al. (1985). Furthermore, volatility affected by the coming news during the period modeled, that was shown in Ross (1989), when he argued the volatility can be considered as an appraise of information stream. A GARCH model is not to be employed only on financial data, but it can be applicable in another types of data, for example forecasting electricity prices for a month of year in mainland Spain and California day ahead with average forecast 9% (Garcia et al., 2005).

5.2 Theoretical Setting and Methodology

The enormous workhorse in econometrics applications is the least squares model. This is an accepted option, because applied econometricians are typically concentrated on determining how much one variable will alter the reaction to alter in some other variable. Econometricians are being requested to predict and investigate the innovations size of the model. In this case, the questions are about volatility, and the standard tools have become the ARCH/ GARCH models. Practically there were no available methods before the preface of ARCH models. The main instrument used in descriptive process was the rolling standard deviation which can be found by using a fixed number of the most recent observations. The least square model supposes that all error terms at any given point when squared have the same expected value. This assumption is the focus of ARCH/ GARCH models which called homoskedasticity. When the variances of the error terms are not the same, the error terms may rationally be expected to be greater for some points of the data than for others, that is what called heteroskedasticity. The coefficients of the regression for an ordinary least square's regression are still unbiased, but the standard errors and confidence intervals estimated by conventional procedures will be too narrow, giving a false sense of precision. Instead of considering this as a problem to be corrected, ARCH and GARCH models solve the problem of heteroskedasticity as a variance to be modeled. As a result, not only are the deficiencies of least square corrected, but a prediction is calculated for the variance of each error term. This forecasting comes out often to be of attention, especially in finance applications (Engle, 1982). Those are the general forms of the models we are going to check in this study:

The autoregressive conditional heteroskedasticity (ARCH) group of models was proposed by Engle (1982). The ARCH model regards as the conditional variance as time dependent defined as follows

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2{}_{t-i} \qquad (5)$$

Where ε_t denotes the error terms, σ_t is the time dependent standard deviation, α_i > 0, i > 0.

The extension of ARCH (q) model named GARCH (p,q) Generalized Autoregressive Conditional Heteroskedasticity model founded by Bollerslev (1986) as follows:

$$\sigma^2{}_t = \omega + \sum_{j=1}^{q} \beta_j \sigma^2{}_{t-j} + \sum_{i=1}^{p} \alpha_i \varepsilon^2{}_{t-i} \tag{6}$$

A higher order of GARCH models denoted GARCH (p,q) can be estimated by choosing either q or p greater than one where q is the order of the autoregressive GARCH term and p is the order of moving average ARCH term. The Threshold GARCH (TARCH) model introduced independently by Zakoian (1994) and Glosten, et al., (1993). The generalized specification for the conditional variance is given by:

$$\sigma^2{}_t = \omega + \sum_{j=1}^{q} \beta_j \sigma^2{}_{t-j} + \sum_{i=0}^{p} \alpha_i \varepsilon^2{}_{t-i} + \sum_{k=1}^{r} \gamma_k \varepsilon^2{}_{t-k} I_{t-k} \tag{7}$$

Where $I_t = 1$ if $\varepsilon_t > 0$ and 0 otherwise.

In this model, good news when $\varepsilon_{t-i} > 0$ and bad news when $\varepsilon_{t-i} < 0$, have differential effects on the conditional variance, good news has an impact of α_i , while bad news has an impact of $\alpha_i + \gamma_i$, if $\alpha_i > 0$, bad news increases volatility, and we say that there is a leverage effect for the i-th order. If $a_i \neq 0$, the news impact is asymmetric.

The EGARCH or exponential GARCH model was proposed by Nelson (1991). The specification for the conditional variance is

$$Log(\sigma^2{}_t) = \omega + \sum_{i=1}^{p} \alpha_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \tag{8}$$

The left –hand side is the unconfirmed variance log. This implies that the leverage influence is exponential, rather than quadratic and the prediction of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma_i < 0$. The impact is asymmetric if $\gamma_i \neq 0$.

Furthermore, the power ARCH (PARCH) model is introduced by Taylor (1986) and Schwert (1989), the standard deviation GARCH model, where the standard deviation is modeled rather than the variance. This model along with several other models is generalized in Ding et al. (1993) with the power ARCH model, the power parameter δ of the standard deviation can be estimated rather than imposed and the optional γ parameters are added to capture asymmetry of up to order *r*.

$$\sigma^{\delta}{}_{t} = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta} + \sum_{i=1}^{p} \alpha_j \left(\left| \varepsilon_{t-i} \right| - \gamma_i \varepsilon_{t-i} \right)^{\delta}$$

(9)

Where $\delta > 0, \left|\gamma_i\right| \leq 1$ for $\mathrm{i} = 1, \ldots, \mathrm{r}$, $\gamma_i = 0$ for all $i > r$, and $r \leq p$

The symmetric model sets $\gamma_i = 0$ for all i. The PARCH model is simply a standard GARCH specification. As in the previous model the asymmetric effects are presented if $\gamma_i \neq 0$.

In this paper, we will study the last model which is the component GARCH (CGARCH) model in which the conditional variance in the GARCH (1, 1) introduced by Engle and Lee (1999) model is given by:

$$\sigma_t^2 = \bar{\omega} + \alpha\left(\varepsilon_{t-1}^2 - \bar{\omega}\right) + \beta\left(\sigma_{t-1}^2 - \bar{\omega}\right) \tag{10}$$

Shows mean reversion to $\bar{\omega}$, which is a constant for all time. By contrast, the component model allows mean reversion to a varying level m_t modeled as:

$$\sigma_t^2 - m_t = \alpha\left(\varepsilon_{t-1}^2 - m_{t-1}\right) + \beta\left(\sigma_{t-1}^2 - m_{t-1}\right) \tag{11}$$

Where;

$$m_t = \omega + \rho\left(m_{t-1} - \omega\right) + \phi\left(\omega_{t-1}^2 - \sigma_{t-1}^2\right) \tag{12}$$

Where $\sigma^2{}_t$ is the volatility, while m_t is the time varying long- run volatility. The first equation describes the transitory component $\sigma_t^2 - m_t$ which converges to zero with powers $\alpha + \beta$. The second equation describes the long-run component m_t , which converges to ω with powers of ρ .

In the first stage, a generic kind of models is specified. This is executed by precise snooping of the major features of the daily returns' volatility series. In general, most of the financial data series presents: high frequency, non-fixed mean and non-fixed variance. While in the second stage we should identify a trial model for the stocks returns data. Due to the altitude volatility in the stock returns data, a logarithmic transformation is applied to smooth the volatility effect. In this trial, the observed Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the stocks volatilities can assist to formulate the choice of the first model Hamilton (1994) and Enders (1995).

When the stationarity satisfied, and ARCH effect for the insurance sector volatility is examined, the next step is to pick the best model according to the least value of AIC, SC, and HQIC criterions. The last stage is the diagnostic checking, in which the ARCH effect in the residuals is tested, in addition to the serial correlation of the residuals, and whether the residuals are normally distributed or not.

On the other hand, the weakness of ARCH models represented by the assumption of positive and negative shocks have the same effects on volatility. In practice, it is well known that asset prices responds differently to positive and negative shocks. Furthermore, ARCH model is rather restrictive, but this constraint becomes complicated for higher order ARCH models. GARCH model is symmetric, so it has a poor performance in reflecting the asymmetry.

5.3 Results and Discussion

5.3.1 Descriptive Statistics

The present analysis is based on many tests, to prepare the insurance sector volatility for GARCH modeling. Volatility of insurance sector is computed via Formula 1. Figure 13 showed its time series volatility graph. While, the descriptive statistics are showed in Table 11, the high volatility in emerging markets is marked by several shifts. The standard deviation was 1.376 (i.e. fluctuating around the mean). The mean, that is, most observations of the time series volatility in all periods of the study concentrated around this value which is equal to 8.806. The median is greater than the mean, that is, there is a negative skewness, for insurance sector volatility. A series volatility showed a positive kurtosis, (sharper peak, longer and fatter tails). The higher kurtosis means more of the variance.

The reasons behind large changes in volatility are related to important events in Jordan specifically or in the whole region. Over the past and subsequent years Jordan is still suffering from critical situations. Those situations are associated with political conditions, reflections of economic and social transformation program adopted by the government, wars in the Middle-East that cause refugee's movements' problems, instability in the whole region, government policies, and the outcomes of the 2008-2009 financial international crises. As a result of the events mentioned, local investors and foreign investors were so hesitated to invest in an environment with these features especially in ASE.

5.3.2 Unit Root Test

A unit root test determines whether a time series variable is stationary or not. Augmented Dickey-Fuller test is employed to check the presence of a unit root as the null hypothesis to specify the stationary of data in levels or at differences, because there is a critical problem associated with non-stationary variable that is the spurious correlation. The further negative ADF, the sturdier rejection of the hypothesis that there are unit roots. The outcomes strongly confirm stationarity at 5% level for the insurance sector volatility series at level, which means definitely no necessity to make transformation for the data. (See Table 12 in Appendix A).

5.3.3 Autocorrelation and Partial Autocorrelation

ACF is the plot of autocorrelations, while PACF is the plot of partial autocorrelations and both of them are very useful when examining stationarity and when selecting from among various nonstationary models. ACF and PACF are the key materials in time series demonstrating (Pankratz, 1983). A huge positive weighty sharp point at first lateness. All of the other ACFs are within the 95% confidence limits. This configuration is usually MA manner of first degree. The PACF for the insurance volatility data showed a large positive significant spike at lag 1 (this implies a PACF of the consecutive couples of observations inside one-time interval is not inside sampling error of 0), moreover a positive and negative weighty sharp point decaying at lags 2, 4. (See Table 13 in Appendix A).

5.3.4 GARCH Models Analysis

To deal with this family of models the data should be stationary. Based on unit root test applied on insurance sector volatility series that is shown in the previous section, insurance sector volatility series are stationary at level, so we do not need to make any transformation on it, and it is the first step to deal with GARCH family models. According to the residuals graph of insurance sector volatility, we can realize that periods of low volatility are followed by periods of low volatility, and periods of high volatility are followed by periods of high volatility. Fluctuations of the residuals are so clear. The value of p-value in heteroskedasticity test is less than 5%, as a result we can reject the null hypothesis that says there is no ARCH effect for the insurance sectors volatility, while the alternative hypothesis says that there is an ARCH effect. When all these justifications are achieved, ARCH family models can be applicable (see Table 14 in Appendix A). Then choose the best fitted model of them according to AIC (Akaike Information Criteria), SC (Schwarz Criterion), and HQC, where AIC, SC, and HQIC (Hannan Quinn Criteria) are calculated as Brooks (2008)

$$\mathrm{AIC} = \left(-2\mathrm{L}/\mathrm{T}\right) + 2\mathrm{k}/\mathrm{T} \tag{13}$$

$$\mathrm{SC} = \left(-2\mathrm{L}/\mathrm{T}\right) + \mathrm{k}\log\left(\mathrm{T}\right)/\mathrm{T} \tag{14}$$

$$\mathrm{HQIC} = -2\mathrm{L} + 2\mathrm{k}\ln\left(\ln\left(\mathrm{T}\right)\right) \tag{15}$$

Where;

L is the log likelihood, k is the number of parameters, and T is the number of observations.

The lower the value the fitted the model. Here are the values of AIC, SC, and HQIC for the insurance sector volatility for ARCH (1) to ARCH (3), GARCH from (1, 1) till (3, 3), TARCH, EGARCH, PARCH, and CGARCH models. It is clear that CGARCH (1, 1) is the best fitted model for insurance sector volatility according to AIC, SC, and HQIC criteria.

The best fitted model according to AIC, SC, and HQIC is CGARCH model given by;

$$\sigma_t^2 - m_t = 0.018469\left(\varepsilon_{t-1}^2 - m_{t-1}\right) + 0.090416\left(\sigma_{t-1}^2 - m_{t-1}\right) \quad (16)$$

Where;

$$m_t = 1.891539 + 0.787696\left(m_{t-1} - 1.891539\right) + 0.052882\left(\omega_{t-1}^2 - \sigma_{t-1}^2\right) \quad (17)$$

The first step in the checking process is to check the serial correlation in the residuals of the insurance sector volatility series under the null hypothesis that says there is no serial correlation in the residuals, and the alternative hypothesis that says there is a serial correlation in the series. According the p-value which is greater than 5% for all lags, we cannot reject the null hypothesis. In other words, there is no serial correlation in the residuals of the series (See Table 13 in Appendix A). The second step is to check whether the residuals had an ARCH effect or not, The ARCH test is a Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals (Engle, 1982). This particular heteroskedasticity description was driven by the observation that in many financial time series, the bulk of residuals appeared to be related to the bulk of latest residuals. ARCH in itself does not cancel the efficiency related to standard Least Square (LS) implication.

On the other hand, disregarding ARCH effects may possibly outcome in loss of efficiency. The null hypothesis claims that there is no ARCH effect in the residuals, while the claim of alternative is the existence of ARCH effect in the residuals. The p-value resulted applying heteroskedasticity is 0.4352 which is clearly greater than 5%, based on this outcome null hypothesis cannot be rejected, in other words there is no ARCH effect in the residuals (See Table 16).

The third step is that residuals must be checked whether it is normally distributed or not, the null hypothesis claims that residuals are normally distributed, while the alternative claims that residuals are not normally distributed. The p-value is less than 5%, as a result the null hypothesis should be rejected, meaning that residuals are not normally distributed, our desire was to get normality in residuals, but unfortunately that was no achieved. (See Figure 14) In the Figure 15 of normal quantiles, if the residuals are normally distributed, the points in the QQ-plots should lie alongside a straight line. The plot indicates that it is sometimes primarily large negative and, in another time, large positive shocks that are driving the departure from normality. Residuals, actual, and fitted for the insurance sector volatility series showed in Figure 2, while the descriptive statistics in Table 15. Here ${\sigma^2}_t$ represent instability, while m_t proceeds the place of 1.893954 and the time varying long- run volatility. The first equation describes the transitory component ${\sigma^2}_t$ - m_t which converges to zero with powers 0.108885. The second equation describes the long-run component m_t , which converges to 1.891539 with powers of 0.787696, so that

m_t approaches 1.893954 very slowly. We used EVIEWS 9.5 student version in running the ARCH, GARCH, TGARCH, EGARCH, PARCH, and CGARCH models (see Tables 17-31 in Appendix A).

The component of GARCH model of Engle and Lee (1999) is considered to improve the account for long-run volatility dependencies. The different short and long-run components allows the CGARCH model to designate volatility dynamics better than the standard GARCH model (Christoffersen, 2004). Finally, after the estimation of the best fitted model, we expect that individuals and firms or any institution included in investment community to exploit and adopt the resulted model in their future investment decisions that can achieve the willingness of right decision-making process, either to get profits and/or avoid losses as much as they could, or at least to minimize it.

Table 3: CGARCH Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.706883	0.040491	215.0329	0.0000
Variance eq	Coefficient	Std. Error	z-Statistic	Prob.
C(2)	1.891539	0.123512	15.31463	0.0000
C(3)	0.787696	0.258187	3.050873	0.0023
C(4)	0.052882	0.078953	0.669790	0.5030
C(5)	0.018469	0.083450	0.221320	0.8248
T-DIST. DOF	8.951359	1.939118	4.616202	0.0000
R-squared	-0.005357	Mean dependent var		8.606138
Adjusted R-squared	-0.005357	S.D. dependent var		1.376948
S.E. of regression	1.380631	Akaike info criterion		3.448478
Sum squared resid	2357.898	Schwarz criterion		3.477435
Log likelihood	-2127.608	Hannan-Quinn criter.		3.459369
Durbin-Watson stat	1.298924			

5.4 Conclusion

We compare six GARCH models (including a number of lags for ARCH and GARCH) in terms of their ability to estimate the conditional variance for the insurance sector volatility series in Amman Stock Exchange. The main findings are the CGARCH model is outperform other models when the models are evaluated. This proposed model is supported by the characteristic of both ARCH effect and the behavior of the series residuals which classified as periods of high volatility followed by periods of high volatility and periods of low volatility followed by periods of low volatility. The proof of the proposed tentative CGARCH model is sustained by AIC, SC, and HQIC criterion and the log likelihood which is the largest one among the models studied. By using CGARCH model, the volatility is modelled as a convex combination of unobserved GARH components where the combination weights are time varying as a function of appropriately chosen state variables. There is no serial correlation in the residuals, and there is no ARCH effect in the residuals, but the residuals are not normally distributed.

Chapter 6

THE ROLE OF OIL PRICE SHOCKS ON FINANCIAL SECTOR'S PERFORMANCES AND STOCK VOLATILITY IN THE ASE

6.1 Introduction

Oil markets continue to play important roles in the economies over the recent decades. A large relevant literature has documented the huge dependency of economies on the oil markets (Al-Abdulhadi, 2014; Kaitibie et al., 2016; Katircioglu, 2017a; Shaeri et al., 2016) where studies has shown the incremental dependency of countries on oil over time (Gokmenoglu et al., 2016). Moreover, there are studies that explored the links between oil markets and financial and/or stock markets (Memis & Kapusuzoglu, 2015; Shaeri & Katircioglu, 2018). Memis and Kapusuzoglu (2015) found that national and international oil prices significantly impact on financial markets in the case of OECD (Organization for Economic Co-operation and Development) countries. In general, it is acceptable to confirm that the rise in the oil prices contribute to the business cycle asymmetries (Shaeri et al., 2016). The recent oil price movements have become a great concern in the economic performance of the countries. It is unavoidable not to consider the important role of the foreign energy dependency of oil exporting as well as oil importing countries.

Although there have been an increasing number of studies about the impacts of oil prices on the macroeconomic performances, the literature on the connection between oil prices and the financial sectors is confined. The issue is very vital particularly for oil-importing and emerging countries. Some studies, for example, allocated with the matter of the profitability of banking sector and their correlation with oil prices (Katircioglu et al., 2018a). Hesse and Poghosyan (2016) studied the association among oil prices and bank profitability in main oil-exporting countries, the outcomes designate that, oil price shocks have indirect impact on bank profitability, channeled through country-specific macroeconomic and institutional variables, while the direct impact is not significant. There are instances of this type of studies using country-specific data or figures such as Brazil (Afanasieff, Lhacer, & Nakane, 2002), Tunisia (Naceur, 2003), India (Badola & Verma, 2006), Taiwan (Ramlall, 2009), Switzerland (Dietrich & Wanzenried, 2009), Japan (Liu & Wilson, 2010), and Turkey (Katircioglu et al., 2018a; Anbar & Alper, 2011; Sayilgan & Yildirim, 2009).

On the other hand, Al-Fayoumi (2009) examined the connection among variations in oil prices and stock market returns in the main oil-importer countries, namely Turkey, Tunisia and Jordan, whose results do not confirm the role of oil prices in variations of stock market returns. A similar scarcity of studies does also emerge in the banking area where searching the role of oil price variations on banking sector volatility deserves attention from researchers.

According to Goedhart, Koller and Wessels (2010), an efficient stock market can be defined as a market in which prices of its stocks reveal essential information about firms. In this case, the market rate of the firm varies in a manner very closed to that of the intrinsic rate of a firm. There is no consistency in the variations with the value and do not confine from exchange financial securities. The alterations in the responsiveness of the investor and irregular business deal charges avoid essential variations in value to be absolutely and nearly mirrored in the prices of the market. Nevertheless, efficiency in markets means that, variations in the prices of assets cannot be mirrored in algorithms, whereas surplus yield is grown as an achievement relatively than a conclusion of a precise forecast. Allen, Brealey and Myers (2011) defined a market as efficient when it is not possible to earn a return higher than the market return. In other words, the value of shares reflects the fair value of the company and is equal to the future cash flows discounted by an alternative cost of capital.

Conversely, several researchers presented by Alvarez et al. (2002, 2008) investigated the market efficiency of the international oil price volatility with the composite scientific research technique established on the practices from the econophysics. They chiefly highlighted on the internal auto-correlation contained in the dynamics of crude oil price. On the other hand, Bopp and Lady (1991) concluded that, the future’s prices in the short- run are efficient, but are non-efficient in the case of long-run by detecting the volatility of prices series in the oil futures market.

Tabak and Cajueiro (2007) and Alvarez et al. (2008) employed more harder fractal techniques, systematically considered the incomes of the crude oil price, they concluded out that there is clear long-range association and memory features in the income series of international oil price in the short- run, that is men, the international oil price market cannot encounter the features of the efficient market in the short-term. Furthermore, they concluded that the influence of auto-correlation is quite restricted, and is insignificant in the future. Thus, the price volatility is dependable on EMH in the long-term.

6.2 Theoretical Setting and Methodology

First of all, all the series are transformed into their natural logarithm to capture growth effects (Katircioglu, 2010; 2009). Zivot and Andrews' (1992) unit root test is adopted for stationary nature of series allowing for one break. Furthermore, unit root tests would give us an idea if crude oil prices converge with financial series of this study under consideration. Secondly, correlation and linear fit will be searched between oil prices and the ASE series in this study. Finally, the responses of the ASE series to changes in oil prices will be examined under the vector autoregressive (VAR) framework using impulse responses and variance decomposition analysis. The vector of six endogenous variables will be estimated in the following order (Blot et al., 2015): oil price (lnOIL), bank index (lnBANK), financial index (lnFIN), financial services index (lnFS), insurance index (lnINS), and real estate index (lnRE). The VAR specification can be proposed as the following:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \ldots\ldots\ldots\ldots + \beta_n y_{t-n} + \varepsilon_t \qquad (18)$$

Where y_{t-n} is the lagged values of y, β_0 is a k × 1 vector of intercepts, β_n is a time-invariant k × k matrix and ε_t is a k × 1 vector of error terms which have stationary process. It is important to note that series in equation (1) have to be the same order of integration.

6.3 Results and Discussion

Table 4 presents descriptive statistics of series at level and natural logarithm forms while Figure 1 plots line graphs of logarithmic series. Figure 1 shows that the ASE series are at a downward trend owing to political and economic problems in Jordan and all the ASE series show a very similar movement during the data period that is many ups and downs in the ASE series exhibit huge similarity. However, oil price series shows considerably different movements with the ASE series (See Table 4), (See Figure 1).

Table 4: Descriptive Statistics

	BANK	FIN	FS	INS	OIL	RE
Mean	4159.738	3338.066	3865.698	2579.432	79.85701	3573.619
Max	6984.500	7473.600	17680.10	5983.500	143.9500	9987.400
Min	3264.400	2277.300	1440.900	1718.000	26.01000	1591.400
Stdev	608.7415	1019.139	3273.835	868.2969	26.76554	2522.226
	lnBANK	lnFIN	lnFS	lnINS	lnOIL	lnRE
Mean	8.323213	8.074508	7.981111	7.807726	4.319430	7.986569
Max	8.851449	8.919132	9.780195	8.696761	4.969466	9.209080
Min	8.090831	7.730746	7.273023	7.448916	3.258481	7.372369
Stdev	0.139385	0.265818	0.700360	0.296181	0.357134	0.582093
N	2968	2968	2968	2968	2968	2968

Table 5 presents the ZA (1992) unit root test results for the series. Results show that all of the ASE series are integrated of order zero, I (0), suggesting that they are stationary series at the levels. However, the oil price series (lnOIL) are not stationary at its level but becomes stationary at its first difference. Thus, lnOIL is integrated of order one, I (1), unlike the ASE series. Results of the ZA (1992) unit root tests supports previous inference from Figure 1 in the sense that oil price movements exhibit difference from those of the ASE series of this study; that is, since oil prices and the ASE series are integrated of different orders, there isn’t any convergence among them towards long term equilibrium path (see Table 5).

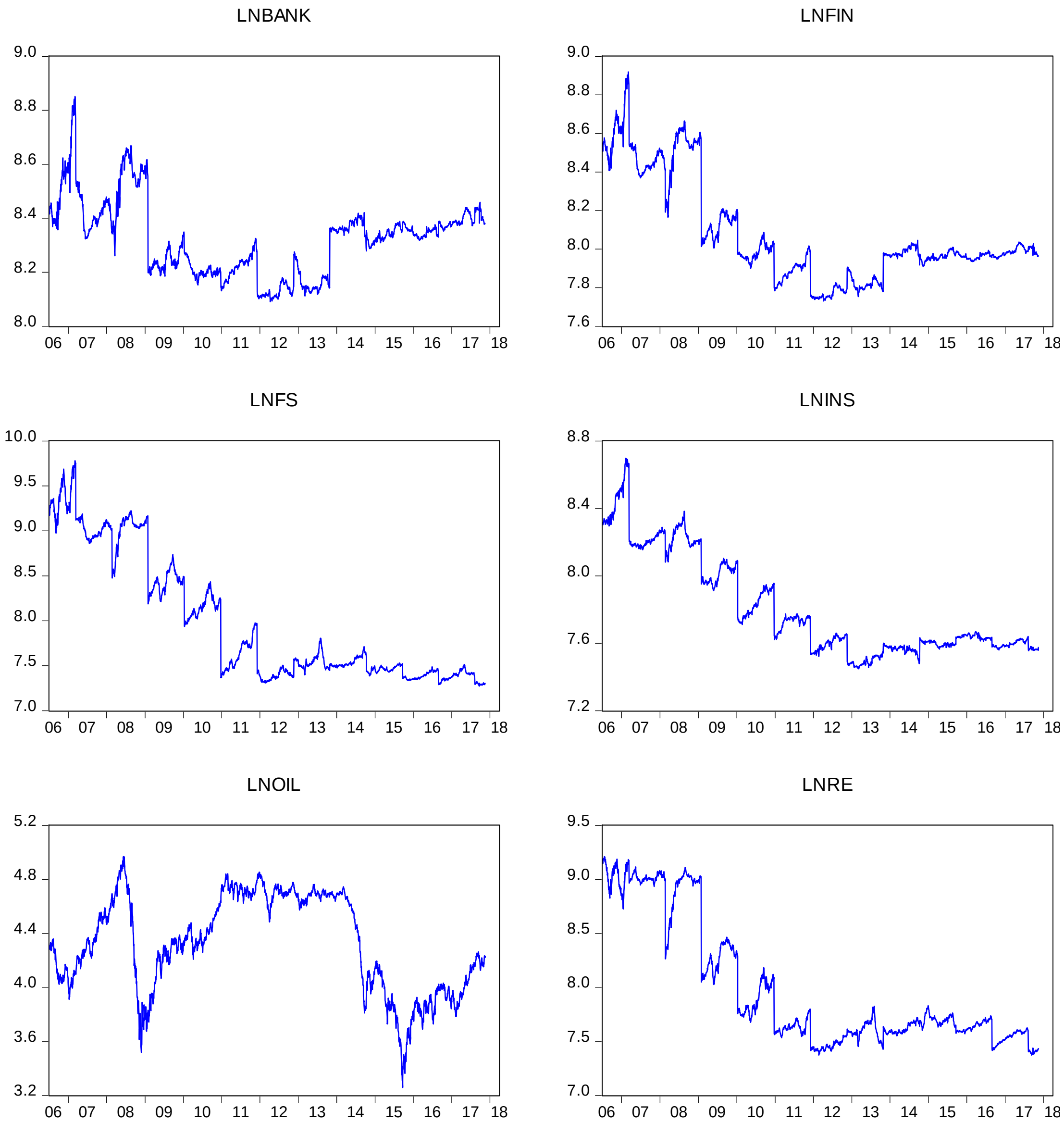

Figure 1: Line Plots of Series over Days

Table 5: Zivot-Andrews (1992) Unit Root Tests

Variable	A. Intercept	B. Trend	C. Both	Decision
lnBANK	-6.154*	-4.369***	-6.155*	I (0)
lnFIN	-6.289*	-4.898*	-6.303*	I (0)
lnFS	-5.427*	-5.557*	-6.675*	I (0)
lnINS	-4.490***	-5.333*	-5.585*	I (0)
lnOIL	-3.635	-2.251	-3.199	I (1)

Note: Option A is the model with intercept, option B is with trend, and C is with both trend and intercept. * and *** denote the rejection of the null hypothesis of a unit root at the 0.01 and 0.10 levels respectively.

Table 5 has shown that oil prices do not converge with the ASE series towards long term equilibrium. In the next step, correlation coefficients and linear fit between oil prices and the ASE series will be searched. Table 6 presents the correlation coefficient matrix. Results show that although the ASE series are correlated with each other at high levels, oil prices are negatively correlated with the ASE series but at very low levels. Even the correlation between oil price and financial services index is not statistically significant. The ASE series that is at the highest correlation coefficient with oil price is banking index ($r = -.368$, $p < 0.01$). The major conclusion from Table 6 is that although the ASE sectors under consideration are negatively affected from oil price movements, their degrees are very low (see Table 6).

Table 6: Correlation Coefficients

		lnBANK	lnFIN	lnFS	lnINS	lnOIL	lnRE
lnBANK	Pearson Correlation	1					
	Sig. (2-tailed)						
	N	2968					
lnFIN	Pearson Correlation	,828**	1				
	Sig. (2-tailed)	,000					
	N	2968	2968				
lnFS	Pearson Correlation	,570**	,927**	1			
	Sig. (2-tailed)	,000	,000				
	N	2968	2968	2968			
lnINS	Pearson Correlation	,601**	,927**	,970**	1		
	Sig. (2-tailed)	,000	,000	,000			
	N	2968	2968	2968	2968		
lnOIL	Pearson Correlation	-,398**	-,197**	-,006	-,054**	1	
	Sig. (2-tailed)	,000	,000	,758	,003		
	N	2968	2968	2968	2968	2968	
lnRE	Pearson Correlation	,625**	,949**	,975**	,952**	-,073**	1
	Sig. (2-tailed)	,000	,000	,000	,000	,000	
	N	2968	2968	2968	2968	2968	2968

Note: **. Correlation is significant at the 0.01 level (2-tailed).

Figure 2 plots the linear fits between oil prices and the ASE series and strongly supports correlation estimates in Table 5. According to Figure 2, there is not any clear linear relationship between oil prices and stock indices in the ASE. But, one more time, Figure 2 supports findings in Table 5 that banking index in the ASE has the highest but negative correlation with oil prices. In the plot of linear fit between lnOil and lnBANK shows that estimated observations are loaded at the bottom part of graph and they are negatively sloped (see Figure 2).

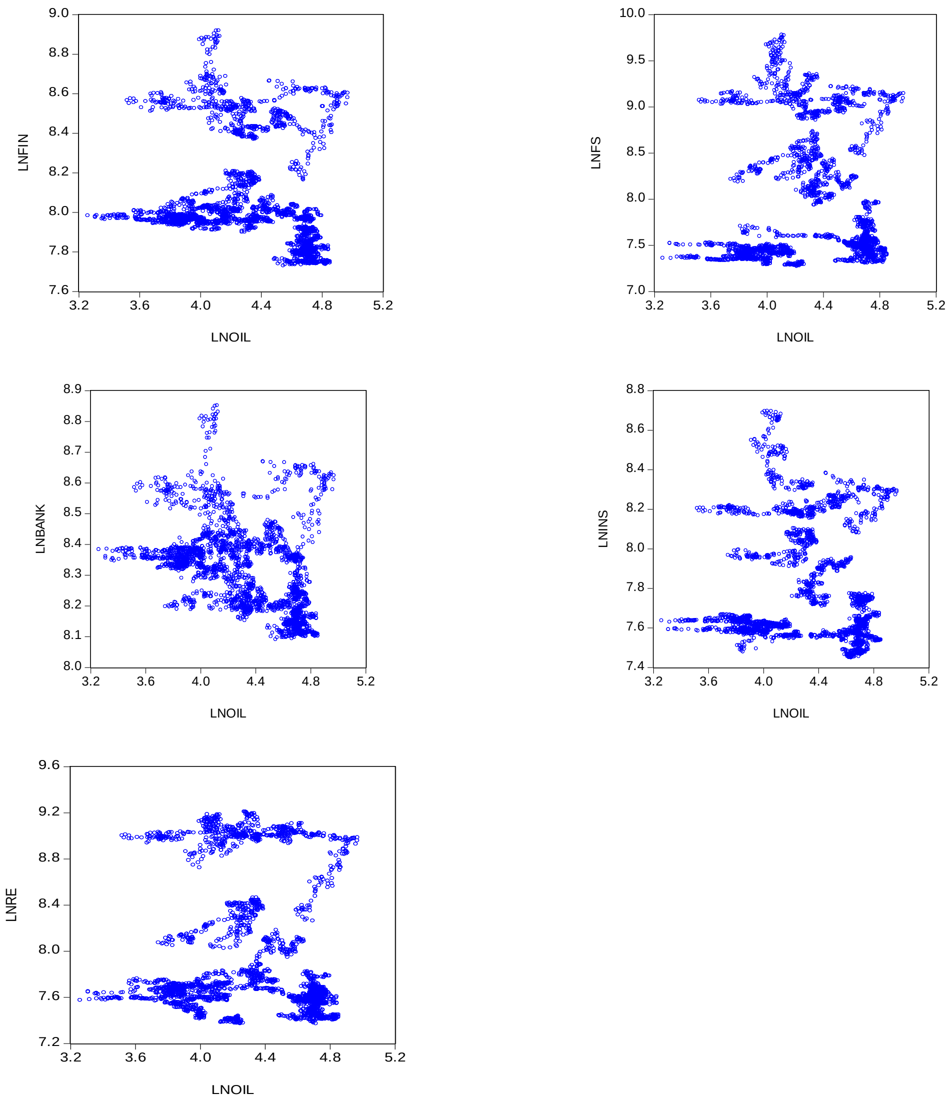

Figure 2: Linear Fit of Series

In the next step, impulse response functions will be examined using the VAR framework. All the series have been differenced at their first orders as per the requirement of the VAR methodology mentioned previously. Figure 3 plots impulse responses of the ASE series against changes or shocks in oil prices. It is clearly seen that the ASE stock indices are highly irresponsive against any shock in oil prices. Those negative reactions of the ASE series towards shocks in oil prices in Figure 3 are not statistically significant (see Figure 3).

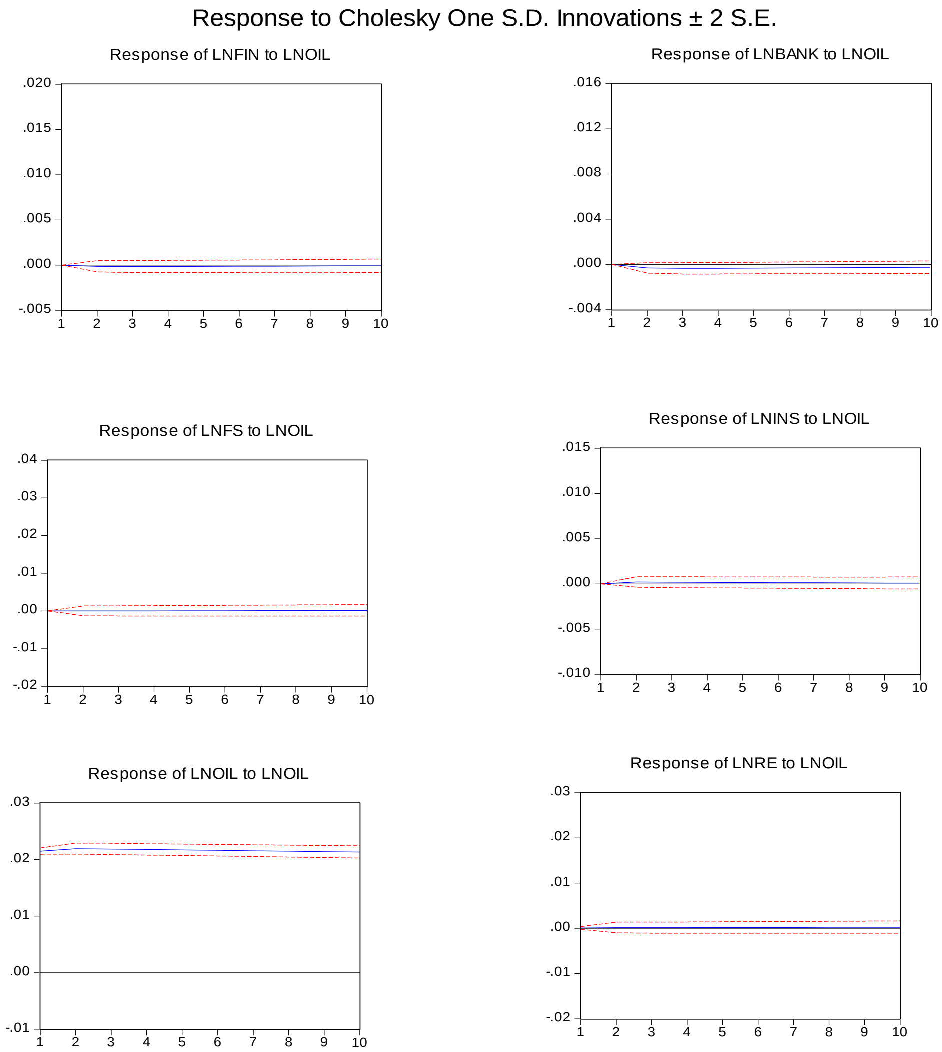

Figure 3: Impulse Response Functions

Finally, Table 7 presents variance decompositions of the ASE series against changes in oil prices. Again, results are very similar to those in correlation and impulse response analyses that quite low levels of the forecast variance of the ASE series are explained by exogenous shocks to international oil prices; that is almost all forecast variances in any period are close to zero (See Table 7).

Table 7. Variance Decomposition of the ASE Series with Respect to Oil Price Changes

Period	lnFIN	lnBANK	lnFS	lnINS	lnRE
1	0.000000	0.000000	0.000000	0.000000	0.000326
2	0.003135	0.029280	0.000000	0.008276	0.001251
3	0.005089	0.043221	0.000000	0.009464	0.001493
4	0.005823	0.049151	0.000000	0.009556	0.001695
5	0.006008	0.051670	0.000004	0.009313	0.001906
6	0.005940	0.052546	0.000000	0.008929	0.002129
7	0.005747	0.052537	0.000135	0.008483	0.002365
8	0.005491	0.052015	0.000228	0.008012	0.002612
9	0.005207	0.051184	0.000346	0.007538	0.002871
10	0.004914	0.050163	0.000488	0.007073	0.003141

6.4 Conclusion

This study searched for the links between stock indices of financial sectors in the Amman Stock Exchange using daily data. Results showed that financial performance of firms in the ASE are at downturn during the data period due to country specific developments; even international oil price movements do not significantly impact on the stock performance of financial sectors in Jordan. Although stock performance in the ASE is negatively related with oil prices, they are not high and statistically significant. Finally, this study has shown that downward trends in the ASE stock performances are independent of international oil price movements and energy sector. It is very interesting to observe that although Jordan is heavily depending on energy and oil imports, banking and financial sector activities are not significantly affected from energy and oil price changes according to the results of this study.

Chapter 7

CONCLUSION AND POLICY IMPLICATIONS

7.1 Summary of Major Findings

Models for ARIMA can be founded by using three stages; identification, estimation, diagnostic checking and the proposed model then can be applied in forecasting. There are many fundamental concepts that are demonstrated to support the fitted model for ASE sectors including mean square error which is definite such as a degree of exactness of the close-fitting model, and the t-value which tests the hypothesis of the study whether acceptance or rejection, finally p-value which tests whether there is a significance or not. We have tested the stationarity of ASE sectors at level and found that it has achieved for banks, insurance, and services, and industry.

The appropriate model Banking sector, is ARIMA (1, 0, 0), defined as:

$$Z_t = 0.002399 + 0.723238 a_{t-1} \qquad (19)$$

The main findings are the CGARCH model that outperforms other models when the models are evaluated for the insurance sector volatility. The proof of the proposed tentative CGARCH model is sustained by AIC, SC, and HQIC criterion and the log likelihood. Finally, banking and financial sector activities are not significantly affected from energy and oil price changes according to the results of this study.

7.2 Policy Implications

Volatility in finance is defined as the degree of financial prices fluctuate, the situation at a large volatility of returns means these returns oscillate over a varied range of outcomes. While, the situation with a small volatility means that these returns or financial prices fluctuate under a wide range of outcomes. The relative changes of volatility are the target of a great deal with respect to research in financial economics, as well as econometrics, and mathematics. This study could be the core of many researches on financial markets in general as well as, in particular, Amman Stock Exchange.

This study's outcomes have important implications for policymakers. Policy makers should take in their consideration the risks while forecasting and planning strategies to improve risk management, portfolio management, asset pricing, and financial decisions. On the other hand, they should not care about oil prices when they take their investment decisions, since there are no interactions between oil prices and financial sectors' performance as what we showed in the entire study.

Policy analysis that focuses on demand for oil or supply of oil alternatives typically underscores the impact of either on prices. But policy could also, in principle, alter volatility directly by increasing the responsiveness of oil supply and demand. How might demand-side government policies be set for those that promote electric vehicles, plug-in hybrids, and public transportation affect elasticity of oil demand? How might government support for oil alternatives, such as biofuels and natural-gas vehicles, affect elasticity of oil demand or of fuel supply? How might government subsidy oil production, such as intangible drilling costs expensing, percentage depletion, and the manufacturing tax credit, which affect elasticity of oil supply? These are the important policy lessons that governments can take into consideration.

7.3 Research Limitations

Considering the limitation of the study, the first problem that the author faced was when choosing the family of models that can be employed in the study, because there are many proposed mechanisms. Other limitation of the study refers to the data availability at the time this study had been carried out.

7.4 Further Research Directions

There are many forecasting methods that can be used to measure the goodness of fit for the time series of Amman Stock Exchange like advanced GARCH models, ARFIMA models. On the other hand, we can use another software in modeling the appreciate model for the financial time series, and then compare its results with other programs results. There are many details can be illustrated in ARIMA models with more explanations**.** We propose that governors do not need to pay too much attention to oil price movements while planning for sustainability and growth in banking and financial sectors in Jordan. Since the results of this study are interesting to our knowledge, we propose that similar comparisons can be studied in the case of the other countries/economies; even similar comparisons can be made between oil price movements and economic sectors of Jordan other than banking and financial markets in order to see if they are sensitive to oil and energy market changes in such an oil-import dependent country. Finally, another choices of the data frequency might be applied, for instance, annually, semiannually, and quarterly for the ASE in the later periods as well as the other countries.

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APPENDICES

Appendix A: List of Tables

Table 8: Summary Descriptive Statistics for Banking Sector in ASE

Estimators	Banking index	Banking index volatility
Mean	8100.468	0.002400
Median	8177.600	0.001383
Maximum	9587.600	0.215351
Minimum	4561.600	0.000000
Std. Dev.	701.5585	0.008572
Skewness	-0.025818	22.93
Kurtosis	2.123420	566.96
Variance	492184.33	0.0000735
Total count	1328	1327

Table 9: Unit Root Test for the Banking Sector Index Volatility in ASE at level

Prob	t-stat	1%	5%	10%
0.000	-14.2539	-3.435089	-2.863520	-2.567874

Table 10: ACF and PACF for the Banking Sector Index Volatility in ASE

Lag	Prob	Q-stat	AC	PAC
1	0.000	312.49	0.485	0.485
2	0.000	313.36	0.026	-0.274
3	0.000	313.74	0.017	0.189
4	0.000	313.77	0.005	-0.128
5	0.000	313.83	0.007	0.098
6	0.000	313.84	0.003	-0.079
7	0.000	313.85	0.003	0.067
8	0.000	313.89	0.005	-0.048
9	0.000	313.94	0.006	0.025
10	0.000	313.95	0.003	-0.017
11	0.000	313.98	0.005	0.019
12	0.000	314.00	0.003	-0.013
13	0.000	315.05	0.028	0.052
14	0.000	322.86	0.076	0.049
15	0.000	327.11	0.056	-0.014
16	0.000	327.14	0.005	-0.004
17	0.000	327.47	-0.016	-0.016
18	0.000	327.78	-0.015	0.000
19	0.000	328.30	-0.020	-0.023
20	0.000	328.44	-0.010	0.020
21	0.000	328.48	-0.006	-0.023
22	0.000	328.51	-0.005	0.016
23	0.000	328.62	-0.009	-0.023
24	0.000	328.69	-0.007	0.017
25	0.000	328.70	-0.003	-0.018
26	0.000	328.71	0.003	0.020
27	0.000	328.75	-0.006	-0.031
28	0.000	328.76	0.002	0.029
29	0.000	328.76	-0.001	-0.035
30	0.000	328.90	-0.010	0.019
31	0.000	329.20	-0.015	-0.028
32	0.000	329.26	-0.006	0.027
33	0.000	329.26	0.001	-0.017
34	0.000	329.27	0.002	0.017
35	0.000	329.29	0.004	-0.009
36	0.000	329.41	-0.009	-0.011

Table 11: Descriptive Statistics of Insurance Sector Index Volatility in ASE

Mean	Med	Min	Max	Var	St. dev	Skew	Kurt
8.606	8.777	2.561	14.551	1.896	1.376	-0.570	4.43

Table 12: Unit Root Test of Insurance Sector

Prob	t-stat	1%	5%	10%
0.000	-5.56	-3.43	-2.86	-2.56

Table 13: ACF and PACF of Actual and Residuals of Insurance Sector Index Volatility in ASE

Series	Actual				Residuals			
Lag	AC	PAC	Q-STAT	Prob	AC	PAC	Q-STAT	Prob
1	0.498	0.498	307.99	0.000	0.022	0.022	0.6109	0.434
2	0.005	-0.323	308.03	0.000	0.015	0.015	0.9033	0.637
3	0.006	0.242	308.07	0.000	-0.036	-0.037	2.5531	0.466
4	0.005	-0.184	308.10	0.000	-0.011	-0.010	2.7036	0.609
5	0.008	0.157	308.17	0.000	0.038	0.040	4.4902	0.481
6	0.009	-0.122	308.28	0.000	-0.017	-0.020	4.8489	0.563
7	0.016	0.123	308.62	0.000	-0.001	-0.002	4.8495	0.678
8	0.018	-0.091	309.04	0.000	0.031	-0.035	6.0741	0.639
9	0.014	0.090	309.26	0.000	0.043	0.041	8.4110	0.493
10	0.011	-0.070	309.41	0.000	-0.041	-0.047	10.549	0.394
11	0.010	0.071	309.53	0.000	-0.022	-0.017	11.137	0.432
12	0.009	-0.056	309.63	0.000	-0.005	0.001	11.168	0.515
13	0.009	0.058	309.72	0.000	0.028	0.024	12.152	0.515
14	0.011	-0.041	309.87	0.000	0.011	0.005	12.303	0.582
15	0.006	0.037	309.91	0.000	-0.050	-0.047	15.442	0.420
16	0.009	-0.018	310.03	0.000	0.006	0.009	15.485	0.489
17	0.005	0.010	310.05	0.000	-0.015	-0.016	15.760	0.541
18	0.010	0.013	310.17	0.000	-0.014	-0.019	16.008	0.592
19	0.010	-0.014	310.28	0.000	-0.023	-0.017	16.659	0.613
20	-0.003	0.008	310.30	0.000	-0.016	-0.011	16.971	0.655
21	0.000	-0.004	310.30	0.000	-0.012	-0.018	17.164	0.701
22	0.004	0.005	310.32	0.000	-0.016	-0.019	17.476	0.737
23	0.007	0.005	310.38	0.000	-0.002	0.003	17.483	0.785
24	0.020	0.021	310.86	0.000	-0.030	-0.025	18.659	0.770
25	0.025	0.002	311.65	0.000	0.007	0.004	18.729	0.810
26	0.015	0.005	311.94	0.000	-0.027	-0.026	19.623	0.809
27	0.004	-0.005	311.96	0.000	0.056	0.058	23.619	0.651
28	0.004	0.010	311.98	0.000	-0.032	-0.032	24.902	0.633
29	0.008	0.000	312.07	0.000	-0.019	-0.020	25.361	0.659
30	0.009	0.007	312.18	0.000	0.021	0.024	25.909	0.680
31	0.006	-0.002	312.23	0.000	-0.028	-0.026	26.894	0.678
32	0.010	0.014	312.36	0.000	0.003	-0.005	26.905	0.722
33	0.014	-0.002	312.60	0.000	0.005	0.012	26.933	0.763
34	0.009	0.006	312.71	0.000	-0.016	-0.019	27.251	0.787
35	0.006	-0.002	312.75	0.000	-0.003	-0.008	27.262	0.822
36	0.003	0.002	312.76	0.000	-0.007	-0.010	27.324	0.850

Table 14: AIC, SC, and HQIC for Different GARCH Models of Insurance Sector Index Volatility in ASE

Model	AIC	SC	HQIC	Log likelihood
ARCH (1)	3.470328	3.482738	3.474995	-2145.133
ARCH (2)	3.469851	3.486397	3.476074	-2143.837
ARCH (3)	3.471449	3.492133	3.479229	-2143.827
GARCH(1,1)	3.470172	3.486719	3.476395	-2144.036
GARCH(1,2)	3.471778	3.492462	3.479558	-2144.031
GARCH(1,3)	3.466200	3.491020	3.475535	-2139.578
GARCH(2,1)	3.471652	3.492335	3.479431	-2143.952
GARCH(2,2)	3.473053	3.497873	3.482388	-2143.819
GARCH(2,3)	3.467724	3.496681	3.478615	-2139.521
GARCH(3,1)	3.472554	3.497374	3.481889	-2143.511
GARCH(3,2)	3.473903	3.502860	3.484794	-2143.346
GARCH(3,3)	3.469037	3.502130	3.481484	-2139.334
TARCH	3.471337	3.492020	3.479116	-2143.757
EGARCH	3.473982	3.494666	3.481762	-2145.395
PARCH	3.474510	3.495193	3.482289	-2145.722
CGARCH	3.448478	3.477435	3.459369	-2127.608

Table 15: Descriptive Statistics of Residuals for the Insurance Sector Index Volatility in ASE

Mean	Med	Min	Max	Var	St. dev	Skew	Kurt
-0.6738	0.0511	-4.3965	4.5192	1.0019	1.0009	-0.6188	4.231

Table 16: Hetroskedasticity test (ARCH test) for the Residuals of Insurance Sector Index Volatility in ASE

	F-statistic	21.81964	Prob. F(1,1235)	0.0000
Variable	Obs*R-squared	21.47556	Prob. Chi-Square(1)	0.0000
	Coefficient	Std. Error	t-Statistic	Prob.
α_0	1.644339	0.112532	14.61220	0.0000
RESID(-1)^2	0.131761	0.028207	4.671150	0.0000
R-squared	0.017361	Mean dependent var	1.893879	
Adjusted R-squared	0.016565	S.D. dependent var	3.512672	
S.E. of regression	3.483456	Akaike info criterion	5.335542	
Sum squared resid	14986.07	Schwarz criterion	5.343821	
Log likelihood	-3298.033	Hannan-Quinn criter.	5.338656	
F-statistic	21.81964	Durbin-Watson stat	2.005464	
Prob(F-statistic)	0.000003			

Table 17: ARCH (1) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.601610	0.043491	197.7782	0.0000
Variance eq	Coefficient	Std. Error	z-Statistic	Prob.
C	1.742680	0.071070	24.52074	0.0000
RESID(-1)^2	0.075887	0.023409	3.241764	0.0012
R-squared	-0.000011	Mean dependent var		8.606138
Adjusted R-squared	-0.000011	S.D. dependent var		1.376948
S.E. of regression	1.376955	Akaike info criterion		3.470328
Sum squared resid.	2345.359	Schwarz criterion		3.482738
Log likelihood	-2145.133	Hannan-Quinn criter.		3.474995
Durbin-Watson stat	1.305869			

Table 18: ARCH (2) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.609849	0.043745	196.8169	0.0000
Variance eq	Coefficient	Std. Error	z-Statistic	Prob.
C	1.669794	0.075559	22.09910	0.0000
RESID(-1)^2	0.071528	0.022430	3.188923	0.0014
RESID(-2)^2	0.043323	0.019846	2.182978	0.0290
R-squared	-0.000007	Mean dependent var		8.606138
Adjusted R-squared	-0.000007	S.D. dependent var		1.376948
S.E. of regression	1.376953	Akaike info criterion		3.469851
Sum squared resid	2345.350	Schwarz criterion		3.486397
Log likelihood	-2143.837	Hannan-Quinn criter.		3.476074
Durbin Watson Stat	1.305873			

Table 19: ARCH (3) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.609374	0.043888	196.1685	0.0000
Variance eq	Coefficient	Std. Error	z-Statistic	Prob.
c	1.675160	0.080513	20.80612	0.0000
RESID(-1)^2	0.071411	0.022435	3.182978	0.0015
RESID(-2)^2	0.043150	0.019909	2.167343	0.0302
RESID(-3)^2	-0.002644	0.017158	-0.154088	0.8775
Adjusted R-squared	-0.000006	S.D. dependent var		1.376948
S.E. of regression	1.376952	Akaike info criterion		3.471449
Sum squared resid	2345.346	Schwarz criterion		3.492133
Log likelihood	-2143.827	Hannan-Quinn criter.		3.479229
Durbin Watson Stat	1.305876			

Table 20: GARCH (1, 1) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.615016	0.044213	194.8510	0.0000
Variance Equation	Coefficient	Std. Error	z-Statistic	Prob.
C	0.839689	0.378737	2.217079	0.0266
RESID(-1)^2	0.071823	0.020833	3.447611	0.0006
GARCH(-1)	0.483461	0.212190	2.278431	0.0227
R-squared	-0.000042	Mean dependent var		8.606138
Adjusted R-squared	-0.000042	S.D. dependent var		1.376948
S.E. of regression	1.376976	Akaike info criterion		3.470172
Sum squared resid	2345.431	Schwarz criterion		3.486719
Log likelihood	-2144.036	Hannan-Quinn criter.		3.476395
Durbin Watson Stat	1.305829			

Table 21: GARCH (1, 2) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	Z-Statistic	Prob.
C	8.617012	0.044304	194.4981	0.0000
Variance eq	Coefficient	Std.Error	Z-Statistics	Prob
C	0.768094	0.380192	2.020279	0.0434
RESID(-1)^2	0.070709	0.021881	3.231523	0.0012
GARCH(-1)	0.487299	0.310195	1.570941	0.1162
GARCH(-2)	0.035366	0.280381	0.126134	0.8996
R-squared	-0.000062	Mean dependent var		8.606138
Adjusted R-squared	-0.000062	S.D. dependent var		1.376948
S.E. of regression	1.376991	Akaike info criterion		3.471778
Sum squared resid	2345.480	Schwarz criterion		3.492462
Log likelihood	-2144.031	Hannan-Quinn criter.		3.479558
Durbin Watson Stat	1.305801			

Table 22: GARCH (1, 3) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.628506	0.044339	194.6052	0.0000
Variance eq	Coefficient	Std. Error	z-Statistics	Prob
C	0.635576	0.291259	2.182167	0.0291
RESID(-1)^2	0.074485	0.017489	4.258932	0.0000
GARCH(-1)	0.531875	0.082883	6.417144	0.0000
GARCH(-2)	-0.613972	0.068653	-8.943137	0.0000
GARCH(-3)	0.672050	0.095136	7.064092	0.0000
R-squared	-0.000264	Mean dependent var		8.606138
Adjusted R-squared	-0.000264	S.D. dependent var		1.376948
S.E. of regression	1.377130	Akaike info criterion		3.466200
Sum squared resid	2345.953	Schwarz criterion		3.491020
Log likelihood	-2139.578	Hannan-Quinn criter.		3.475535
Durbin Watson Stat	1.305538			

Table 23: GARCH (2, 1) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.619257	0.044558	193.4373	0.0000
Variance eq	Coefficient	Std.Error	z-Stat	Prob
C	0.496351	0.477133	1.040279	0.2982
RESID(-1)^2	0.072811	0.022568	3.226368	0.0013
RESID(-2)^2	-0.022267	0.037087	-0.600416	0.5482
GARCH(-1)	0.686870	0.280011	2.453012	0.0142
R-squared	-0.000091	Mean dependent var		8.606138
Adjusted R-squared	-0.000091	S.D. dependent var		1.376948
S.E. of regression	1.377010	Akaike info criterion		3.471652
Sum squared resid	2345.547	Schwarz criterion		3.492335
Log likelihood	-2143.952	Hannan-Quinn criter.		3.479431
Durbin Watson Stat	1.305764			

Table 24: GARCH (2, 2) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.618349	0.044608	193.2009	0.0000
Variance eq	Coefficient	Std.Error	z-Stat	Prob
C	0.304293	0.984160	0.309190	0.7572
RESID(-1)^2	0.074382	0.023011	3.232441	0.0012
RESID(-2)^2	-0.044530	0.092430	-0.481771	0.6300
GARCH(-1)	1.004995	1.307709	0.768516	0.4422
GARCH(-2)	-0.195817	0.722806	-0.270913	0.7865
R-squared	-0.000079	Mean dependent var		8.606138
Adjusted R-squared	-0.000079	S.D. dependent var		1.376948
S.E. of regression	1.377002	Akaike info criterion		3.473053
Sum squared resid	2345.518	Schwarz criterion		3.497873
Log likelihood	-2143.819	Hannan-Quinn criter.		3.482388
Durbin Watson Stat	1.305780			

Table 25: GARCH (2, 3) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.628988	0.044412	194.2929	0.0000
Variance eq	Coefficient	Std. Error	z-Statistic	Prob
C	0.677183	0.399694	1.694251	0.0902
RESID(-1)^2	0.073715	0.018061	4.081469	0.0000
RESID(-2)^2	0.008420	0.025666	0.328041	0.7429
GARCH(-1)	0.501339	0.149165	3.360976	0.0008
GARCH(-2)	-0.606012	0.067350	-8.997954	0.0000
GARCH(-3)	0.665057	0.106824	6.225713	0.0000
R-squared	-0.000276	Mean dependent var		8.606138
Adjusted R-squared	-0.000276	S.D. dependent var		1.376948
S.E. of regression	1.377137	Akaike info criterion		3.467724
Sum squared resid	2345.980	Schwarz criterion		3.496681
Log likelihood	-2139.521	Hannan-Quinn criter.		3.478615
Durbin-Watson stat	1.305523			

Table 26: GARCH (3, 1) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.618778	0.044553	193.4498	0.0000
Variance eq	Coffecient	Std.Error	z-Statistic	Prob
C	0.368881	0.809193	0.455864	0.6485
RESID(-1)^2	0.071377	0.022295	3.201415	0.0014
RESID(-2)^2	-0.009037	0.047576	-0.189954	0.8493
RESID(-3)^2	-0.026083	0.035610	-0.732470	0.4639
GARCH(-1)	0.768649	0.493934	1.556175	0.1197
R-squared	-0.000084	Mean dependent var		8.606138
Adjusted R-squared	-0.000084	S.D. dependent var		1.376948
S.E. of regression	1.377006	Akaike info criterion		3.472554
Sum squared resid	2345.531	Schwarz criterion		3.497374
Log likelihood	-2143.511	Hannan-Quinn criter.		3.481889
Durbin-Watson stat	1.305773			

Table 27: GARCH (3, 2) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.620403	0.044653	193.0522	0.0000
Variance eq	Coefficient	Std. Error	z-Statistic	Prob.
C	0.478753	1.082718	0.442177	0.6584
RESID(-1)^2	0.071081	0.022212	3.200062	0.0014
RESID(-2)^2	0.013550	0.089290	0.151749	0.8794
RESID(-3)^2	-0.035005	0.036605	-0.956293	0.3389
GARCH(-1)	0.504505	1.204554	0.418831	0.6753
GARCH(-2)	0.192737	0.665528	0.289600	0.7721
R-squared	-0.000107	Mean dependent var		8.606138
Adjusted R-squared	-0.000107	S.D. dependent var		1.376948
S.E. of regression	1.377022	Akaike info criterion		3.473903
Sum squared resid	2345.585	Schwarz criterion		3.502860
Log likelihood	-2143.346	Hannan-Quinn criter.		3.484794
Durbin-Watson stat	1.305743			

Table 28: GARCH (3, 3) Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.628868	0.044340	194.6070	0.0000
Variance eq	Coefficient	Std. Error	z-Statistic	Prob.
C	0.801885	0.599364	1.337892	0.1809
RESID(-1)^2	0.080141	0.021623	3.706223	0.0002
RESID(-2)^2	0.002069	0.028095	0.073644	0.9413
RESID(-3)^2	0.014941	0.026401	0.565913	0.5715
GARCH(-1)	0.488637	0.186359	2.622023	0.0087
GARCH(-2)	-0.653272	0.108827	-6.002842	0.0000
GARCH(-3)	0.643971	0.130058	4.951430	0.0000
R-squared	-0.000273	Mean dependent var		8.606138
Adjusted R-squared	-0.000273	S.D. dependent var		1.376948
S.E. of regression	1.377135	Akaike info criterion		3.469037
Sum squared resid	2345.973	Schwarz criterion		3.502130
Log likelihood	-2139.334	Hannan-Quinn criter.		3.481484
Durbin-Watson stat	1.305527			

Table .29: TARCH Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error		Prob.
C	8.649419	0.044752	193.2735	0.0000
Variance eq	Coefficient	Std. Error		
C	0.468709	0.214136	2.188843	0.0286
RESID(-1)^2	0.048033	0.014530	3.305771	0.0009
RESID(-1)^2*(RESID(-1)<0)	0.029734	0.025427	1.169377	0.2423
GARCH(-1)	0.687711	0.122988	5.591673	0.0000
R-squared	-0.000989	Mean dependent var		8.606138
Adjusted R-squared	-0.000989	S.D. dependent var		1.376948
S.E. of regression	1.377628	Akaike info criterion		3.471337
Sum squared resid	2347.653	Schwarz criterion		3.492020
Log likelihood	-2143.757	Hannan-Quinn criter.		3.479116
Durbin-Watson stat	1.304593			

Table 30: EGARCH Model of Insurance Sector Index Volatility in ASE

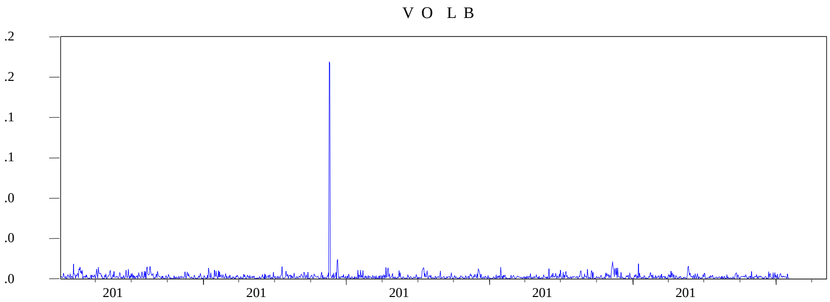
Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.674797	0.045398	191.0823	0.0000
Variance eq	Coefficient	Std. Error	z-Statistic	Prob.
C(2)	0.042486	0.057983	0.732739	0.4637
C(3)	0.122528	0.029451	4.160464	0.0000
C(4)	-0.038961	0.018642	-2.089928	0.0366
C(5)	0.779991	0.103802	7.514219	0.0000
R-squared	-0.002488		Mean dependent var	8.606138
Adjusted R-squared	-0.002488		S.D. dependent var	1.376948
S.E. of regression	1.378660		Akaike info criterion	3.473982
Sum squared resid	2351.169		Schwarz criterion	3.494666
Log likelihood	-2145.395		Hannan-Quinn criter.	3.481762
Durbin-Watson stat	1.302642			

Table 31: PARCH Model of Insurance Sector Index Volatility in ASE

Mean eq	Coefficient	Std. Error	z-Statistic	Prob.
C	8.674552	0.045349	191.2828	0.0000
Variance eq	Coefficient	Std. Error	z-Statistic	Prob.
C(2)	0.308150	0.152304	2.023262	0.0430
C(3)	0.058791	0.015841	3.711330	0.0002
C(4)	0.348689	0.137956	2.527549	0.0115
C(5)	0.729387	0.117814	6.190989	0.0000
R-squared	-0.002471	Mean dependent var		8.606138
Adjusted R-squared	-0.002471	S.D. dependent var		1.376948
S.E. of regression	1.378648	Akaike info criterion		3.474510
Sum squared resid	2351.128	Schwarz criterion		3.495193
Log likelihood	-2145.722	Hannan-Quinn criter.		3.482289
Durbin-Watson stat	1.302665			

Appendix B: List of Figures

Figure 4: Banking Sector Index



Figures 5: Volatility of Banking Sector Index

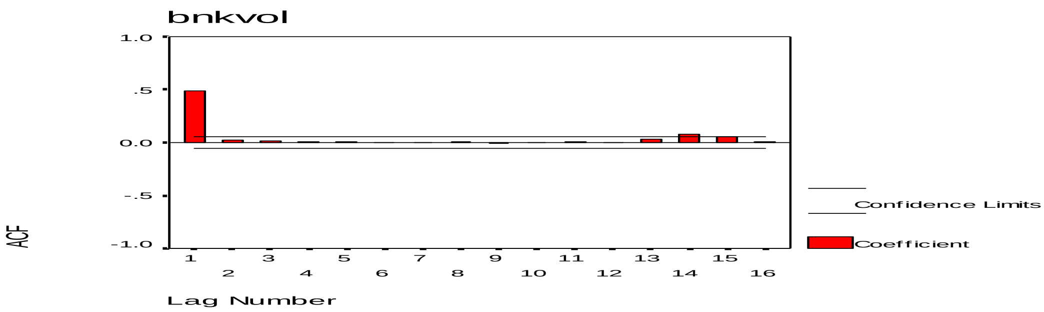


Figure 6: Autocorrelation of Banking Sector Volatility

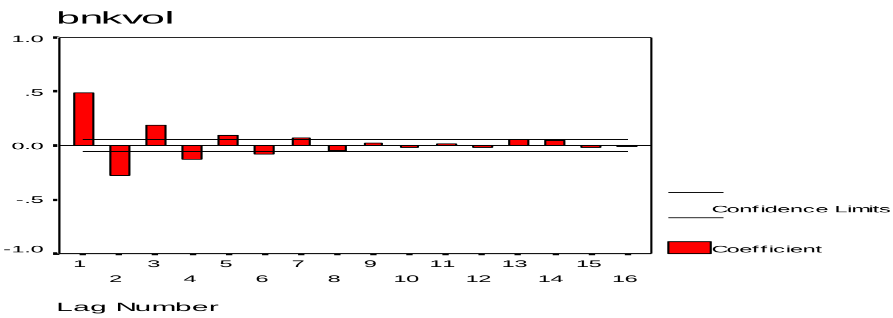


Figure 7: Partial autocorrelation of Banking Sector Volatility

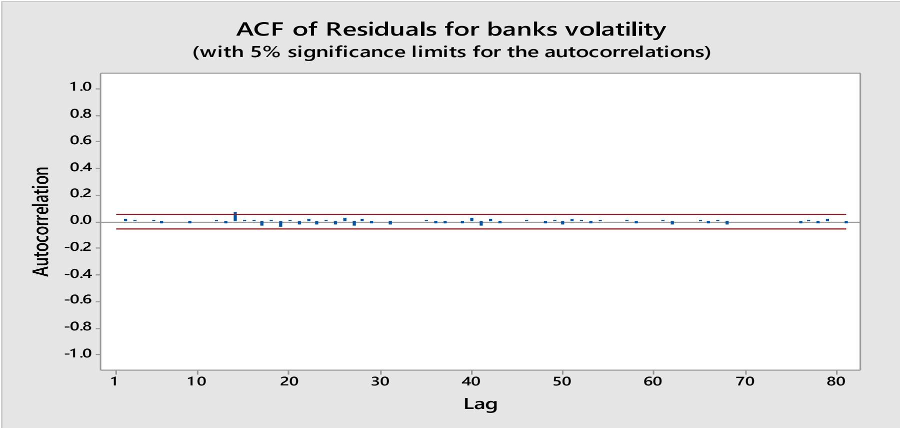


Figure 8: Autocorrelation of Residuals: Banking Sector Volatility

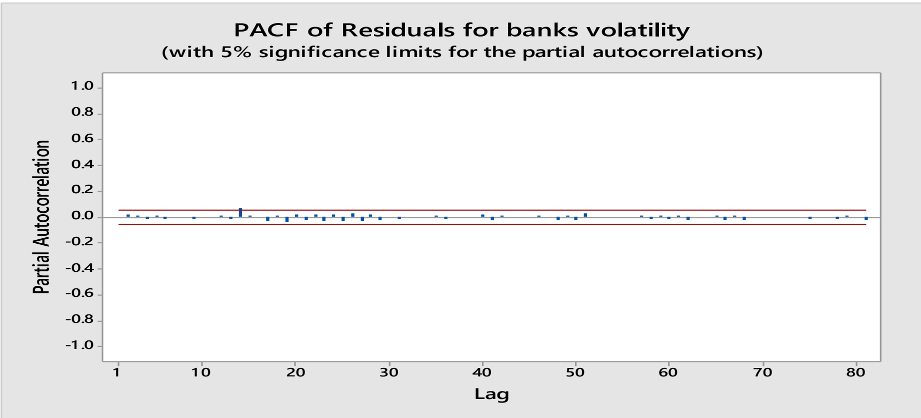


Figure 9: Partial Autocorrelation of Residuals: Banks Sector Volatility

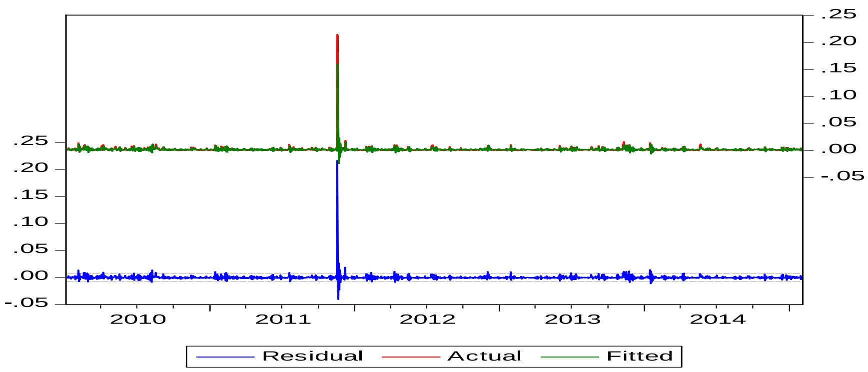


Figure 10: Actual, Fitted, Residual Graph for Banking Sector Volatility

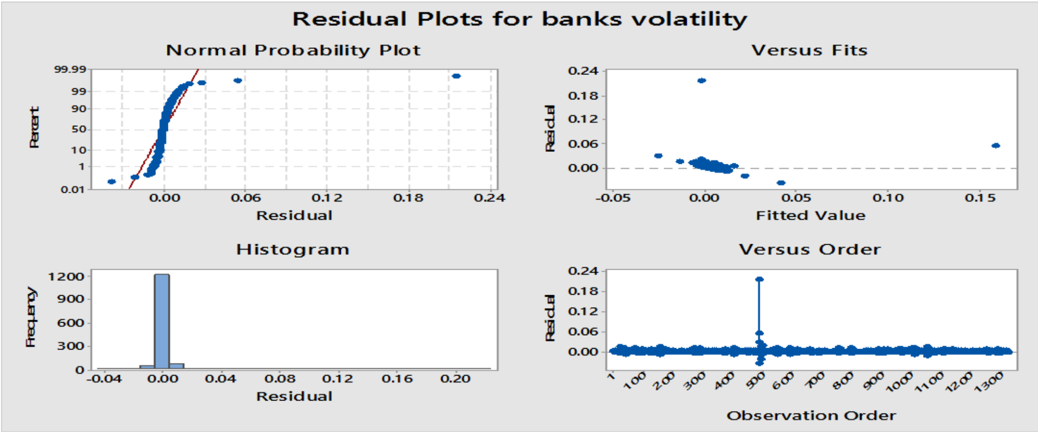


Figure 11: Four in One Residual Plots for Banks Sector Volatility

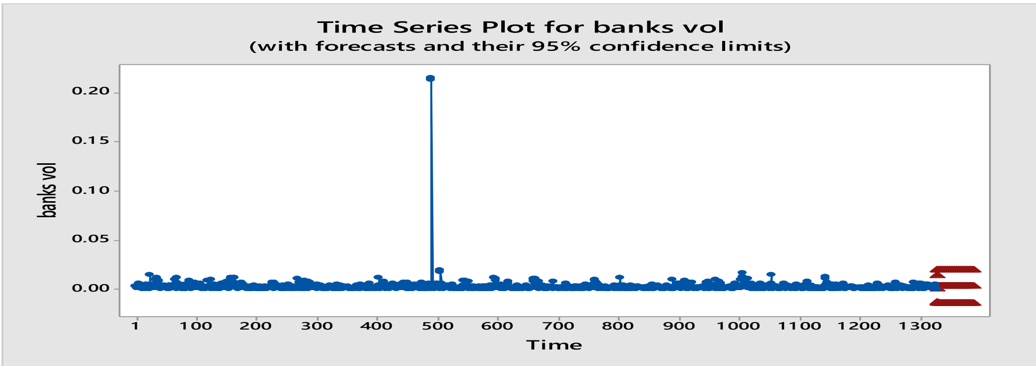


Figure 12: Actual and Forecasts Volatility Banking for ASE

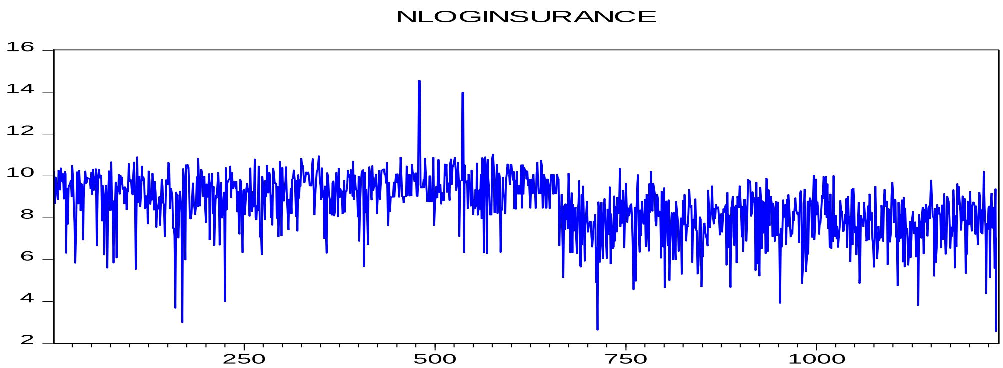


Figure 13: Graph of Insurance Sector Volatility

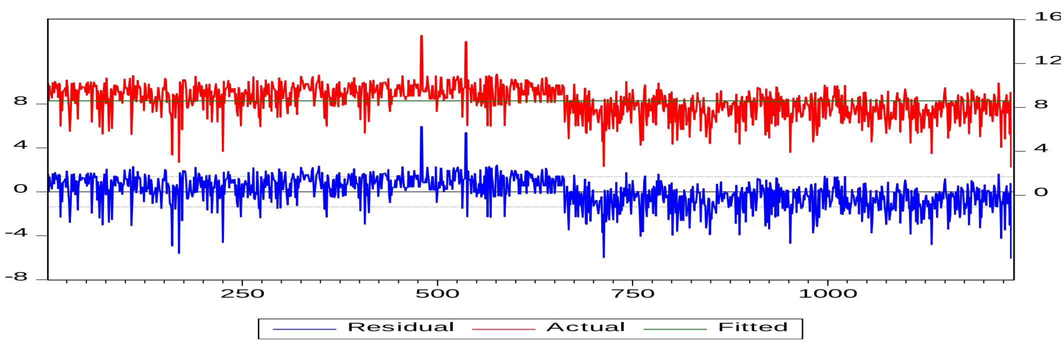


Figure 14: Graph of the Residuals, Actual, Fitted

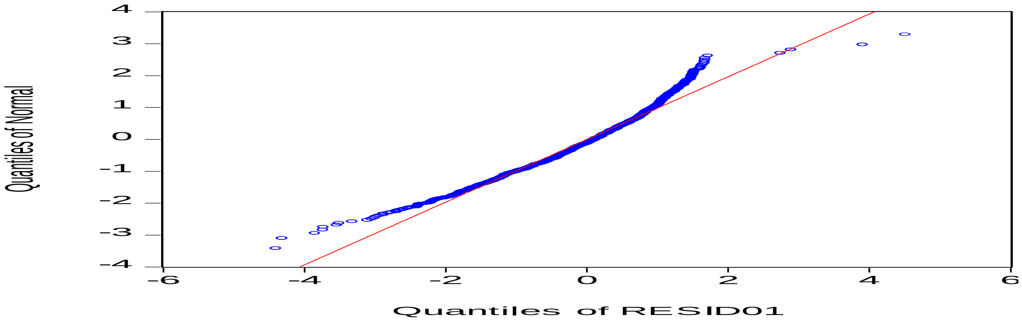


Figure 15: Graph of the Quantiles of Residuals Insurance Sector Volatility