A PANEL IN GARCH ANALYSIS OF STOCK RETURN

VOLATILITY IN AN EMERGING MARKET:

A CASE STUDY OF EGYPT

BY

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A THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS

FOR THE AWARD OF THE DEGREE

DOCTOR OF PHILOSOPHY (FINANCE)

SCHOOL OF ECONOMICS AND FINANCE

COLLEGE OF LAW AND BUSINESS

UNIVERSITY OF WESTERN SYDNEY

JULY 2006
A PANEL IN GARCH ANALYSIS OF STOCK RETURN VOLATILITY IN AN EMERGING MARKET: A CASE STUDY OF EGYPT

ABSTRACT

The modelling of stock market volatility is considered to be important for practitioners and academics in finance due to its use in forecasting aspects of future returns. The GARCH class models have now firmly established themselves as one of the foremost techniques for modelling volatility in financial markets.

The application of GARCH class models in developed and emerging markets (including the Egyptian Stock Market) provides evidence of GARCH effects in stock returns. However, most of the studies conducted on modelling the volatility of stock returns are based on the aggregated market index. This thesis argues that this will not reflect significant differences of variation in the pattern of volatility associated with different stocks. However, in order to examine the similarities and differences between the conditional variance structures of stocks from the same or different industries in the same equity market, this thesis estimates pooled-panel models. These novel models are used to test for similarities and differences in the conditional variance equation in panels of time series within a general to specific framework of nested tests. This is done using panel samples of sector indices and stocks from the Egyptian Stock Market covering the period from 1997 to 2002.

The results suggest that there are similarities in the temporal volatility structures of stocks from the same sector or industry, but there are significant differences in the temporal volatility structures of stocks from different sectors or industries. This suggests that using indices alone for modelling the volatility of an equity market, which is the method used in the majority of studies cited in the literature, may not be appropriate. The thesis concludes with a discussion of some of the implications of these results and suggestions for further research.
STATEMENT OF AUTHENTICATION

I, Walid Bakry, declare that this thesis has not been submitted, either in whole or in part, for a degree at this university or any other academic institution. I also certify that the work presented in this thesis is, to the best of my knowledge and belief, my own work and original except as acknowledged in the text.

Walid Bakry

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Signature of Candidate
DEDICATION

TO MY FAMILY AND IN MEMORY OF MY MOTHER
ACKNOWLEDGMENTS

This work would never have been completed without my supervisors. First and foremost, I am forever indebted to my principal supervisor Dr. Roger Ham, who has been very supportive throughout. His keen mind, abilities and expert guidance put me on the right track and enabled me to complete this research. I would like to thank him for his hard work and patience. I am also grateful to my co-supervisor, Dr. Michael Rafferty, for his support and encouragement.

I wish to thank Professor Raja Junankar for his valuable support especially in determining an appropriate environment for postgraduate studies in the School of Economics and Finance. I am grateful to both the academic and administrative staff at the School of Economics and Finance of UWS: Gloria Graham, Dr. John Ablett, Trish O’Brien, and Jo Roger for their friendly support. I would also like to extend my appreciation to Mark Reed for his excellent editing and proof-reading of the final draft of this thesis.

I would like to express my gratitude to my fellow PhD students in the School of Economics and Finance of UWS. Special thanks go to my friends Hussam El-Malkawi and Mohammad Magableh for their kind advice and continuous encouragement. I would like to thank a special friend Joyce Tapper for her valuable assistance and support. Finally, a special thanks to Natalie Spark and her family, Meredith Arnold, Muneer and Nasser Hamaid, Omar Besiso, and Richard Gronvall who were so kind and supportive and were my family during my stay in Australia. Thank you all, without your support this study would have not been possible.

Walid Bakry
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<td>ACWI</td>
<td>All Country World Index</td>
</tr>
<tr>
<td>ARCH</td>
<td>Autoregressive Conditional Heteroskedasticity</td>
</tr>
<tr>
<td>ARMA</td>
<td>Autoregressive Moving Average</td>
</tr>
<tr>
<td>CASE</td>
<td>Cairo and Alexandria Stock Exchanges</td>
</tr>
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<td>CMA</td>
<td>Capital Market Authority</td>
</tr>
<tr>
<td>CMAI</td>
<td>Capital Market Authority Index</td>
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<tr>
<td>DGP</td>
<td>Data Generating Process</td>
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<tr>
<td>ECM</td>
<td>Egyptian Capital Market</td>
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<td>ESM</td>
<td>Egyptian Stock Market</td>
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<tr>
<td>EFGI</td>
<td>Egyptian Financial Group Index</td>
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<tr>
<td>EMFI</td>
<td>Emerging Markets Free Index</td>
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<tr>
<td>EMH</td>
<td>Efficient Market Hypothesis</td>
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<tr>
<td>EGARCH</td>
<td>Exponential Generalised Autoregressive Conditional Heteroskedasticity</td>
</tr>
<tr>
<td>FIGARCH</td>
<td>Fractionally Integrated Generalised Autoregressive Conditional Heteroskedasticity</td>
</tr>
<tr>
<td>GARCH</td>
<td>Generalised Autoregressive Conditional Heteroskedasticity</td>
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<tr>
<td>GARCH-M</td>
<td>Generalised Autoregressive Conditional Heteroskedasticity in Mean</td>
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<tr>
<td>GDP</td>
<td>Gross Domestic Product</td>
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<tr>
<td>GDR</td>
<td>Global Depository Receipts</td>
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<tr>
<td>GICS</td>
<td>Global Industry Classification Standard</td>
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<tr>
<td>HFI</td>
<td>Hermes Financial Index</td>
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<tr>
<td>HL</td>
<td>Half Life</td>
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<tr>
<td>IFC</td>
<td>International Finance Corporation</td>
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<tr>
<td>IMF</td>
<td>International Monetary Fund</td>
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<tr>
<td>IPO</td>
<td>Initial Public Offerings</td>
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<tr>
<td>L.E.</td>
<td>Livre Égyptien</td>
</tr>
<tr>
<td>LM</td>
<td>Lagrange Multiplier</td>
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<tr>
<td>LLR</td>
<td>Likelihood Ratio Test Statistics</td>
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<tr>
<td>LRT</td>
<td>Likelihood Ratio Test</td>
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<tr>
<td>MCSD</td>
<td>Misr for Clearing, Settlement and Central Depository</td>
</tr>
<tr>
<td>MENA</td>
<td>Middle East and North Africa</td>
</tr>
<tr>
<td>ML</td>
<td>Maximum Likelihood</td>
</tr>
<tr>
<td>MSCI</td>
<td>Morgan Stanley Capital International Inc.</td>
</tr>
<tr>
<td>OTC</td>
<td>Over the Counter</td>
</tr>
<tr>
<td>PIPO</td>
<td>Prime Index for Initial Public Offerings</td>
</tr>
<tr>
<td>S&amp;P</td>
<td>Standard and Poor’s</td>
</tr>
<tr>
<td>SIC</td>
<td>Schwarz information criteria</td>
</tr>
<tr>
<td>SIRCA</td>
<td>Securities Industry Research Centre of Asia-Pacific</td>
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<tr>
<td>SV</td>
<td>Stochastic Volatility</td>
</tr>
<tr>
<td>USD</td>
<td>United States Dollar</td>
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<tr>
<td>WFE</td>
<td>World Federation of Stock Exchanges</td>
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CHAPTER ONE

1. CHAPTER 1: INTRODUCTION

1.1 Introduction

Stock market volatility has been a significant topic of interest in the finance literature for more than four decades. Dating back to Fama (1965, 1970) pioneering work on the random walk model and the efficient market hypothesis (EMH), stock market volatility has been of critical importance for all subsequent research related to market efficiency. In an efficient market, all available information is reflected in current stock prices such that it is not possible to predict future prices. However, the existence of certain financial phenomena such as seasonality, end of the week effect, January effect, and volatility clustering makes it possible to predict stock prices and the magnitude of stock price movement. Price predictability is considered one of the most important aspects of earning abnormal returns, thus making the stock market volatility a crucial topic of analysis.

Some of the earliest studies of stock market volatility, Mandelbrot (1963) and Fama (1965) have shown that volatility in financial time series tends to cluster. That is, large changes in the price of an asset are often followed by other large changes, and small changes are often followed by other small changes. This would suggest that the price changes of the next period are related to the current period price changes and, therefore, ensure a predictable component of stock prices. The implications of this are so wide and far reaching that the literature on stock market volatility has exploded with econometric models designed to capture this volatility clustering phenomenon.
One important implication of volatility clustering is that when volatility clusters within the returns of financial assets, the random walk model, pioneered by Fama (1965), is no longer valid because of its prediction that the movements in stock returns are identically and independently distributed is violated. That is, when volatility clusters, the distributions of financial returns over time are now related.

The most popular model to develop out of the literature to capture this volatility clustering is the Autoregressive Conditional Heteroskedasticity (ARCH) family of models. The ARCH model, first proposed by Engle (1982) imposes an autoregressive structure on the conditional variance that allows volatility shocks to persist over time. This was later generalised by Bollerslev (1986) to include lagged conditional variances. The ability of these ARCH classes of models to identify patterns of volatility clustering has led to their extensive application to stock market returns, not only in developed markets (see, for example, Bollerslev, Chou and Kroner (1992), and Chappel, Padmore and Pidgeon (1998)), but to a lesser extent in emerging markets (see, for example, De Santis and Imrohoroglu (1997), and Su and Fleisher (1998)). The majority of the findings from this research have been strongly in support of the volatility clustering hypothesis.

The interest in stock market volatility has grown significantly, specially in recent years, with the general observation that stock markets around the world are becoming increasingly integrated and more volatile. This interest in stock market volatility has extended beyond the experience of developed markets, and has now focussed on emerging markets for two main reasons.
Firstly, the emerging markets relevance as an investment alternative has improved and is reflected in its increasing share of the world’s capital markets. The tremendous potential of emerging markets has attracted the attention of global portfolio managers as well as financial economists who suggest that there are diversification opportunities which should be exploited (see Agtmael and Errunza (1982), Errunza (1983) and Hartmann and Khambata (1993)). For this reason, the volatility of emerging markets has become increasingly important.

Secondly, it is well known that emerging markets exhibit greater volatility than developed capital markets. Emerging capital markets also have differing characteristics such as higher average returns, lower correlations with developed markets, and more predictable returns (Bekaert and Harvey (1997)). Each of these features has made the volatility of emerging markets a topic of interest.

Given that emerging capital markets exhibit different volatility characteristics to developed capital markets and are forming a greater proportion of world capital market activity, the literature on emerging markets is still relatively limited. One example is the emerging equity market in Egypt, the focus of this thesis. Egypt has been identified by the International Finance Corporation (IFC) as one of twenty promising emerging markets. Similar to other emerging markets, Egypt has taken significant steps toward the development of its capital markets. Measures that have been taken include privatisation, economic liberalisation, and relaxation of foreign exchange controls and easing of regulations on profits, investment and operation of financial institutions. The combination of each of these factors has made Egypt one of the strongest markets in the Middle East and North African (MENA) region. With
only a small amount of literature examining volatility on the Egyptian Stock Market (ESM), there appears to be scope for further research in this market. The next section explains the motivation for this thesis.

1.2 Motivation of This Research

The motivation for this thesis is the current practice of examining stock market volatility through the analysis of conditional variance structures associated with returns on the aggregated stock market index. It is the contention of this thesis that indices are highly aggregated phenomena, which will not reflect significant differences of variation in the pattern of volatility associated with different stocks. In this thesis, it is argued that the conditional variance of the return on a particular stock can be summarised in two components, the individual or stock specific risk and the sectoral or industrial component of risk. Further, it is argued that this latter component will be reflected in the temporal structure of the conditional variance. This is because stocks within the same sector or industry will react to the same temporal shocks to that sector or industry. In this way, it is argued that stocks in the same sector will exhibit similar patterns of conditional variance and stocks from different sectors will exhibit different patterns of conditional variance.

Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models have been extensively applied to individual time series. However, in order to examine the similarities and differences between the conditional variance structures of stocks in the same or different industries in the same equity market, it is necessary to use pooled-panel methods. That is, novel methods to estimate and test for fixed effects in the variance equation in panels of time series will be used to analyse the similarities
and differences in variance structures. These will be used within a general to specific framework to test the general hypothesis that stocks in the same sector or industry exhibit similar temporal patterns of variance, and stocks in different sectors or industry exhibit different temporal patterns of conditional variance.

To begin with, the majority of the literature on stock market volatility has generally considered market volatility at the aggregate level; that is, basing their analysis on market indices (Xu and Malkiel (2003)). For example, unit root tests have mostly been conducted on market indices. Similarly, the more advanced ARCH/GARCH models have also employed market level data (Bollerslev (1986)). This is due to the importance placed on the performance of the market in the theories of risk and return. Also, it is usually assumed that investors hold well diversified portfolios so that idiosyncratic risk is minimised and only systematic risk is priced (Campbell, Burton and Yexiao (2001)). However, in recent years, the focus on market level volatility has often been criticised (see, for example, Duffee (1995), Campbell, Burton and Yexiao (2001), and Xu and Malkiel (2003)).

In fact, it should also be emphasised that the EMH, as first proposed by Fama (1965), was tested using individual stock level data, which demonstrates the importance of examining stock level data. There are many reasons why the study of volatility at the individual stock level is important. Firstly, Campbell, Burton and Yexiao (2001) have argued that market returns are only one part of the return to the individual stock. Industry level and idiosyncratic firm level shocks are also important components of individual stock returns. Therefore, it is not sufficient to just examine market indices. An explanation for this is that arbitrageurs who trade to exploit differences in
individual stocks face risks that are related to idiosyncratic return volatility, not aggregate market volatility. When firm level volatility is high there are going to be large pricing errors between firm and market volatility. Moreover, in terms of event study analysis, the major determinant of abnormal returns is the difference between the returns of the market and the individual stock returns. Thus, the individual stock returns form an important part of the analysis (Campbell, Burton and Yexiao (2001)).

The behaviour of the volatility of individual stocks has received far less attention in the literature when compared with studies on market indices. Xu and Malkiel (2003) have shown that the volatility of individual stocks can increase even when the volatility of the market as a whole has remained constant, as long as correlations among stocks are declining. Furthermore, Xu and Malkiel (2003) show that when the total volatility of an individual stock is broken down into systematic volatility and idiosyncratic volatility, idiosyncratic volatility has trended upwards. While idiosyncratic volatility can be eliminated by holding a well diversified portfolio, individual investors are usually limited by wealth constraints or choose not to hold a well diversified portfolio. Thus, individual investors will still be interested in the specific risk of the securities they hold, justifying a need to study stock level data.

Moreover, it has also been identified in the literature that basing an analysis on index data can lead to false perceptions. Laurence (1986) has argued that the use of market index data may lead to false perceptions of price change dependence, even when price changes of individual shares represented by the index are independent, because stocks which are not traded frequently affect the market index. This situation seems more serious in the case of emerging markets which are characterised as being thin markets.
For this reason, modelling volatility for each sector will be done not only using indices but also using the daily prices of the most active stocks represented in each of these indices.

Another problem with using index data is the problem of aggregation. Market indices are constructed so as to track the average performance of the market. It is possible that, as a result of the averaging for the sector, the volatilities of the individual stocks may cancel each other out. Therefore, the estimated volatility may be lower than what would otherwise be the case. In undertaking an analysis at the individual stock level, the thesis will provide greater depth and knowledge of the volatility dynamics of the ESM, as well as overcoming this averaging problem. Further, the thesis, in the form of general to specific modelling, will provide an empirical framework within which to test for the similarities and differences in temporal volatility patterns of stocks in different sectors listed on the same market.

In summary, the literature has shown that there are problems with basing volatility analysis on index data. The literature has also shown that individual stock volatility is becoming more important relative to the market portfolio, especially when individual investors do not have a sufficiently large portfolio to be representative of the market portfolio. These investors are therefore concerned with individual stock data.

Most of the studies that have attempted to model volatility on the ESM, or even in the region, have mainly been done on the index level (see, for example, Appiah-Kusi and Menyah (2003), Omet, Khasawneh and Khasawneh (2002), Mecagni and Sourial (1999), Sourial (2002), Moursi (2000), and Mohieldin and Sourial (2000)) or even on
a weekly or monthly stock level (see Dahel and Laabas (1998)), but not on the individual stock level. That is why this study expands on the existing literature by not only examining the ESM on the index level, but also on the individual stock level.

1.3 Objectives of the Research

This thesis has two related objectives. The first is the development of a procedure to model volatility that is based on the general to specific approach pioneered by Hendry (1995). This procedure will be used to test for the similarities and differences in volatility between panels of stocks in the same sector or industry and panels of stocks in different sectors and industries. It should be made clear here that the focus of testing from general to specific models is the inter-sectoral similarities and differences in volatility manifested by different panel or pooled structures in the variance equation. This is somewhat different from the traditional use of general to specific modelling where the focus has been on different temporal structures nested with a general autoregressive distributed lag model.

The second related aim of this research is to set up methods of estimating models with panel fixed effects in the variance equation with a GARCH structure. Panel data analysis with financial data offers many advantages over standard time series and cross-sectional studies. Firstly, panel data allows the researcher greater flexibility in modelling the differences in behaviour across individuals by increasing the sample size. Panel data contains greater degrees of freedom and more sample variability than either cross-sectional or time series data and, therefore, improves the efficiency of econometric estimates and increases the precision in estimation (see, for example, Cameron and Trivedi (2005, p.697), and Hsiao (2003, p.'s 3, 7)). Secondly, due to the
fact that panel data contains information on inter-temporal dynamics and the individuality of entities, panel data helps to control for the effects of omitted or unobserved variables. Panel data also generates more accurate predictions for individual outcomes by pooling the data rather than generating the outcome from the variable in question. It allows a more accurate analysis of a particular variable by supplementing observations of the variable in question with other similar variables (see, for example, Cameron and Trivedi (2005, p.697), and Hsiao (2006, p.5)).

Another reason for using panel data instead of a single time series is that the limiting distributions of the test statistics in panel data remain asymptotically normal, instead of following non-conventional distributions, and are approximately normally distributed for samples with sizes generally encountered in financial data (see, for example, Levin and Lin (1993), Quah (1994), and Pesaran, Shin and Smith (2000)).

This is particularly important in this thesis where panels constitute long time series and panel stationarity is therefore a consideration. However, the rationale for using panel methods in this study is determined by the objectives of the study. It is only through the utilisation of panel methods that hypotheses around similarities and differences in stock returns volatilities can be tested.

1.4 Significance of the Research

This research extends the limited literature on volatility of the ESM. However, this work takes that literature in a new direction. Rather than working at high levels of market aggregation and extending into more complex GARCH structures on single time series of indices, this study extends the analysis of volatility through the analysis
of different GARCH structures within panels of stocks. That is, the work is at a considerably greater level of disaggregation.

Working with disaggregated data and testing for similarities and differences in volatility patterns necessitates the development of pooled-panel estimation in GARCH models within the framework of nested tests. The methodology developed in the thesis is not parochial but it is portable and can be used in a panel context for other equity markets or for panels of any financial phenomena which are thought to exhibit temporal volatility patterns.

A recent development modelling conditional heteroskedasticity is the multivariate GARCH specification (see, for example, Wang, P. (2003, p.'s 39-43), and Harris and Sollis (2003, p.'s 221-25)). These are vector models in volatility equations with the object of identifying the “contagion” or “spillover” of shocks in conditional variance from one series to another. That is, multivariate GARCH specifications utilise vector models of GARCH structure. An issue with these vector models is that they lead to a large number of parameters to be estimated and convergence is a problem when vector series are extended beyond two (Tsay (2002, p.'s 357-394)). Whilst the panel methods developed in this thesis are not a substitute for multivariate GARCH models, they are complementary to them and they extend the means for analysing relationships between the volatility structures of different time series, but without testing for the direction of impulse or cause from one series to another.
1.5 Thesis Structure

This thesis is presented in six further chapters. This current chapter has provided an overview of the research topic, motivation, objectives and significance of the thesis. The remainder of the thesis is organised as follows.

Chapter 2 introduces the theoretical considerations and relevant prior work on stock market volatility. It begins with an introduction to stock market volatility, outlining the importance of volatility, the stylised facts about volatility and some of the basic measures of financial market volatility. The EMH is then described and linked with financial market volatility. The chapter then goes on to examine some of the basic explanations of stock market volatility. The two major empirical models that are used to identify stock market volatility, GARCH and stochastic volatility (SV) models, are presented. Some of the empirical findings in the developed, emerging, MENA and Egyptian markets are described. Finally, the literature related to stock market volatility and circuit breakers is identified in this chapter.

Chapter 3 provides an overview of the Egyptian capital market (ECM). Key areas identified include: the government structure, the major sectors in the Egyptian economy, and the market liberalisation programs that have been used by the Egyptian government to reinvent its capital market and contribute to economic progress. Another important area identified which has significant implications for market volatility is the area of rules and regulations governing activity on the Cairo and Alexandria Stock Exchanges (CASE). The chapter then provides an introduction to the market indices used as benchmarks for the performance of the ESM and thus are indicators used to measure market volatility. The last part of the chapter presents the
ECM statistics. Firstly, the statistics highlights the performance of the ECM in terms of four different variables. This is followed by a description of the securities traded on the ECM and the market participants involved in trading on the ECM. Each of these factors having potential implications for stock market volatility. Finally, the performance of the ECM is compared with other markets.

Chapter 4 describes the research methods and models employed in this thesis. The chapter starts with the provision of a general framework for modelling volatility, drawing on Chapter 2. Using the general to specific methodology and with imposing restrictions on a general model, four nested models are proposed and described as further potential specifications of volatility dynamics on the ESM. The chapter then describes the methods used to estimate the unknown parameters of the proposed models and introduces the Likelihood Ratio Test (LRT) procedure used to determine the best model specification for each of the data panels used. Furthermore, the chapter presents methods of measuring the persistence in volatility exhibited on the ESM. Finally, the chapter presents a detailed description of the preliminary tests, including panel unit root and panel stationarity tests, used in this thesis in order to determine if prices in each data panel are stationary in levels or first differences. This is necessary to determine whether the volatility analysis should take place on prices or on returns.

An important part of any empirical work is a transparent account of the data used. This is the subject of Chapter 5. First, the sample period selection criterion is described. This is followed by a detailed description of the sector indices employed in this analysis, followed by a description of the individual stocks used and the method used to classify these stocks into different panel sectors. Finally, the chapter presents
an analysis of the descriptive statistics of the panel indices and each of the constructed panel sectors.

The results of the empirical analysis are given in Chapter 6. It starts with the presentation of the results of the panel unit root and stationary tests used in the thesis. The main finding here is that all panels are unit root processes in levels, but are first difference stationary. That is, it is appropriate to model volatility in terms of returns measured by logged differences. The chapter then presents the results of estimating the five proposed volatility models, including the general model, followed by an analysis of the estimated parameters of each model. Following from that, the chapter provides an analysis of the LRT results which are used to identify the most parsimonious model and discriminate similarities and differences in volatility structures between series. Finally, the chapter ends with an analysis of the persistence in the volatility of each of the data panels.

Finally, Chapter 7 concludes the thesis. It starts with an overview of the thesis in terms of the objectives and results. This is followed by a section dealing with the implications of the results for modelling the volatility structures of stock market series, especially in terms of the use of stock market indices versus individual stocks. This study can only fill a small gap in the literature on GARCH models and volatility of financial markets. As is frequently the case, whilst answering some important questions others are raised. This study forms the basis for further work and the concluding chapter outlines areas for future research, notably: alternate pooled-panel GARCH models; applications to other equity markets; and the augmentation of pooled-panel GARCH equations with relevant exogenous variables.
CHAPTER TWO

2. CHAPTER 2: STOCK MARKET VOLATILITY

2.1 Introduction

The behaviour of stock returns has been a topic of interest in academic circles in finance, particularly in the last four decades. Some of the questions that have been addressed in the literature include: What are the causes of stock market volatility? Has such volatility increased over time? Has international financial integration led to faster transmission of volatility across international stock markets? What role, if any, do regulators play in the volatility process? These issues are significant because of the wide and varying impact that volatility has for the world economy. At the individual level, high volatility in financial asset returns (where volatility is beyond a certain threshold) increases the risk of loss to individual investors and, therefore, raises concern about market stability.

Stock market volatility varies greatly across countries. The literature makes a distinction between developed and emerging markets based on their differing characteristics. The general assumption is that the world’s developed stock markets are more liquid and efficient and thus experience lower levels of stock price variation and return volatility when compared to their emerging stock market counterparts. Many previous studies have suggested evidence of emerging stock markets being characterised by higher levels of price volatility1. As such, the examination and modelling of stock price volatility in an emerging market such as Egypt has the potential to offer further insight for understanding stock market behaviour.

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1 See, for example, Appiah-Kusi and Menyah (2003), Bekaert and Harvey (1997), De Santis and Imrohoroglu (1997), Kawakatsu and Morey (1999), Salomons and Grootveld (2003), and Schaller and Van Norden (1997).
Stock market volatility is of critical importance to market efficiency. The EMH is one of the most highly researched concepts in finance and forms the basis for examinations of different financial markets. Stock market volatility implies that there are often large fluctuations in stock prices, but this is not necessarily in contravention with the EMH. This is the case when the fluctuations in stock prices are random and, therefore, unpredictable. One particular form of volatility, known as ‘volatility clustering’ contravenes the EMH as this implies that small (large) price changes are followed by small (large) price changes and thus variance in price changes may be predicted. Modelling volatility clustering is the focus of this thesis.

This chapter is divided into 10 sections. Section 2.1 gives an overview of stock market volatility. Section 2.2 gives an introduction to stock market volatility, exploring the importance of volatility, the stylised facts of the volatility process, its definition and measurement. Section 2.3 introduces the EMH theory and relates it to the volatility literature. This is followed by a section which gives an overview of the literature that has attempted to explain the causes of stock market volatility. Section 2.5 describes the ARCH/GARCH class of volatility models and is followed by a section which introduces SV models as opposed to the ARCH/GARCH models. Section 2.7 examines the empirical evidence for the ARCH/GARCH class models in three key market areas: the developed, emerging, and Africa and MENA markets. A closer examination is provided for the ESM, which is a focus of this thesis. Section 2.8 explains the ARCH/GARCH class of models in terms of their application to panel data. Section 2.9 examines the literature on the relationship between circuit breakers and stock market volatility. The final section provides a brief conclusion of the main topics covered in this chapter.
2.2 Introduction to Stock Market Volatility

2.2.1 Importance of Volatility

The modelling of stock market volatility is considered to be important for practitioners and academics due to its use in forecasting aspects of future returns. These forecasts can then be used in risk management, derivative pricing and hedging, market making, portfolio selection and many other financial activities. The predictability of volatility is an important task in financial markets.

Practitioners and academics have paid considerable attention to volatility as evidenced by the fact that at least 93 published and working papers study the forecasting abilities of various volatility models. Many more have been written on the subject of modelling volatility alone without the forecasting aspect. This reflects the importance of volatility in investment, security valuation, risk management and monetary policy making (Poon and Granger (2003)).

In relation to economic and financial time series, numerous models have been proposed to represent conditional volatility. The basic assumption when modelling volatility is that volatility can be decomposed into predictable and unpredictable components with the research concentrating on the predictable component of volatility. In financial time series, the predictable component of volatility is motivated by the fact that the risk premium is a function of volatility (Pagan and Schwert (1990)). Therefore, it is important to understand the determinants of volatility because of its relationship to risk. However, volatility is not the same as risk.
When volatility is interpreted as uncertainty, it becomes the key input into investment decisions and portfolio creations. In fact, volatility is the most important variable in the pricing of derivative securities. In addition, it is possible to buy derivative securities that are created on volatility itself. In order to price these instruments, accurate measures of volatility are needed (Poon and Granger (2003)).

Financial risk management has become critical for many financial institutions around the world with the introduction of the first Basle Accord in 1996. The Basle Accord makes it compulsory for financial institutions to forecast stock price volatility in order to set aside reserve capital against their value-at-risk. Thus, the measurement of volatility is important for all financial institutions.

The main reason why there is concern over financial market volatility is the belief that it can adversely affect real economic activity. The possibility that financial market volatility has such wide repercussions for the economy as a whole clearly necessitates a greater understanding of the volatility process. It is then possible for policy makers to find solutions to reduce financial market volatility.

### 2.2.2 Stylised facts about Financial Market Volatility

The volatility process is concerned with the evolution of the conditional variance of the stock return over time. This is a topic of interest because, as shown in Figure 2-1, the variability of the Standard and Poor’s/International Finance Corporation
(S&P/IFC) Global-Egypt’s returns\(^2\) over the period January 1996 to December 2003 varies over time and appears in clusters (Tsay (2002)).

![Figure 2-1 S&P/IFC Global-Egypt Index Returns (January 1996 to December 2003)](image)

Source: Securities Industry Research Centre of Asia-Pacific (SIRCA) (2005)

There are several salient features about financial time series and financial market volatility which are now well documented within the large amount of literature examining volatility. Prior to examining these features, it should be noted that volatility requires a significant number of regular time series observations and that it is not directly observable from return data over a single period (Tsay (2002)). The key characteristics of volatility observed over time include fat tail distributions of risky asset returns, volatility clustering, asymmetry, mean reversion and co-movements of volatilities across assets and financial markets. Recent research has shown that the correlation between the volatility of the return on assets is stronger than the

\(^2\) Index return \( \left( r_t \right) \) is calculated as the natural log difference in the closing sector index between two dates, \( p_t \) being the sector index at time \( t \). That is, \( r_t = \ln \left( \frac{p_t}{p_{t-1}} \right) = \ln \left( p_t \right) - \ln \left( p_{t-1} \right) \).
correlation between the returns on assets. However, both tend to increase during bear markets and financial crises (Poon and Granger (2003)).

Firstly, it is well established that the unconditional distribution of asset returns has heavy tails. Typical kurtosis estimates range from 4 to 50 indicating very extreme non-normality (Engle and Patton (2001)).

A second salient feature is the clustering of large and small movements, of either sign, in the price process. This was one of the first documented features of the volatility process of asset prices. Mandelbrot (1963) and Fama (1965) both reported evidence that large changes in the price of an asset are often followed by other large changes and small changes are often followed by other small changes. This behaviour has been reported in numerous studies\(^3\) and such “clustering” can be seen in Figure 2-1. The implication of volatility clustering is that volatility shocks today will influence the expectation of volatility some periods in the future. This is known as volatility persistence. Specifically, volatility is said to be persistent if today’s return has a large effect on the forecast variance some periods into the future (Engle and Patton (2001)).

Thirdly, it is also generally accepted that volatility is mean reverting. Volatility clustering implies that there will be periods of high volatility, periods of low volatility and periods of normal levels of volatility. The normal level of volatility is then the level of volatility to which volatility will eventually return. Most practitioners agree that volatility forecasts should converge to this same normal level of volatility. Also,

\(^3\) See, for example, Chou (1988), Schwert (1989), and Brooks and Lee (1997).
mean reversion in volatility implies that current information has no effect on the long-run forecast (Engle and Patton (2001)).

Fourthly, innovations may have an asymmetric impact on volatility. It is usually assumed in models of conditional volatility that the asset is affected symmetrically by positive and negative innovations. However, in the case of equity returns, the effects of positive and negative shocks may impact on the volatility differently. Generally, it has been found that negative price shocks have a stronger effect on volatility than similar positive shocks to prices. Research beginning with Black (1976) has shown that stock returns are negatively correlated with changes in returns volatility. That is, volatility rises with bad news but falls with good news. This type of asymmetry has been ascribed to the leverage effect, where, as the price of a stock fall its debt to equity ratio rises increasing the volatility of returns to holders of that stock.

In addition, volatility may be affected by exogenous variables. Most volatility models assume that the volatility series depends only on information contained in that series past realisations. However, other variables may contain relevant information for the volatility of a series. There is a wide range of research that has examined various factors that may have an impact on volatility. This may include company announcements, macroeconomic announcements and time of the day effects (Engle and Patton (2001)). Moreover, even though it is generally accepted that volatility is mean reverting, other characteristics of the volatility process include the fact that volatility generally evolves over time in a continuous manner. This implies that volatility does not show evidence of jump diffusion; that is, volatility jumps are rare.

4 See also Christie (1982), Nelson (1991) and Glosten, Jagannathan and Runkle (1993).
However, there is a growing literature which provides evidence of a jump diffusion process (see Eraker (2004)). In summary, the key characteristics of volatility are that it exhibits kurtosis, clustering, persistence and mean reversion.

### 2.2.3 Definition of Volatility and its Measurement

In finance, volatility is the term used to denote the standard deviation, $\sigma$, or variance, $\sigma^2$. The unconditional population mean for the random variable return, $R_t$, is:

$$ \mu = E[R_t]. \quad (2.2.1) $$

The unconditional variance (the second centred moment) is:

$$ \sigma^2 = E\left[ (R_t - \mu)^2 \right]. \quad (2.2.2) $$

The sample variance is estimated as:

$$ \hat{\sigma}^2 = \frac{1}{T-1} \sum_{t=1}^{T} (R_t - \bar{R})^2, \quad (2.2.3) $$

where $\bar{R}$ is the sample mean return, and $T$ is the sample size. The sample standard deviation statistic $\hat{\sigma}$ is a distribution free parameter representing the second moment characteristic of the sample. Only when $\sigma$ is attached to a specific distribution, can the required probability density and cumulative probability density be derived analytically (Poon and Granger (2003)).
Moreover, the predictable component of volatility in a series is the conditional variance of that series $\sigma^2_t$. The conditional variance is:

$$Var(R_t | \Omega_t) = \left[ E \left[ \left( R_t - E[R_t | \Omega_t] \right) \right] \right]^{\Omega_t},$$  \hspace{1cm} (2.2.4)

where $\Omega_t$ is the information set at time $t$ and $E[R_t | \Omega_t]$ is the conditional mean return.

The different ways of modelling $\sigma^2_t$ depend on how the conditional variance varies with information available at time $t$, and what information is being conditioned on the variance. The most common variable included in the conditional variance is the history of the series being analysed (Pagan and Schwert (1990)).

Further, the study of stock market volatility is borne out of the earlier empirical models of the relationship between risk and return. The models of Sharpe (1964), Lintner (1965), and Mossin (1966) have shown that asset price is directly related to either its own variance, or to the covariance between its return and the return on a market portfolio. Thus, volatility models have been developed based on the association of variance with risk, and the fundamental trade-offs between risk and return. Therefore, it is common for studies to use the variance of asset returns as proxies for market volatility.

Variance measures continue to be used as a basic measure of volatility in studies that use more sophisticated econometric techniques in measuring volatility. For example, Du and Wei (2004) used the standard deviation of the monthly returns of major
market indices as a measure of volatility. Comparing the differences in volatility across markets, Du and Wei (2004) found that emerging markets exhibit greater volatility than developed markets. They found that Italy is almost twice as volatile as the United States (U.S.) while China and Russia have volatility measures which are 350 percent and 650 percent greater than the volatility of the U.S. market.

Similarly, Goetzmann and Jorion (1999) examined the performance characteristics of emerging and developed markets to gain further understanding of the development of particular emerging markets. Using the standard deviation as a proxy for market volatility, it was found that the average standard deviation of dollar returns for the emerging markets sample was 34.8 percent, while the average standard deviation of dollar returns for the developed markets was only 19.8 percent.

Due to the simplicity of the standard deviation as a proxy for market volatility, there are obvious shortcomings. The most common identified in the literature proposes that the standard deviation measure ignores pertinent information that affects the random process generating the variable in question (Engle (1982)) and it distorts the volatility pattern due to smoothing (Bini-Smaghi (1991)). Furthermore, the existence of heteroskedastic errors is a serious problem in cross-sectional and time series data (Darrat and Haj (2002)). For these reasons the development of stronger measures of volatility was necessary.

Extending the standard deviation measure, Shiller (1979, 1981a), and LeRoy and Porter (1981) are pioneers in studying volatility and developing volatility tests (also known as variance bound tests). These volatility tests were based on the dividend
discount model and decomposed the variance of the market price and forecast error. If the variance of stock prices was greater than the \textit{ex post} present values, then the variance bound was violated. If a variance bound violation existed, then this was regarded as evidence against the EMH\textsuperscript{5}.

Shiller (1981a) and LeRoy and Porter (1981) found evidence of variance bound violations. It was concluded that the variability of stock market indices could not be accounted for by information regarding future dividends, considering dividends do not seem to vary enough to justify the price movements. Following on from Shiller (1981a) and LeRoy and Porter (1981), much research went into applying these measures to study efficient market models in various contexts\textsuperscript{6}.

The literature on stock market volatility has significantly progressed in terms of the complexity of methods used to model volatility. The basic volatility measure of standard deviation has been replaced by more advanced econometric techniques based on the modelling of the conditional variance. The conditional heteroskedastic models can be classified into two general categories. The first category, known as the ARCH class of models, specifies an exact function to govern the evolution of $\sigma^2_t$ over time. The second category uses a stochastic equation to describe $\sigma^2_t$. The SV model belongs to this category (Tsay (2002)).

\textsuperscript{5} Whether or not a violation of the variance bound implies that the EMH is false is still being debated in the literature (Dahel (1999)).

\textsuperscript{6} See, for example, Shiller (1981a, 1981b), Singleton (1980), and Meese and Singleton (1983).
2.3 Efficient Markets and Stock Market Volatility

An efficient market is where current asset prices tend to incorporate all available information at any given time. Future returns will therefore be unpredictable based on past information. Volatility clustering models suggest that the conditional information set that includes past stock returns can be used to show a systematic pattern of time dependence in stock returns. This time dependence can then be used to improve the predictability of future returns. Therefore, the existence of volatility clustering contradicts market efficiency. The following will include a discussion of the efficient markets literature and will show how volatility clustering is linked to market efficiency.

2.3.1 The Efficient Market Hypothesis (EMH)

The EMH is based on the notion that in an efficient capital market, prices adjust fully and instantaneously to all available, relevant information. According to Fama (1970) there are three forms of market efficiency. Each form depends on the subset of information that is included in the information set and thus is reflected in stock prices.

The weak form of market efficiency suggests that current stock prices reflect all information contained in past stock prices. Therefore, it is not possible for an investor to consistently earn abnormal returns from trading based on historical prices alone.

The semi-strong form of market efficiency suggests that current stock prices reflect all publicly available information. Therefore, it is not possible for an investor to make abnormal returns based on publicly available information. The strong form of market efficiency suggests that current stock prices reflect all available information; this includes all private and public information. Consequently, it is not possible for an
investor to earn abnormal returns by trading based on private or publicly held information.

Furthermore, the fact that stock market prices are assumed to reflect all available information at any given time means that the current price of an asset should be a good estimate of the intrinsic value, due to competition among market participants. In a world of uncertainty, the intrinsic value of an asset is unknown. Therefore, market participants will have differing opinions as to the intrinsic value of assets, causing asset prices to wander around its intrinsic value. Competition among investors ensures that any price discrepancies will not be large enough to be used profitably. That is, stock market prices are random walk. Market prices adjust instantaneously to new information as soon as it becomes available, so that only competitive rates of return are likely to be earned (El-Erian and Kumar (1995)).

Early studies on stock price behaviour have been concerned with testing the random walk model. The random walk model is based on two basic hypotheses. The first is that successive values of returns on an individual stock are independent, and the second is that stock returns conform to some probability distribution. This thesis concentrates on the first hypothesis; the main issue being whether successive stock price changes exhibit any systematic patterns, that is volatility clustering, or whether they are indistinguishable from a random walk model.

The first contribution to the random walk literature, both on a theoretical and empirical level, was that of Bachelier (1900). This, however, remained undetected for more than fifty years. The most comprehensive attempt since that time to examine
stock return behaviour, and one of the most cited papers in the finance literature, is Fama (1965).

Fama (1965) tested for the applicability of the random walk model in the U.S. capital market using daily closing prices of thirty stocks comprising the Dow Jones industrial average covering a five year period. In an attempt to test the assumption that successive values of returns are independent, Fama (1965) applied serial correlation and runs tests. The serial correlation coefficients were small and generally not significantly different from zero. The observed runs were also less in number than expected from a random process. He concluded that although there were slight dependencies, these did not violate the conditions of market efficiency.

Fama’s work stimulated the interest of others and several attempts were made to study stock price behaviour in other capital markets. Solnik (1973) tested the random walk model for European markets using 234 securities from eight major European stock markets.\(^7\) The estimated serial correlation coefficients, although small in magnitude, were larger than those estimated by Fama (1965) for the U.S. market. Moreover, the coefficients were found to be fairly stable over time. As a result, Solnik (1973) concluded that the European capital markets are less efficient than the U.S. capital market. The inefficiencies in the European markets may be explained by market thinness, loose requirements for disclosure of information and lack of control on insider trading. However, these dependencies are not of a magnitude that could allow an investor to earn excess returns (after adjusting for transaction costs).

\(^7\) The countries studied were the United Kingdom, France, Germany, Italy, Netherlands, Belgium, Switzerland and Sweden.
Conrad and Juttner (1973) examined stock price behaviour for Germany using daily closing prices of 54 stocks for the period January 1968 to April 1971. Applying the same techniques used in previous studies (serial correlation and runs tests), Conrad and Juttner (1973) did not find any support for the random walk process. The runs test rejected the random walk hypothesis. The serial correlation coefficients for most stocks were significantly greater than zero.

This conclusion is in contrast to the results of Solnik (1973), who found a much lower coefficient for Germany (one of the eight European countries studied by him). Conrad and Juttner (1973) argued that the failure of the random walk model in describing the behaviour of stock prices in Germany might be due in part to three particular factors. First, there is the problem of the close connections between business cycles. Secondly, there is the failure to assess the available information concerning the economic factors that determine the company profits. Thirdly, during the period under consideration, there exists a psychologically conditioned overestimation of good, as well as bad news.

Jennergren and Korsvold (1975) investigated stock price behaviour for Norway and Sweden, using daily prices for 15 stocks from Norway and 30 stocks from Sweden covering the period 1967 to 1971. The results were not consistent with the random walk model. Significant positive correlations were found for the first lag, although for higher order lags the coefficients were generally small and had mixed signs.

On the other hand, Errunza (1979) found the random walk model to be appropriate for the Brazilian capital markets. Using 64 of the most traded securities for the period
1971 to 1975, and applying serial correlation and runs tests, Errunza (1979) found strong support for the random walk model. Moreover, he applied tests of market models and found that the Brazilian stock market appears to be weak form efficient. Further, the Brazilian stock market is characterised by a strong market factor, consistent with a single factor return generating process. It must be mentioned, however, that Errunza (1979) used monthly data for his analysis.

Errunza and Losq (1985) investigated the behaviour of stock prices for a group of ten emerging markets. Using monthly return series for 191 securities over the period December 1975 to April 1986, they found the probability distribution of stock returns to be lognormal with some securities exhibiting non-stationary variances. They also investigated the independence hypothesis by studying the distribution of the first order serial correlation coefficient for each security. The results showed the average correlations to be small, although higher than those observed in the developed markets. Errunza and Losq (1985) also performed the runs test and found support for independence. This led to the conclusion that emerging markets, although not as efficient as the U.S. capital market, are comparable to the smaller European markets studied by Solnik (1973).

Laurence (1986) examined stock price behaviour in Malaysia and Singapore. The daily closing price for 16 stocks from Malaysia and Singapore were selected for the analysis. The results showed slight deviations from the weak form efficiency hypothesis on the two exchanges. The mean absolute serial coefficients for Malaysia and Singapore were 0.041 and 0.078 respectively. The weak form efficiency hypothesis on the two exchanges. The mean absolute serial coefficients for Malaysia and Singapore were 0.041 and 0.078 respectively. The weak form efficiency

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8 The countries studied were Argentina, Brazil, Chile, Greece, India, Korea, Jordan, Mexico, Thailand and Zimbabwe.
characteristics of the Stock Exchange of Singapore and Kuala Lumpur Stock Exchange are similar to the characteristics found in developed stock markets like the New York Stock Exchange. Laurence (1986) suggests that from these findings, in small markets such as Stock Exchange of Singapore and Kuala Lumpur Stock Exchange, price-forming information may be disseminated very rapidly despite the lack of sophisticated communications technology, hoards of analysts, large numbers of business journals and intensive market regulation.

Butler and Malaikah (1992) examined the efficiency of stock markets in Kuwait and Saudi Arabia. Butler and Malaikah (1992) used daily data on 35 Saudi stocks from June 1986 to September 1989, and 36 Kuwait stocks from October 1985 to December 1988 to conduct their analysis. They applied serial correlation and runs tests to examine the nature and extent of serial dependence. The mean lag one autocorrelation coefficient for Kuwait stocks was found to be 0.053, with 36 percent of the stocks having a statistically significant lag one autocorrelation coefficient at the 95 percent confidence level. In contrast, all 35 Saudi stocks were found to exhibit negative and statistically significant autocorrelation with a mean coefficient equal to −0.471. This is opposite in sign and larger in magnitude compared with autocorrelation coefficients reported in other studies. Examining the information and operational inefficiency in Saudi Arabia, Butler and Malaikah (1992) identified trading delays, illiquidity, market fragmentation and the absence of official market makers as major factors contributing to inefficiency.

In summary, the empirical evidence shows that stock returns in developed markets seem to be consistent with the random walk model. On the other hand, the random
walk model does not seem to be valid in emerging markets, but the results are by no means conclusive. Since the random walk implies that stock prices cannot be predicted, another popular method for examining the validity of the EMH is identifying predictable volatility patterns in stock prices. The most common volatility patterns studied include seasonal effects and volatility clustering. In general, there are many ways in which stock market volatility and market efficiency are linked. This makes volatility an important phenomenon to study.

2.3.2 Volatility and Market Efficiency: The Implications

The key function of financial markets in the economy is to provide a method of channelling funds from savers to investors. As part of the allocation process, the prices of financial assets will exhibit some form of price volatility as economic values across economic activities fluctuate. These fluctuations in prices are a normal occurrence in the efficient functioning of markets. Price fluctuations only become a problem when it begins to exhibit excessiveness, or shows patterns that can be predicted, for example volatility clustering. This is detrimental to the financial system, as stock prices should act as signals for resource allocation. That is, any observable pattern of volatility is going to affect the efficiency of the resource allocation function and ultimately the economy. It is for this reason that market volatility patterns have serious implications for market efficiency. For example, economic models with representative agents commonly show that where volatility increases, agents will save less, resulting in reduced investment, and hindering economic development.

There are a number of ways in which stock market volatility could harm market efficiency. The basic premise is that prices guide economic activities. When assets are
underpriced, resources will not be invested in them, whereas when assets are overpriced, too much will be invested in them. Thus, when prices are exhibiting volatility patterns that are not explained by economic fundamentals, it becomes clear that economic activity will occur in an *ad hoc* manner that is counterproductive. This will have a wide impact on all market participants and regulators, including portfolio managers, regulators, legislators, lawyers, corporate managers, builders, homeowners, collectors, conservators and others (Shiller (1989)).

One of the most important channels through which stock price volatility affects economic activity and efficiency is consumer spending (see, for example, Starr-McCluer (1998), Ludvigson and Steindel (1999), and Poterba (2000)). Stock price volatility affects consumer spending through the wealth effect. This is evidenced by the positive relationship between stock prices and consumer spending. As stock prices rise, consumer wealth rises, thus increasing aggregate consumer spending and vice versa. That is, stock prices are directly impacting on the consumer spending function. In the case of falling stock prices, consumer spending falls and as consumer confidence deteriorates, there will be further reductions in consumer spending.

Similarly, stock price volatility filters through to economic activity via business investment (see, for example, Hu (1995), Levine and Zervos (1996), and Arestis, Demetriades and Luintel (2001)). Generally, an increase in stock market volatility increases the risk of equity investment and investors will move their funds to less risky assets. As such, the cost of equity will rise, causing further reductions in investment.
Apart from volatility disrupting the smooth functioning of the financial system, structural and regulatory changes in the market may be needed to control market volatility. However, these structural and regulatory changes could potentially add to distortions in market activity, hindering the efficient functioning of financial markets (Cunado Eizaguirre, Gomez Biscarri and Perez de Gracia Hidalgo (2004)).

For investment purposes, it is important for market participants to have information on volatility to be able to make rational decisions regarding portfolio diversification. Some research has been conducted to provide insight into the behaviour of emerging market stock price volatility. For example, Eden and Jovanovic (1994) suggest that volatility in stock prices can result from changes in the level of the available public information over time.

An important characteristic of stock markets is that of price volatility, as this may undermine the ability of stock markets to promote an efficient allocation of investment. The undesirable effects of volatility were recognised early in the literature, notably by Keynes (1936) who stated that:

“As an organisation of investment markets improves, the risk of the predominance of speculation does…increase…Speculators may do no harm as bubbles on a steady stream of enterprise…a serious situation can develop…when enterprise becomes the bubble on a whirlpool of speculation. When the capital development of a country becomes a by-product of the activities of a casino, the job is likely to be ill done…It is usually agreed that casinos should, in the public interest, be inaccessible and expensive. And perhaps the same is true of stock exchanges”: p. 158-59 (cited in Arestis, Demetriades and Luintel (2001)).

The recent literature has not been conclusive on whether the effects of stock market volatility on economic activity are good or bad. As stated earlier, a certain degree of price volatility in the stock market is desirable and reflects the arrival of new
information in an efficient market. However, volatility patterns such as volatility clustering tend to cause inefficiency in resource allocation, higher interest rates due to increased uncertainty and, consequently, less investment and economic growth (see Ferderer (1993), and De Long (1989)).

Similarly, where capital markets are segmented, risk premiums may be directly affected by the volatility of equity returns in the particular market. Higher volatility, therefore, implies that there are higher capital costs. Higher volatility also has the potential to increase the value of the ‘option to wait’, hence delaying investments (Bekaert and Harvey (1997)).

In summary, the adverse effect of volatility on market efficiency, and ultimately economic activity, is clear in the literature. As a result, it is important to examine empirically whether volatility patterns such as volatility clustering are evidenced in practice. Prior to an analysis of models of stock market volatility, it would be useful to briefly examine the causes of stock market volatility. This is the focus of the next section.

2.4 Causes of Stock Market Volatility

One of the main things that can be concluded from the literature on stock market volatility is that there is evidence of high volatility. This high volatility is a concern due to the fact that economic agents participate more in financial markets and are exposed to greater risk. This has resulted in the need to reduce volatility. However, it is not possible for policy makers to set effective policies to reduce volatility without a
clear understanding of the causes of such volatility (Ayuso, Nunez and Perez-Jurado (1996)).

Unfortunately, very little is known about the factors that determine volatility. As a result, there is no well accepted general structural model of volatility. However, the economic literature points out several potential factors that could partially explain financial price volatility (Ayuso, Nunez and Perez-Jurado (1996)). The most common explanation is that of the EMH, where the volatility of prices is directly related to the rate of flow of information to the market. In an arbitrage free economy and using a simple model, the two were found to be identical. This result links volatility tests to the EMH which specify the information set that is used by the market for pricing assets (Ross (1989)). However, the EMH does not offer an explanation when prices change due to factors other than the fundamentals (that is, there exists a relation between volatility in speculative markets and volatility of economic variables) and the expectations about them.

Moreover, the empirical evidence suggests that financial market prices can deviate widely and frequently from fundamental valuations. For example, Shiller (1989) has not been able to explain the causes of volatility changes of stock prices well. Schwert (1989, 1990) examined whether microeconomic and macroeconomic factors can explain stock market volatility. He found that stock market volatility is not closely related to the volatility of economic variables such as inflation, money growth, or industrial production. While financial leverage and trading activity seem to be related to stock price volatility, they can only explain a small proportion of the change in stock volatility over time.
Similarly, numerous other studies have examined the effects of particular economic variables on stock market volatility. For example, Officer (1973) examined the effects of volatility in business cycle variables, while Merton (1980), Poterba (2000), and French, Schwert and Stambaugh (1987) related stock market volatility to the volatility of expected return\(^9\).

Other common factors used to explain stock market volatility include market characteristics, such as asset concentration, market development, market integration, and market microstructure. The following briefly discusses these characteristics.

Firstly, the level of asset concentration refers to the degree of diversification and concentration in particular market indices for each country. Essentially, the market indices of a stock market reflect the aggregation of the individual sectors in the economy. Consequently, if economic activity is spread evenly through different sectors of the economy, the volatility changes in each of the industries are likely to cancel each other out, therefore resulting in less volatility in the aggregate market index. The opposite is the case where economic activity is concentrated in one or two sectors. In this case, the volatility in these sectors will dominate the volatility of the market index (Bekaert and Harvey (1997)).

Secondly, the maturity of a market also contributes to stock market volatility. It is reasonably expected that a relatively new market will be more volatile than a long established market. This is because the average experience and skills of the investors and market regulators are likely to improve with market maturity. As noted by

Cornelius (1993), it takes time for the price discovery process to become known. As markets operate and market microstructure develops, emerging stock markets are likely to become more efficient.

Market integration refers to the independence between stock markets; that is, how much a local stock market is dependent on changes in foreign stock markets. When a stock market is open to international financial investment, then the local stock market volatility is going to be affected by the events of the foreign stock market. As such, world market factors are going to affect the volatility of local markets if markets are integrated. Bekaert and Harvey (1997) have argued against this, suggesting that the higher volatility and returns in emerging markets are due to local factors preceding the emergence and the integration with international markets. In examining the affect of local factors on stock market volatility\(^{10}\), Bekaert and Harvey (1997) found that local factors were significant determinants of volatility. Of the proxies estimated, credit risk was the most dominant local factor contributing to stock market volatility.

Lastly, market microstructure has been shown to be a significant factor contributing to market volatility. Market microstructure refers to the regulations and structures that govern how the market operates. For example, Mecagni and Sourial (1999) examined the implications of the introduction of circuit breakers on the ESM and found that pricing limits imposed distortions in pricing, rather than helping to reduce volatility. This finding is consistent with the view that market microstructure can actually increase volatility.

\(^{10}\) See also Erb, Harvey and Viskanta (1995) and Diamonte, Liew and Stevens (1998).
To be able to forecast stock market volatility, it is important to have a good understanding of the factors that determine stock market volatility. Many common factors contribute to volatility in both developed and emerging stock markets. Experience suggests that emerging markets experience greater volatility than developed markets and it will become clear that each of these factors is potentially more pronounced in emerging markets. In addition, emerging markets are subject to further adverse factors that may contribute to market volatility.

The literature on the differences in market volatility between developed and emerging markets has clearly shown that emerging markets exhibit significantly greater market volatility than that experienced in developed markets. A number of studies examined this specific phenomena and offered explanations for the greater volatility experienced in emerging markets.

Firstly, the availability and release of information in emerging markets is usually less than that in developed markets. This suggests a greater level of uncertainty in the emerging markets and, hence, causes greater volatility in these markets.

Secondly, firms in emerging markets have been subject to less investment research than firms in developed markets. This has been due to the fact that the data availability in emerging markets was lacking, and the reliability of this data was questionable. Recently, the increasing availability of data and information in emerging markets has seen more research devoted to these markets. As a result, investors and market participants in emerging markets are more educated and aware. This will potentially reduce the volatility in these markets.
Thirdly, El-Erian and Kumar (1995) suggested that the structural and institutional features of emerging markets are usually fragmented and, therefore, are less efficient in detecting and discriminating among investment opportunities. Moreover, dichotomy between organised and unorganised money markets also affects the volatility in emerging markets.

In summary, many potential and actual imperfections\(^\text{11}\) create inefficiencies, even in the most researched and regulated stock exchanges. The fact is, these inefficiencies are usually more prominent in emerging markets, and this potentially increases the probability of higher stock market volatility in emerging markets.

In general, the factors contributing to market volatility relate to the speed at which the market accommodates shocks and incorporates relevant information into prices. The improved speed at which financial transactions occur will lead to changes in market volatility, so that there is a link between the efficiency of the market and the changes in volatility dynamics. The faster the information is incorporated into prices, the lower the volume of trading necessary to bring prices to their warranted levels. As a result, the period of increased volatility due to the arrival of new information is shorter. In an efficient market, volatility should exhibit fast mean reversion (Cunado Eizaguirre, Gomez Biscarri and Perez de Gracia Hidalgo (2004)).

Whilst the theory is incomplete in modelling stock market prices, there are empirical models drawn from econometrics that have been used to analyse volatility in financial phenomena, generally, and stock market volatility specifically. The two empirical

\(^{11}\) Some examples of imperfections may include disinterested shareholders and information not being freely available.
models are the GARCH model and the SV model. Since the focus of this thesis is to analyse and model the volatility of the ESM, it is, therefore, important that these two models are examined as suitable venues for that analysis. This will be done in the next two sections of this chapter.

2.5 ARCH/GARCH Class Conditional Volatility Models

A rich but complex group of time series models is the ARCH family, which is extensively reviewed in Bera and Higgins (1993) and Bollerslev, Chou and Kroner (1992). ARCH class models make use of sample standard deviations but formulate the conditional variance, $h_t$, of time series via Maximum Likelihood (ML) procedure.

The first example of an ARCH model is the ARCH ($q$) of (Engle (1982)) where $h_t$ is a function of lagged past square residuals. In GARCH ($p,q$) additional dependencies are permitted on $p$ lags of past realisations of the variance. The GARCH is a more parsimonious model than ARCH, and GARCH (1,1) is the most popular structure for many financial time series (Poon and Granger (2003)).

The Exponential GARCH (EGARCH) model (Nelson (1991)) removes the need for imposing constraints on the parameters of the model so that the variance remains positive by specifying the conditional variance in logarithmic form. This model, therefore, takes into account the fact that a negative shock may lead to higher conditional variance than a similar positive shock. Other asymmetric dependencies are modelled in the Threshold GARCH (Zakoian (1994)), Golsten-Jagannathan-Runkle GARCH (Glosten, Jagannathan and Runkle (1993)), Quadratic GARCH among others.

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12 See also Campbell, Lo and MacKinlay (1997), Hentschel (1995), and Schwert (1989, 1990) for a review of some of these studies.
such as the ‘GARCH in mean’ or GARCH-M models and multivariate GARCH models. In the GARCH-M model, the volatility measured by the square root of the conditional variance enters the conditional mean. That is, volatility captured by the conditional variance has a direct influence on asset prices.

The ARCH class models have now firmly established themselves as one of the foremost techniques for modelling volatility in financial markets. They have the ability to model the volatility of a financial time series that is clustering and mean reverting, which are two of the most important stylised facts of financial time series suggested in the current literature. They are so successful that the ARCH models have bred an extensive literature in their own right. ARCH models are applicable to a wide range of financial instruments.

The importance of volatility clustering in the analysis of prices of financial assets is the proposition that the random walk model is now no longer an appropriate description of the price generating process. The random walk model assumes that price movements are independently and identically distributed, and when volatility clusters, this assumption is violated. That is, when volatility clusters, the distributions of financial returns over time are related and can be forecast.

2.5.1 The ARCH Model

The ARCH model of Engle (1982) provides a systematic framework for modelling this type of volatility process. The basic premise is that the mean asset return is serially uncorrelated, but is dependent. This dependence is usually modelled as a simple quadratic function of its lagged values (Tsay (2002)).
Specifically, the ARCH process imposes an autoregressive structure on the conditional variance that permits volatility shocks to persist over time. It can therefore allow for volatility clustering. The general form of the model, denoted by ARCH($q$), is:

$$y_t = x_t' \phi + \varepsilon_t,$$  \hspace{1cm} (2.5.1)

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t),$$  \hspace{1cm} (2.5.2)

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \nu_t,$$  \hspace{1cm} (2.5.3)

$$\nu_t \sim \text{IIN}(0, h_t)$$  \hspace{1cm} (2.5.4)

where:

$y_t$ is the dependent variable;

$x_t$ is a vector of explanatory variables;

$\phi$ is a vector of regression parameters;

$\varepsilon_t$ is the conditional disturbance which is normally distributed with mean zero and variance $h_t$;

$\Omega_{t-1}$ is the information set conditioning the disturbance; and

$t$ is the time index.

The conditional variance, $h_t$, is parameterised as a function of the information set, $\Omega_{t-1}$, which normally comprises the previous innovations, $\varepsilon$. Extending the work of Mandelbrot (1963), if these errors are large in absolute value then they are likely to be
large in the future. Consequently, the conditional variance of the series is observed as a weighted sum of past squared disturbances.

Using lag notation the conditional variance $h_t$ can be written as:

$$h_t = \alpha_0 + \alpha(L)\varepsilon_i^2 + \nu_t; \quad (2.5.5)$$

where

$$\alpha(L) = \sum_{i=1}^{q} \alpha_i L^i.$$ 

To ensure the conditional variance is positive, an inequality restriction must be imposed on the variance equation (2.5.3):

$$\alpha_0 > 0 \text{ and } \alpha_i \geq 0, \forall i.$$ 

To ensure that the process is stationary, it is also required that:

$$\sum_{i=1}^{q} \alpha_i < 1.$$ 

The right hand side of equation (2.5.3) contains two components, the expected volatility and a random component, $\nu_t$. The expected volatility of $h_t$ in (2.5.3) is further divided into two components, the time varying component in the summed lagged terms and the mean variance, $\alpha_0$, to which the time varying component reverts. That is, $h_t$ is a stationary process.
A practical problem with (2.5.3) is that large values of $q$ often lead to the violation of the non-negativity and stationary conditions stated in the previous paragraph. The GARCH model pioneered by Bollerslev (1986) is a solution to this problem and it can also provide a more parsimonious specification.

### 2.5.2 The GARCH Model

Due to the large number of parameters needed to accurately model the ARCH process, Bollerslev (1986) generalised the ARCH process by allowing the conditional variance to be a linear function of $p$ lagged conditional variances in addition to $q$ past squared errors. In other words, GARCH $(p,q)$ implies the following form of the conditional variance:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \nu_t . $$

(2.5.6)

The conditional variance equation given in (2.5.6) is a function of three terms:

- $\alpha_0$ is a constant term;
- $\varepsilon_{t-i}^2$ (The ARCH term), which is news about volatility from the previous periods, and is measured as the lag of the squared residual from the mean equation; and
- $h_{t-j}$ (The GARCH term), which is the variance from previous periods.

Using lag notation the conditional variance $h_t$ can be written as:

$$h_t = \alpha_0 + \alpha (L) \varepsilon_t^2 + \delta (L) h_t + \nu_t.$$  

(2.5.7)
where $\alpha(L) = \sum_{i=1}^{q} \alpha_i L^i$ and $\delta(L) = \sum_{j=1}^{p} \delta_j L^j$.

To ensure the conditional variance is positive, an inequality restriction must be imposed on the variance equation (2.5.6):

$$\alpha_0 > 0, \quad \alpha_i \geq 0, \quad \forall i \quad \text{and} \quad \delta_j \geq 0, \quad \forall j.$$  

To ensure that the process is stationary, it is also required that:

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \delta_j < 1.$$  

An ordinary ARCH model is a special case of a GARCH specification, in which there are no lagged forecast variances in the conditional variance equation; that is, a GARCH (q, 0), and $\delta_1 = \delta_2 = \ldots = \delta_p = 0$.

Also, it is easy to show that the GARCH specification is parsimonious and requires fewer lags to cover the variance as a function of time in a series (Wang, P. (2003, p.36)). Taking the GARCH (1,1) specification:

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \delta_1 h_{t-1} + \nu_t.$$  \hspace{1cm} (2.5.8)

Excluding the stochastic term $\nu_t$ and lagging by one period:
\[ h_{t-1} = \alpha_0 + \alpha_i \varepsilon_{t-2} + \delta_t h_{t-2}. \]  

(2.5.9)

Substituting (2.5.9) into (2.5.8) without the stochastic term to get:

\[ h_t = \alpha_0 + \alpha_i \varepsilon_{t-1}^2 + \delta_t \left( \alpha_0 + \alpha_i \varepsilon_{t-2}^2 + \delta_t h_{t-2} \right). \]  

(2.5.10)

Now lagging (2.5.9) once:

\[ h_{t-2} = \alpha_0 + \alpha_i \varepsilon_{t-3}^2 + \delta_t h_{t-3}, \]  

(2.5.11)

and substituting into (2.5.10):

\[ h_t = \alpha_0 + \alpha_i \varepsilon_{t-1}^2 + \delta_t \left( \alpha_0 + \alpha_i \varepsilon_{t-2}^2 + \delta_t \left( \alpha_0 + \alpha_i \varepsilon_{t-3}^2 + \delta_t h_{t-3} \right) \right). \]  

(2.5.12)

Multiplying out the brackets and factoring gives:

\[ h_t = \alpha_0 \left( 1 + \delta_t + \delta_t^2 \right) + \alpha_i \left( \delta_t^0 \varepsilon_{t-1}^2 + \delta_t^1 \varepsilon_{t-2}^2 + \delta_t^2 \varepsilon_{t-3}^2 \right) + \delta_t^3 h_{t-3}. \]  

(2.5.13)

Continued lagging \( h \), back substitution and factoring, leads to the distributed lag expression:

\[ h_t = \frac{\alpha_0}{1-\delta_t} + \alpha_i \sum_{i=1}^{\infty} \delta_t^{i-1} \varepsilon_{t-1}^2. \]  

(2.5.14)
This distributed lag expression shows how the GARCH (1,1) captures the time varying volatility effect of higher order lags. However, recall that \(0 \leq \delta_i < 1\), so that higher order lags in (2.5.14) will rapidly diminish in importance.

A useful analysis in the GARCH framework is to find persistence in variance. That is, how permanent is a shock to volatility (Lamoureux and Lastrapes (1990b)). It is measured by the sum of parameters in the variance equation; that is,

\[
\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \delta_j. \tag{2.5.15}
\]

The closer the sum to unity, the greater is the persistence of shock to volatility.

A related aspect to the concept of persistence is the concept of half life (HL) of volatility shocks, which measures the number of days over which a shock to volatility diminishes to half its original size (Lamoureux and Lastrapes (1990b)). HL is measured as:

\[
HL = 1 - \left(\log 2 / \log \lambda\right), \tag{2.5.16}
\]

where \(\lambda\) is the sum of the GARCH parameters in the variance equation.

Even though GARCH models with a conditional normal distribution allow unconditional error distributions to be leptokurtic, they might not fully explain the high level of kurtosis in observed distributions of return series. It has been suggested
in the literature that the assumption of a leptokurtic conditional distribution in
GARCH models might be more appropriate. Such a distribution can better account for
the level of kurtosis observed in financial data than does the normal conditional
distribution. This allows a distinction between conditional heteroskedasticity and
conditional leptokurtic distribution. Either of these could generate the fat tailedness
observed in the emerging markets financial data.

In summary, the ARCH model introduced by Engle (1982) formulates time varying
conditional variances in time series. The GARCH model provides a more flexible
framework to capture various dynamic structures of conditional variance. This is due
to the GARCH model incorporating the time varying conditional variance and the
covariances of the stochastic process. Thus, the conditional variance of the time series
depends upon the squared residuals of the process, which is the square of the lagged
innovation. It can, therefore, be regarded as a reduced form of a more complicated
dynamic structure for the time varying conditional second order moments.

Despite the limitations, the superiority of the ARCH class of models has been
demonstrated by Pagan and Schwert (1990), and Pagan (1996) who show that the
GARCH models perform well in comparison with alternative methods for modelling
conditional volatility of stock returns. That is, with the exception of a possible
asymmetric leverage effect, a GARCH (1,1) is enough to account for the volatility
dynamics of financial time series.
2.6 Stochastic Volatility (SV) Model

An alternative model consistent with volatility clustering and excess kurtosis is the SV model. SV arises when conditional second moments are not only variable, but also follow some dynamics in their own right. This latent variable approach, where an innovation is added as an additional process explaining the conditional variance, offers certain econometric advantages (Barnes and De Lema (1999)).

This statistical approach of treating volatility as an unobserved variable and filtering this through to the model is similar to the approach taken in the ARCH/GARCH models. Both types of models filter the volatility from the return observations. The key difference between them is the source of the noise. In the ARCH/GARCH type models, the randomness of the variance, $\sigma^2$, is caused by a function of the past innovations, and referred to as a one-factor model. The SV model, however, has two sources of noise. The variance is modelled with an additional innovation process $\eta_t$.

In general terms, $\sigma_t = f(\eta_t, \eta_{t-1}, \eta_{t-2}, ...)$ for some function $f$ and is, therefore, regarded as a two factor model (Barnes and De Lema (1999)).

Specifically, the standard SV model is defined by (Barnes and De Lema (1999)):

$$y_t = \sigma_t z_t,$$  \hspace{1cm} (2.6.1)

where $\sigma_t = \sigma \exp(v_t/2)$, $z_t$ is an independent and identically distributed process with zero mean and unit variance, $\sigma$ is a positive constant and $v_t$ is some time process that is independent of $z_t$. The process $y_t$ satisfies:
1. \( E[y_t | \sigma_t] = 0 \) (Constant conditional mean)

2. \( V[y_t | \sigma_t] = \sigma_t^2 \) (Time varying conditional variance)

3. From 1, \( y_t \) is a martingale difference sequence with respect to \( \{\sigma_t\} \) and, therefore, \( y_t \) is a white noise process if \( E[y_t^2] < \infty \).

If \( v_t \) is distributed Gaussian, it follows that \( y_t \) is covariance stationary and strictly stationary, a property that does not necessarily hold for a GARCH process.

Most commonly, the \( v_t \) process is an order one autoregressive process (AR (1)):

\[
v_t = \mu + \phi v_{t-1} + \eta_t, \quad \eta_t \sim N(0,1) \tag{2.6.2}
\]

with \( \eta \) independent of \( z_t \). Letting \( x_t = \log y_t^2 \), then:

\[
x_t = \omega + v_t + \epsilon_t, \tag{2.6.3}
\]

where \( \omega = \ln \sigma^2 + E(z_t^2) \) and \( \epsilon_t = \ln z_t^2 - E[\ln z_t^2] \). From (2.6.3), it follows that \( x_t \) is an autoregressive integrated moving average process with innovations \( \epsilon_t \) that are distributed as the logarithm of a chi square distribution with one degree of freedom. That is, a heavily skewed distribution.

In the SV modelling framework, volatility is subject to innovations that may or may not be related to those that drive returns. Modelling volatility as a stochastic variable
leads to fat tail distributions of returns. The autoregressive variable allows persistence in the model, and correlation between the two innovation terms in the volatility process and returns process causes asymmetry in the volatility (Hull and White (1987)).

Furthermore, SV models are a relatively new development in the literature and these models were designed as an improvement to the ARCH class models. However, in comparing the two types of models, they both have their advantages and disadvantages. The SV models allow the error term to enter the volatility equation and thus are more flexible than the GARCH models in this regard. In addition, theoretically, the SV models are easier to analyse due to the similarities with the options pricing models. In practice, the SV model equations cannot be estimated through ML and this makes them more difficult to estimate. On the other hand, the ARCH/GARCH models are easier to estimate because their likelihood function is simple to write and evaluate (Barnes and De Lema (1999)).

Moreover, these two models are so closely related that they are often considered to be complementary rather than competing models. In fact, it has been shown that from a practical forecasting perspective, it is difficult to distinguish the performance of standard ARCH and SV models (Anderson, Bollerslev, Christoffersen and Diebold (2005)).

Finally, this latent stochastic variable approach was introduced in the theoretical finance literature on option pricing (Hull and White (1987)). The application of SV
type models to financial data has accelerated due to their use in theoretical finance and the recent advances in estimation techniques (Kim, Shephard and Chib (1998)).

However, the empirical variance model followed in this thesis will be the ARCH/GARCH structure. There are several reasons for this:

1. The focus of this thesis is to apply panel fixed effects within the variance equation. This is easier to handle within GARCH models.

2. The objective of this thesis is to analyse the similarities and differences between different stocks in the same sector using nested tests from a general to a specific model. Again, this is facilitated within GARCH type models utilising pooled and panel data structures.

3. The method of this thesis is innovative and will fill a gap in the current literature. However, it is necessary for this innovative analysis to be compared with existing methods to see if it is an improvement. This suggests using the ARCH/GARCH volatility structure because it is currently much more widely used than the SV model.

In summary, the focus of this thesis is on the examination of the volatility structures in the ESM using GARCH models with pooled-panel forms in the variance equation. Therefore, it is important that a review of the use of GARCH models in the empirical analysis of various equities markets is undertaken. The next section will review some of the empirical applications of the ARCH/GARCH class models. Firstly, the empirical evidence for developed markets is examined. Secondly, the empirical evidence for emerging markets is discussed. Thirdly, the empirical evidence for the
African and the MENA markets is reviewed. Lastly, empirical evidence specifically on the ESM is examined.

### 2.7 Empirical Evidence of Volatility with ARCH/GARCH Models

#### 2.7.1 Developed Markets

Many papers have explored the structure of several large stock markets that operate in developed countries around the world (see Bollerslev, Chou and Kroner (1992), Chappel, Padmore and Pidgeon (1998)). As such, this review will concentrate on a few of the main contributions to the volatility literature.

French, Schwert and Stambaugh (1987) examined the relation between stock returns and stock market volatility for the U.S. capital market using daily values of the S&P composite portfolio from January 1928 to December 1984. Monthly return volatility, measured by the monthly standard deviation, was calculated from daily values of the S&P index. They used ARCH and GARCH models to examine the nature of volatility. The estimates of the ARCH model suggest a strong relation between recent squared errors and the estimate of the volatility. This was also verified by the GARCH parameters, which indicate that current volatility is significantly affected by past volatilities. The results suggest that the expected market risk premium (the expected return on a stock portfolio minus the Treasury bill yield) is positively related to the predictable volatility of stock returns.

Lamoureux and Lastrapes (1990a), however, showed that lagged squared residuals or past volatilities explain very little about current volatility, if the rate of information flow is accounted for. Using daily information that flows into the market, Lamoureux
and Lastrapes (1990a) estimated a GARCH (1, 1) model for a sample of 20 actively traded stocks from the U.S. capital market. They found the parameters of the model to be highly significant when volume was not included in the model. The parameters, however, become insignificant when volume was introduced, and which itself now appeared to have significant positive coefficients for all stocks. This led the authors to conclude that the ARCH effects vanish after accounting for the rate of information flow, measured by trading volume, and that the variance of daily price increments is positively related to the rate of daily information arrival.

Similarly, in another paper, Lamoureux and Lastrapes (1990b) showed that the persistence in variance, measured by the sum of GARCH parameters, may be overestimated if structural or deterministic shifts in variance are not accounted for. Using daily closing prices of 30 common stocks and the value weighted index of the New York Stock Exchange for the period January 1963 to November 1979, they estimated a GARCH (1, 1) model and found that the sum of the parameters is close to one for most stocks, which is an indication of strong persistence.

This issue has recently been revisited by Mikosch and Starica (2004), who showed, through Monte Carlo simulation studies, that there is a relationship between “long memory” processes in volatility and models which are Integrated GARCH. Further, Mikosch and Starica (2004) argued that Integrated GARCH parameters may be spurious because of long memories generated by structural shifts in the variance. Davidson (2004), however, is more sanguine about Integrated GARCH and Fractionally Integrated GARCH (FIGARCH) models. He argued that GARCH parameters summing close to one are not spurious and are an indication of persistence.
in volatility. This has limited implications for this thesis. Whilst there is evidence of FIGARCH in the ESM (see Sourial (2002)) and the outcomes of the GARCH estimates in this thesis may approach one, the focus is on the conditional variance as an indicator of structural differences in volatility.

Lamoureux and Lastrapes (1990b) also estimated the HL of volatility shocks. The average HL was found to be approximately 32 days. To test their hypothesis, that is, to control for structural or deterministic shifts in the variance, they divided the sample into 14 non-overlapping samples and estimated the GARCH model by including binary variables to incorporate shifts in variance. The process significantly reduced the sum of the parameters and the average HL fell to 4.43 days, thus supporting the authors’ hypothesis that ignoring shifts in variance over time might overestimate the persistence in variance.

Corhay and Rad (1994) extended the ARCH framework to the European capital markets. Five European capital markets were selected for the analysis. The analysis was conducted on the local indices of these countries covering the period January 1980 to September 1990. The preliminary analysis showed the presence of serial dependence in some indices, which was removed by applying a first order autoregressive process. They estimated several ARCH (q) and GARCH (p,q) models using different values of p and q and used the Schwarz Information Criteria (SIC) to select appropriate models that explain the return generating process in European markets.

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13 The countries studied were France, Germany, Italy, Netherlands and the United Kingdom.
14 See Schwarz (1978) for more details.
Errunza, Kedrith, Omesh and Padmanabhan (1994) examined the ARCH effects in some developed and emerging markets using monthly data from January 1976 to April 1991. In the preliminary analysis, serial dependence was found to be present in emerging markets, but not in developed markets. After removing serial dependence (where present) through autoregressive (AR) and moving average (MA) processes, the presence of ARCH effects in all markets was tested. Significant ARCH effects were found in all of the emerging markets and two of the developed markets, Japan and Germany. Further, GARCH (1,1) models for all markets showing significant ARCH effects were examined. Significant coefficients were found for lagged variance terms in all markets indicating that current volatilities in these markets are significantly affected by past volatilities. In an attempt to test for the existence of serial dependence after controlling for ARCH effects, the authors found that serial dependence was present in Brazil and Mexico. Therefore, returns in these markets are predictable.

In summary, the application of ARCH/GARCH class models in developed markets has provided evidence of ARCH/GARCH effects in stock returns. That is, there is volatility clustering in these markets. This suggests that stock prices are not following a random walk, and hence it is possible to predict stock prices, which is in contradiction with the EMH.

### 2.7.2 Emerging Markets

As suggested above, the majority of the literature in the area of stock market behaviour has concentrated on the large developed stock markets. This is due to

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15 The countries studied included: Canada, France, Germany, Italy, Japan, United Kingdom and the U.S. as developed markets and Argentina, Brazil, Chile, Greece, India, Korea, Mexico and Thailand as emerging markets.
several factors. Importantly, developed stock markets have been established for long periods of time and, consequently, there is stronger and more reliable data available. Moreover, these markets account for the majority of trade and have been important markets to study and understand. On the other hand, less research has been conducted on smaller emerging capital markets for the opposite reasons. However, in recent years, emerging markets have been receiving more attention as their importance in the world financial markets has increased\textsuperscript{16}. In particular, this has been due to their liberalisation efforts, strong economic development and the diversification benefits that these markets offer. Of the emerging markets, studies commonly examine those in Europe, Latin America and South Asian countries, while the literature on the African and MENA region is relatively scarce.

The majority of markets, whether they are developed or emerging, appear to exhibit non-normality in the distribution of returns, which usually takes the shape of a leptokurtic distribution (Mandelbrot (1963), Fama (1965)). In general, the developed markets’ returns distributions exhibit significant negative skewness while emerging markets show positive skewness (Aggarwal, Inclan and Leal (1999)). In fact, it is now well known that emerging markets have vastly different characteristics from developed markets (Bekaert and Harvey (1997)).

In the last 15 years emerging equity markets have dramatically improved, witnessing significant growth in size and relative importance. Combined with strong economic growth, globalisation trends and liberalisation policies, emerging equity markets have

come to the attention of international investors\textsuperscript{17}. These markets offer diversification benefits to international investors due to their reduced correlation with world markets. Emerging markets are of interest to individuals, national and multinational businesses, and pension funds that are seeking to diversify their portfolio to reduce systematic risk. This information is necessary for investors to be able to make rational decisions. Consequently, it is becoming increasingly important to understand and investigate stock price behaviour in emerging markets.

The generally accepted view is that emerging markets experience greater volatility than developed markets. Emerging markets are also characterised by low liquidity, thin trading, and possibly less informed investors with access to less reliable information. Benartzi and Thaler (1995) have also suggested that in the early years of an emerging markets’ operation, investors may not be acting rationally. In emerging markets, investors may be loss averse rather than risk averse and, therefore, are adversely affecting the efficiency of these stock markets. In addition, in emerging markets, investors may not always respond instantaneously to information. These factors affect the volatility and efficiency of stock markets, and make them an interesting case to study.

Very few papers have studied returns predictability in emerging markets with GARCH type models. De Santis and Imrohoroglu (1997) studied the dynamics of expected stock returns and volatility in emerging financial markets. In particular, they attempted to answer the question of whether the volatility of stock returns changes over time in emerging markets. The countries covered in this study were grouped into

\textsuperscript{17}International Monetary Fund (2004a) provides a summary of the issues and developments in the recent experience of emerging markets as net capital exporters.
three geographical regions, Europe, Asia and Latin America\textsuperscript{18}. Using the weekly S&P/IFC market indices from December 1988 to May 1996, a GARCH (1,1) model was estimated. The evidence suggested that for the majority of countries in the study, the GARCH parameters are significant. That is, there is time varying volatility clustering. As such, current information is relevant for predicting future volatility. Moreover, the persistence of the conditional variance process (measured by the sum of the ARCH and GARCH coefficients) is high and close to an Integrated GARCH model.

Su and Fleisher (1998) studied the dynamic behaviour of risk and returns in the Chinese stock market. The shares traded on the Chinese stock exchanges are divided into two categories, A and B shares. The “A shares” are only available to the Chinese, while the “B shares” are only available to foreigners. Su and Fleisher (1998), in examining the stock market volatility, applied their analysis to both the A and B shares, using daily stock market indices for the period 1990 to 1996. A GARCH (1,1) model was estimated under three alternative formulations of the error generating process, to capture the effect of local and global information variables on the conditional mean of stock market excess returns. After determining that the GARCH model with stable error distributions is the best fit, they found that stock market excess returns could be predicted from past information and that the variance of stock market excess returns is time varying, mildly persistent and has a fat tailed distribution.

\textsuperscript{18}That is: Europe/Mid-east (Greece, Turkey), Asia (India, Korea, Malaysia, Philippines, Taiwan, China, Thailand), and Latin America (Argentina, Brazil, Chile, Colombia, Mexico, Venezuela).
Aggarwal, Inclan and Leal (1999) also applied a GARCH analysis in examining the kind of events that cause large shifts in volatility for a number of emerging stock markets. The data used for this study was the weekly rates of return calculated from the daily market indices for 16 developed and emerging markets\textsuperscript{19}, and the Morgan Stanley Capital International (MSCI) regional market indices\textsuperscript{20} for the period May 1985 to April 1995. Completing the analysis separately for each of the countries and regional MSCI market indices, 9 emerging markets, 3 developed markets and all of the regional MSCI market indices had significant ARCH and GARCH coefficients. The results suggested that the large changes in volatility are related to important country specific political, social and economic events. For the majority of the series, the sum of the ARCH and GARCH coefficients is close to one. If this is not a spurious manifestation of FIGARCH due to structural changes in volatility, then the results imply the existence of extreme persistence in volatility.

Siourounis (2002) estimated GARCH type models including the standard GARCH (1,1), EGARCH-M (1,1), and the Leverage GARCH (1,1) to determine their validity in the emerging capital market of the Athens Stock Exchange. Using daily closing prices of the Athens Stock Exchange General Price Index for the period January 1988 to October 1998, they found strong evidence that there is volatility clustering in the Athens Stock Exchange with all the estimated coefficients significant at the one percent level. That is, the null hypothesis of no ARCH or GARCH effects in all lags is rejected. In addition, the coefficient for the lagged conditional variance suggests that 78 percent of past volatility carries on in the next period.

\textsuperscript{19} Countries studied include: Japan, Germany, Hong Kong, Singapore, United Kingdom and the U.S. as developed markets and Argentina, Brazil, Chile, India, Korea, Malaysia, Mexico, the Philippines, Taiwan and Thailand as emerging markets.

\textsuperscript{20} The MSCI regional indices modeled include: the World, Emerging, Far East and Latin American.
Cunado Eizaguirre, Gomez Biscarri and Perez de Gracia Hidalgo (2004) analysed whether the volatility of the Spanish stock market changed significantly between 1941 and 2001. Using monthly series of an index of Spanish stock prices, they estimated a GARCH (1,1) model. The ARCH and GARCH coefficients were found to be significant, suggesting strong evidence of conditional heteroskedasticity in the Spanish stock market. In addition, market volatility was found to be quite persistent, with the sum of ARCH and GARCH parameters equal to 0.99. In order to capture the changing behaviour of volatility they estimated a GARCH (1,1) model and allowed for a structural break in the parameters of the variance equation. The structural break was determined endogenously, and was found to exist in June 1972. The results suggest that volatility has changed significantly over the period 1941 to 2001, with volatility being higher after June 1972 but with less persistence.

In summary, as with the developed markets literature, the evidence suggests that emerging markets are more volatile than developed markets and that they also exhibit ARCH/GARCH effects in stock prices.

### 2.7.3 African and MENA Markets

Studies of return predictability in the African stock markets are few even though some of the markets such as Egypt, South Africa, and Zimbabwe were established towards the end of the nineteenth century. This section will examine some of the ARCH/GARCH studies applied to various countries in the African and Middle East region.
Dahel and Laabas (1998) examined the behaviour of stock prices in four Gulf Cooperation Council countries. Using weekly stock prices over the period September 1994 to April 1998, they applied various measures to test for the weak form of market efficiency. The distributions of returns in these markets are skewed to the right, with a leptokurtic distribution. Moreover, the results of a standard LM test for ARCH (1) confirmed the existence of ARCH effects in the returns in all four markets.

Omet, Khasawneh and Khasawneh (2002) examined the efficiency of the Jordanian stock exchange by studying the relationship between returns and conditional volatility. A GARCH-M model was estimated for five daily stock market returns indices, including: the general market index, the banking, industrial, insurance and services sector indices for the period 1992 to 2000. The GARCH-M specification allows for the inclusion of a time varying conditional standard deviation as a regressor. For all indices, the results for the significance of the ARCH and GARCH parameters support the hypothesis that the conditional variance changes over time as a result of volatility clustering and temporal dependence.

Appiah-Kusi and Menyah (2003) tested for the weak form of market efficiency for 11 African stock markets. Using the weekly returns index for each market, an EGARCH-M model was estimated. The estimated coefficients of the efficiency parameter in the mean equation for Egypt, Kenya, Mauritius, Morocco, and Zimbabwe were not significant, implying that the price dynamics in these markets are of the weak form efficiency. The coefficients of past volatility shocks and past

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21 Bahrain, Kuwait, Oman and Saudi Arabia.
22 Countries examined include: Botswana, Egypt, Ghana, Ivory Coast, Kenya, Mauritius, Morocco, Nigeria, South Africa, Swaziland and Zimbabwe.
conditional variances were found to be statistically significant for Egypt, Ivory Coast and Zimbabwe. This indicates that, for these countries, volatility terms are predictable using past information. The results for Mauritius and Kenya are mixed, suggesting difficulty in forecasting volatility. Moreover, the degree of volatility persistence is strong in all markets with the exception of the Ivory Coast.

Hassan (2003) examined how globalisation and country risk affect stock market return volatility and predictability. In addition, he explained how to structure portfolios so that a mean-variance efficient portfolio can be created. Beginning with an analysis of volatility, Hassan (2003) used an extended version of the GARCH-M (1,1). Specifically, he followed Engle, Lilien and Robins (1987) by allowing shocks in local factors (political, financial and economic) to affect conditional variance. Therefore, if the sum of the persistence parameters in this model adds to one, then this can be interpreted as the effect of political, financial and economic risks persisting over time. This model was applied to two groups of countries. The first group consisted of the MENA countries including Egypt, Jordan, Morocco, Tunisia and Turkey. The second group consisted of other African countries, namely Ivory Coast, Kenya, Nigeria, South Africa and Zimbabwe. The data used were the monthly dollar total returns for the period 1984 to 1999, dependent on data availability. The results suggested that the ARCH/GARCH effects existed in all markets except for Morocco. The persistence parameters for the sample period showed that for Ivory Coast, Jordan, Kenya, Nigeria, Turkey and Zimbabwe volatility decayed over time. That is, the sum of the ARCH and GARCH parameters was less than one. However, for Egypt, Morocco, South

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Africa and Tunisia, the parameters were not significantly different from unity. Therefore, volatility in these markets persisted for long periods.

In summary, the literature in the African and Middle East region strongly suggests the existence of volatility clustering of stock price returns. This is evidence against the EMH in these markets. The next section will examine some ARCH/GARCH studies specific to Egypt.

2.7.4 The Egyptian Stock Market

The ARCH/GARCH literature has extensively examined the developed markets and to a lesser extent emerging markets. In recent years, the ARCH/GARCH literature has continued to expand with numerous extensions to the basic model in addition to its wider application across different markets. Apart from the basic ARCH/GARCH models, extensions to these models have been applied to the Egyptian and other emerging markets\(^{24}\).

One of the first applications of ARCH/GARCH to the ESM was Mecagni and Sourial (1999). They examined the behaviour of stock returns in the ESM, using the four most widely known Egyptian market indices. These include the Capital Market Authority Index (CMAI), the Egyptian Financial Group Index (EFGI), Hermes Financial Index (HFI) and the Prime Index for Initial Public Offerings (PIPO). They applied a GARCH-M, which allows the mean returns to be specified as a linear function of time varying conditional second moments. They found that the conditional variance changes over time because of volatility clustering effects. This is indicated by

statistically significant ARCH and GARCH coefficients in the GARCH models for all four indices. However, the persistence parameters are considerably less than one, implying that shocks to volatility decay within a few time lags.

Mohieldin and Sourial (2000) provided a detailed analysis of the development, performance and key characteristics of the ESM. Using the daily closing prices for two of the major market indices in Egypt, that is the CMAI and EFGI, for the period January 1993 to September 1998, they tested for the presence of volatility clustering. Estimating a parsimonious GARCH (1,1) model it was found that the indices exhibited volatility clustering. The sum of the ARCH and GARCH coefficients was close to one, and was significant at the 5 percent significance level. The HL of the shock suggested that volatility would persist and decay after a period of about 40 to 50 days.

Moursi (2000) examined the performance of different variants of the GARCH model using data from the Egyptian stock exchange. The efficiency of the GARCH models was tested and examined in comparison to benchmark estimates obtained from four conventional conditional heteroskedasticity parameterisations including the linear GARCH, Golsten-Jagannathan-Runkle GARCH, EGARCH and Threshold GARCH. The analysis was based on the CMAI for the period January 1994 to December 1999. The significant ARCH and GARCH coefficients for the four separate estimations were indicative of strong volatility clustering. The degree of persistence of shocks in each of the models was moderate with the sum of the ARCH and GARCH coefficients close to one. It was concluded that each of the GARCH models was able to capture the skewness and excess kurtosis of the standardised GARCH residuals. In
addition, the variant GARCH models were an improvement to the conventional GARCH parameterisations.

Sourial (2002) expanded on this research by testing for the existence of a long-term memory process in the stock returns on the ESM. Applying Fractional autoregressive integrated moving average and FIGARCH models, S&P/IFC Global-Egypt index weekly returns were used during the period January 1996 to June 2001. A parsimonious GARCH (1,1) model was estimated, where it was found that the GARCH parameters were both significant. Therefore, conditional volatility was time variant and there were volatility clustering effects. Overall, Sourial (2002) concluded that a long-term memory process existed, which suggests that the ESM is not a weak form efficient market.

Farag, Ragab and El-Temsahy (2004) explored the applicability of ARCH modelling and its generalisations to an empirical study of real asset returns for the ESM. The sample consisted of 46 of the most active firms from the S&P/IFC Global index for the period 1996 to 2000. Active stocks were selected based on market size, trading activity and sector representation. The GARCH model was found to be more effective than the ARCH model in controlling volatility in the ESM.

Tooma and Sourial (2004) investigated the impact of regulatory policies on conditional volatility estimation in the ESM. Four variations of the GARCH model, namely, GARCH, EGARCH, Golsten-Jagannathan-Runkle GARCH and Asymmetric Power ARCH, were estimated under different density functions (Gaussian normal

25 The long memory process is simply that observations in the past are highly correlated with observations in the future. That is, evidence of volatility clustering.
distribution, Student-t distribution, skewed Student-t, and Generalised Exponential Distribution). Using two of the major daily market indices (EFGI and HFI) for the period January 1993 to December 2001, they found evidence that the implementation of circuit breakers caused volatility to cluster in the ESM. Comparing unconditional volatility before and after the introduction of circuit breakers, volatility was found to be higher when circuit breakers were in place confirming the Mecagni and Sourial (1999) findings. Moreover, the results suggest that post circuit breakers implementation, negative shocks tended to have a stronger impact on conditional volatility, compared to positive shocks. That is, there was an asymmetric affect of shocks on volatility causing investors’ behaviour to change. In particular, investors’ risk aversion has increased, reducing the welfare to market participants and leading to pricing inefficiency.

In summary, the results of the ARCH/GARCH analysis in the ESM are consistent with the results of other emerging markets. That is, there is evidence of volatility clustering. This suggests that the EMH is not applicable in the ESM. The general conclusion is that volatility clustering is a common finding in stock markets around the world, regardless of whether it is a developed or emerging stock market.

So far, there is no evidence of the utilisation of panel model structures to analyse differences in volatility patterns between stocks in the ESM. Further, these findings appear to be true for all stock markets irrespective of their status. The objective of this thesis is to estimate the significance of individual fixed effects in GARCH variance equations with a view to analysing the differences and similarities between the variance patterns of different stocks in the same sector as well as the market as a
whole. The next section examines the literature on ARCH/GARCH model application to pooled and panel data.

2.8 Modelling Volatility Using Panel ARCH/GARCH

The application of panel data methods to financial data is a relatively new development in the literature. Since the literature has shown that financial series exhibit ARCH/GARCH processes, a further development in this literature has been to apply ARCH/GARCH methods to pooled and panel data, rather than simply time series data. Pooling data gives the advantage of a significant increase in sample size. However, if the data comprises longitudinal data sets, it might be possible to enrich the variance equation with group specific effects. This would reduce the unexplained variance in the stochastic component of the conditional variance equation. Further, it could be used to examine differences in volatilities between cross-sectional units. The following is a review of the available theoretical and empirical literature on modelling ARCH/GARCH processes in a pooled and panel data context.

Kitazawa (2000) applied an exponential ARCH type specification to estimate a fixed effect panel data model using a large number of stocks ($N \to \infty$) issued over a short period of time ($T$ fixed). The work explored the leverage effect (the negative association between the stock return today and the stock returns volatility tomorrow) associated with the deregulation in the Japanese stock market. The estimated model was as follows:

\begin{align*}
y_{it} &= \phi y_{i,t-1} + \varepsilon_{it}, \quad (2.8.1) \\
\varepsilon_{it} &= f_i + \nu_{it}, \text{ and} \quad (2.8.2)
\end{align*}
\[ E_{t-1}[\nu^2_i] = h_i = \exp(g_i + \gamma y_{i,t-1}) \]  

(2.8.3)

where:

- \( y_{it} \) is the stock return of the \( i^{th} \) stock issued at time \( t \);
- \( \phi \) and \( \gamma \) are unknown common parameters across all stocks to be estimated;
- \( g \) is a stock specific constant and functions to establish heterogeneity in volatility;
- \( \epsilon \) is the disturbance to the mean equation (2.8.1) comprising \( f \) and \( \nu \);
- \( f \) is the stock issue-specific additive fixed effects which controls for the heterogeneity of the stock issue;
- \( \nu \) is an identically and independently distributed disturbance over indices \( i \) and \( t \);
- \( i \) and \( t \) are the individual and time indices respectively.

The sign of the estimated parameter \( \gamma \) is important, with \( \gamma < 0 \) implying the existence of the leverage effect. Kitazawa (2000) used a balanced panel data set consisting of the daily overnight stock returns for 1,167 stocks over the period from the 1\(^{st}\) of June to the 3\(^{rd}\) of July in 1998. Kitazawa (2000) found that the leverage effect was associated with the Japanese deregulatory period. This is an important model in the application of panel methods within the variance equations. Not only are there panel fixed effects in the mean equation (2.8.1) through the parameter \( f \), but there also are panel fixed effects in the variance equation (2.8.3) through the parameter \( g \). Whilst the model is described as ARCH, it appears not to include the autoregressive structure of variances usually associated with ARCH/GARCH models. This thesis will estimate variance equations containing stock specific effects and an autoregressive structure.

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Cermenó and Grier (2001) developed pooled-panel GARCH models, firstly with complete parameter homogeneity and then allowing heterogeneity of the intercepts in the mean and variance equations. Cermenó and Grier (2001) proposed four particular models and a methodology to determine the most suitable one to be used. The four models are (with nomenclature and taxonomy added for this thesis):

Model 1: (The Pooled Model)

\[
y_{it} = \mu + \phi y_{i,t-1} + \mathbf{x}_i' \mathbf{\beta} + \epsilon_{it}, \quad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T
\]

\[
\epsilon_{it} \sim \mathcal{N}(0, h_i)
\]

\[
h_i = \alpha_0 + \sum_{m=1}^{q} \alpha_m \epsilon_{i,t-m}^2 + \sum_{n=1}^{p} \delta_n h_{i-t-n}.
\]  

Model 2: (The Panel Fixed Effects in Mean with Pooled GARCH Model)

\[
y_{it} = \mu_i + \phi y_{i,t-1} + \mathbf{x}_i' \mathbf{\beta} + \epsilon_{it}, \quad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T
\]

\[
\epsilon_{it} \sim \mathcal{N}(0, h_i)
\]

\[
h_i = \alpha_0 + \sum_{m=1}^{q} \alpha_m \epsilon_{i,t-m}^2 + \sum_{n=1}^{p} \delta_n h_{i-t-n}.
\]

Model 3: (The Pooled Mean with Panel Fixed Effects in GARCH Model)
\[
y_{it} = \mu + \phi y_{i,t-1} + \beta' x_{it} + \epsilon_{it}, \quad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T
\]  
(2.8.8)

\[
\epsilon_{it} \sim N(0, h_{it})
\]

\[
h_{it} = \alpha_0 + \sum_{m=1}^{q} \alpha_m \epsilon_{i,t-m}^2 + \sum_{n=1}^{p} \delta_n h_{i,t-n}.
\]  
(2.8.9)

Model 4: (The Panel Fixed Effects in Mean and GARCH Model)

\[
y_{it} = \mu_t + \phi y_{i,t-1} + \beta' x_{it} + \epsilon_{it}, \quad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T
\]  
(2.8.10)

\[
\epsilon_{it} \sim N(0, h_{it})
\]

\[
h_{it} = \alpha_0 + \sum_{m=1}^{q} \alpha_m \epsilon_{i,t-m}^2 + \sum_{n=1}^{p} \delta_n h_{i,t-n}.
\]  
(2.8.11)

where for all models:

\( y_{it} \) is the dependent variable;

\( x_{it} \) is a \( k \) vector of explanatory variables in the mean equation;

\( \beta \) is a \( k \) by 1 vector of coefficients;

\( \phi \) is the AR parameter which assumes that \( |\phi| < 1 \), and \( \gamma + \delta < 1 \) to ensure stationarity of each cross-section in the panel;

\( \mu \) is a constant in the mean equation;

\( \epsilon_{it} \) is the disturbance term with time dependent variance \( h_{it} \);

\( \alpha_0 \) is the mean variance;
\( \alpha_m \) and \( \delta_n \) are parameters associated with the time dependent aspects of the conditional variance;

\( N \) and \( T \) are the number of cross-sections and time periods in the panel respectively; and

\( m \) and \( n \) are the number of lags on the ARCH and GARCH terms respectively.

Cermeno and Grier (2001) applied their Pooled-Panel model to two sets of data. Firstly, the conditional variance of the investment process was tested to determine whether it was time dependent with the market value of the firm, and the value of the stock of plant and equipment. The data included a panel of five large U.S. firms\(^{26}\) over the period from 1935 to 1954. Secondly, a panel of quarterly inflation rates from January 1991 to April 1999 covering seven Latin American countries\(^{27}\) was used to test if the inflation uncertainty, as represented by the conditional variance of the error term, could be best described by a GARCH process. Cermeno and Grier (2001) developed a model selection process which suggested that the first application can be well approximated by a dynamic panel ARCH (1) model, that is Model 4, but with \( \delta_1 = \delta_2 = \ldots = \delta_p = 0 \), and the second application can be well approximated by a pooled ARCH (1) model, that is Model 1, but with \( \delta_1 = \delta_2 = \ldots = \delta_p = 0 \).

The important models for this thesis are Models 3 and 4 where both models have panel fixed effects in the variance equation. A useful nomenclature here is panel fixed effects in GARCH. These should be distinguished from Model 2, which is a panel fixed effects in mean, but simply uses a common variance equation across \( i \). This model could be described as a panel model with GARCH errors. This thesis will be

---

\(^{26}\) Companies studied are: General Motors, Chrysler, General Electric, Westinghouse and U.S. Steel.

\(^{27}\) Countries studied are: Argentina, Brazil, Chile, Colombia, Mexico, Peru and Venezuela.
estimating the former, that is, models with panel fixed effects in GARCH. Further, unlike Cermeno and Grier (2001), the fixed effects in GARCH will be a true GARCH model with \( \delta_1 \neq \delta_2 \neq \ldots \neq \delta_p \neq 0 \).

Cermeno and Grier (2001) tested the hypothesis that appreciation in the real exchange rate creates more uncertainty. They applied a panel model with GARCH errors that allowed for individual effects in the mean equation, but assumed all the parameters in the variance equation to be homogeneous. Moreover, the variance was not only a function of the previous errors and previous variances, but was also conditioned by previous real exchange rates. This is Model 2, equations (2.8.6) and (2.8.7) of Cermeno and Grier (2001), but with a variance equation restricted to a GARCH (1,1) and augmented with a lagged realisation of the dependent variable:

\[
h_{it} = \alpha_0 + \alpha_1 e_{it-1}^2 + \delta_1 h_{i,t-1} + \gamma y_{i,t-1}.
\]  

(2.8.12)

Cermeno and Grier (2001) used the monthly J.P. Morgan’s trade weighted real exchange rate index for a sample of 14 countries (later dividing the sample into two regional sub-samples: seven Latin American and seven East Asian countries) covering the period from January 1971 to December 2000, with 1990 as a base year.28 The results suggested significant conditional heteroskedasticity, and that as the real exchange rate appreciated, it became more uncertain. Moreover, the results showed that the proposed model describes Latin American countries more than East Asian countries. In other words, an appreciation in real exchange rates in Latin American countries studied were: Argentina, Brazil, Chile, Colombia, Hong Kong, Indonesia, Malaysia, Mexico, Peru, Singapore, South Korea, Taiwan, Thailand, and Venezuela.
countries increases uncertainty about future real exchange rates more than East Asian countries.

It must be made clear, however, that neither Cermeno and Grier (2001) nor Grier and Grier (2001) actually estimated a GARCH variance model with panel fixed effects in it. Cermeno and Grier (2001) estimated Model 3, that is equations (2.8.8) and (2.8.9), and Model 4, that is equations (2.8.10) and (2.8.11), with fixed effects in the variance equations. However, they estimate these as panel in ARCH models as the GARCH terms are restricted to $\delta_1 = \delta_2 = \ldots = \delta_p = 0$. Nevertheless, it is innovative in that Cermeno and Grier (2001) appear to provide the only example of a panel fixed effects in ARCH model. The empirical work in this thesis will estimate panel in GARCH models where $\delta_1 \neq \delta_2 \neq \ldots \neq \delta_p \neq 0$.

The similarity between Kitazawa (2000) and Cermeno and Grier (2001) is that both estimated panel fixed effects in the variance equation. That is, the mean volatility was fixed at different levels for individuals in the cross-sections.

Plümper and Troeger (2004) developed a model to estimate the effect of changes in the key currency (Germany/Euro Zone) real interest rate, on the interest rates of the countries outside the European currency union. However, it was argued that since the interest rates could be time dependent, not accounting for variance heterogeneity over time would give biased and inefficient estimates. Therefore, they estimated a panel fixed effects model, but with a pooled GARCH equation. That is, Model 2 in equations (2.8.6) and (2.8.7) of Cermeno and Grier (2001).
Using monthly data covering the period from 1973 to 2002, Plümper and Troeger (2004) applied the panel fixed effects in mean with pooled GARCH, which is Model 2 in equations (2.8.6) and (2.8.7) of Cermeño and Grier (2001), to six different linear mean models. The real interest rate changes of Great Britain, Sweden, Denmark, Switzerland and Norway were regressed on the real interest rate changes of the key currency (Germany/Euro Zone) markets for all specified mean models. Parameters representing various changes to the market were included. This included a parameter to represent the change in interest rate in Germany before and after 1990 when the European monetary union countries fully liberalised capital accounts and enforced their monetary policy coordination. Another parameter was included (before and after 1994) when the European monetary union began to coordinate the interest rate policies for the European Union. In addition, a parameter was inserted (before and after 1999) when the European monetary union countries fixed their exchange rate and introduced the Euro. Finally, parameters were included to control for the growth of GDP and the level of the real interest rates in Britain, Sweden, Denmark, Switzerland and Norway, as well as for the German growth rate and changes in the exchange rate.

The results suggested that for all different model specifications, and for the whole period under study, changes in the key currency’s interest rates had a significant effect on the decision of the non-European monetary union countries to adjust their interest rates. That is, de facto monetary autonomy of countries outside the European monetary union declined because of the harmonisation of central bank policies in the European monetary union and the introduction of the Euro. Moreover, both ARCH and GARCH terms were positive and significant in all models indicating a high
degree of heteroskedasticity and justified the use of the panel fixed effects in mean with pooled GARCH model.

Kling (2004) conducted an event study with the aim of detecting the impact of events like mergers by observing the deviation of daily return from the normal stock price movement for 46 companies, where the normal returns were estimated for the sample of the year 2000 during an estimation period starting at July 1, 1999. Any significant deviation from this normal stock price movement served as a hint that the merger possesses an economic impact on the firm’s market value; that is, abnormal returns. The day of the announcement of a merger was regarded as the event day around which the event window was constructed. The event window started fifteen days prior to the public announcement and ended fifteen days afterwards.

Kling (2004) estimated a GARCH \((p,q)\) model with panel fixed effects in the mean equation to test for the uncertainty in daily abnormal returns caused by events like mergers. The variance equation was estimated with all parameters common for all cross-section units. That is, the variance equation was a pooled estimate and the full model was Model 2 in equations (2.8.6) and (2.8.7) of Cermeno and Grier (2001). This is the specification named as panel fixed effects in mean with pooled GARCH in this thesis.

Andritzky, Bannister and Tamarisa (2005) tested for the effect of announcements on the volatility of the daily change in global bond spread using daily percentage changes in country’s sub-indices of the Emerging Market Bond Index–Global for 12 emerging
markets covering the period from January 5, 1998 to July 15, 2004. They used a completely pooled model, where all parameters in both the mean and the variance equations were common for all cross units. They estimated Model 1, equations (2.8.4) and (2.8.5) of Cermeno and Grier (2001); that is, the specification referred to as the pooled model in this thesis. However, they augmented the GARCH variance equation with binary variables representing days of the week and announcement days, which are important in determining the effects of announcements on volatility.

Whilst the work cited in this section claims to undertake panel GARCH studies, a clear distinction must be made between Kitazawa (2000) and Cermeno and Grier (2001) on the one hand, and the other remaining papers. The latter group did not attempt panel estimation in the variance equation even though they may or may not have done so in the mean equation. Thus, they estimated pooled variance equations. Those pooled variance equations may be estimated without individual effects in the mean equation, such as Andritzky, Bannister and Tamarisa (2005). Therefore, this is simply a pooled data model which fails to exploit the possibilities of individual effects in both the mean and variance equations, which is Model 1, equations (2.8.4) and (2.8.5) of Cermeno and Grier (2001). Alternatively, the pooled variance equation can be estimated along with panel fixed effects in the mean equations, for example Kling (2004). This type of model should be described as a panel fixed effects model but with a pooled GARCH variance equation, that is Model 2, equations (2.8.6) and (2.8.7) of Cermeno and Grier (2001).

Countries studied are: Brazil, Chile, China, Colombia, Korea, Malaysia, Mexico, Poland, South Africa, Thailand, Turkey, and Venezuela.
On the other hand, Kitazawa (2000) and Cermeno and Grier (2001) estimated variance equations that attempt to differentiate the individual variances between individuals in the panel. This was done with fixed effects in the variance equation, that is, panel fixed effects in GARCH. In terms of the GARCH model of volatility, this would give a common temporal pattern of variance amongst individuals in the panel, but with that temporal change occurring around individual specific mean variances. Such an equation could be estimated with common parameters in the mean model. In this case, the model is best described as a pooled mean model with panel fixed effects in GARCH, that is Model 3 equations (2.8.8) and (2.8.9) of Cermeno and Grier (2001). Alternatively, the panel fixed effects in GARCH model could be estimated with fixed effects in the mean equation and is best described as a panel in mean with panel fixed effects in GARCH model, that is Model 4 equations (2.8.10) and (2.8.11) of Cermeno and Grier (2001).

Even though Kitazawa (2000) estimated the variance equation with fixed effects, the variance equation is not a GARCH process because it does not contain lagged realisations of squared errors or variances. Cermeno and Grier (2001), on the other hand, estimated a panel fixed effects model, but with panel fixed effects in ARCH and no GARCH terms. Both papers are important in terms of introducing panel fixed effects in the variance equation. However, this thesis aims to go a step further by estimating fixed effects within a true GARCH model and using these estimates in a framework of general to specific modelling to identify similarities and differences between the volatility patterns of groups of sector indices and stocks in the ESM.
2.9  Circuit Breakers and Stock Market Volatility

2.9.1  Background

Stock market volatility literature has generally shown that in recent years there has been a greater amount of volatility surrounding financial assets. The causes of this volatility have been studied extensively due to the policy implications of imposing regulations. Volatility has been shown to have adverse consequences for the various stock exchanges around the world and the popular opinion has been to introduce some form of “circuit breaker” to protect the market from large fluctuations.

Circuit breakers are an automatic response, usually a halt or slow down in activity at an exchange, triggered by certain occurrences in trading. Circuit breakers are designed to reduce stock market volatility and were instituted following the world financial market crashes in October 1987 and October 1989.\(^{30}\)

The two most common forms of circuit breakers used by various stock exchanges are the trading halt and the price limit. A trading halt is a temporary suspension in the trading of a particular security on one or more stock exchanges, usually in anticipation of a news announcement or to correct an order imbalance. A trading halt may also be imposed for purely regulatory reasons. During a halt, open orders may be cancelled and options may be exercised. On the other hand, price limits are literal boundaries that pre-specify the maximum range upwards and downwards, in which security prices are permitted to move within a single day of trade. If bids and offers match within the bounds prescribed by the limit, then trading takes place as usual. If not,\(^{30}\)

\(^{30}\) Following the 1987 U.S. stock market crash, many questions were raised regarding the causes of the crash and preventative measures which could be introduced to prevent such crashes in the future. The recommendations put forward included the introduction of circuit breakers ((Phylaktis, Kavussanos and Manalis (1999)).
trading stops (France, Kodres and Moser (1994)). Trade can immediately take place again as long as the buyers and sellers price stays within the limit bound. Price limits are usually specified by a percent based on the closing price of previous days. Daily price limits are currently in place on many stock markets\textsuperscript{31}. One of the justifications for the introduction of price limits is that they ideally reduce the wild day-to-day swings in stock prices. Thus, the main difference between a trading halt and a price limit is that a trading halt completely ceases trade, whereas with price limits trading still occurs as long as it is within the price band.

This section will primarily focus on the literature relating to price limits and stock market volatility. This is because Egypt is the focus of this thesis and there is a current and ongoing debate on whether price limits on CASE and many other stock markets should be removed. Over the past ten years, there have been three levels of price limits imposed on CASE. These are presented in Table 2-1.

<table>
<thead>
<tr>
<th>Period</th>
<th>Price Limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>4/1/1994 to 1/2/1997</td>
<td>No Limit</td>
</tr>
<tr>
<td>2/2/1997 to 21/7/2002</td>
<td>5 % Limit</td>
</tr>
<tr>
<td>22/7/2002 to Present</td>
<td>10 % Limit</td>
</tr>
</tbody>
</table>

Source: Medhat and Eskandar (2006)

The debate regarding price limits focuses on the effectiveness of price limits; that is, whether price limits actually reduce volatility. One side of the literature proposes that price limits provide a “cooling off” period and, therefore, reduce market volatility.

\textsuperscript{31} For example, Austria, Belgium, Egypt, France, Greece, Italy, Japan, Korea, Malaysia, Mexico, The Netherlands, Spain, Switzerland, Taiwan and Thailand (Kim (2001)).
On the other side, it is argued that, for various reasons, price limits may actually increase stock market volatility. This debate remains unresolved. However, it will be shown that despite there being price limits on CASE, studying volatility in this period is relevant since prior research has shown that price limits have been unsuccessful in reducing stock market volatility and, in fact, volatility has increased as a result of price limits (Medhat and Eskandar (2006)).

2.9.2 The Debate—Rationale For and Against Price Limits

The debate on the effectiveness of price limits centres on two hypotheses, the over-reaction hypothesis and the information hypothesis. The over-reaction hypothesis assumes that investors tend to over react to new information, so that price limits give them time to reassess information and reduce stock market volatility. Therefore, price limits have a positive impact on the stock market. On the other hand, the information hypothesis implies that price limits only slow down the process of price adjustment, and have no effect or possibly increase stock market volatility (Phylaktis, Kavussanos and Manalis (1999)).

2.9.2.1 Pro Price Limits

Prior to the 1980s world stock markets crash, very few theoretical papers had developed behavioural models to explain price limits. One of the first and most cited models to be developed was by Brennan (1986), who developed a general model of price limits and margins for the futures market. It was concluded from this model that price limits have the effect of reducing default risk in less liquid financial markets. However, this is not necessarily the case for more liquid financial markets. Reducing default risk may then lead to lower volatility on the market.
Moreover, Greenwald and Stein (1991) in their theoretical study showed that circuit breakers provide a calming effect on the market in times of market turbulence. In their model, buyers withhold orders in response to large volume shocks due to high transactional risks. This gives the participants time to digest and learn about the flow imbalances and facilitates price movement to equilibrium. The results show that circuit breakers can reduce the transactional risks in stock markets and, therefore, reduce market volatility.

Similarly, Kodres and O'Brien (1994) examined the welfare effects of price limits by developing a four-stage futures market model with risk averse investors. It was shown in their model that when prices become volatile, shocks to liquidity and fundamentals might occur between the time investors decided to trade, and the time trade orders were executed. This gives rise to implementation risk that cannot be transferred with contingent claims. Kodres and O'Brien (1994) showed that price limits partially ensure implementation risk. Therefore, when price fluctuations are caused by news about fundamentals, then price limits can be set so that trade can be *ex ante* Pareto superior to unconstrained trade. That is, limits can improve the welfare of market participants because the price limit allows the risk to be shared among market participants.

Furthermore, the exchanges have put forward various justifications for the implementation of price limits which have their foundations in the over-reaction hypothesis\(^{32}\). Basically, there are two attributes to price limits that are argued to have

\(^{32}\) It has been suggested that panic behaviour caused the excessive volatility which led to the 1987 U.S. stock market crash (see Greenwald and Stein (1991)). It is believed that price limits could have prevented the price free-fall by firstly not allowing prices to fall by a given amount per day, but also giving frenzied traders time to cool-off (Kim and Rhee (1997)).
the effect of reducing stock market volatility. Firstly, they establish price constraints and secondly, provide time for rational reassessment during times of panic (Kim and Rhee (1997)).

Price limits are considered necessary by a stock exchange due to the effects of “excessive” speculation and “mob psychology” on the pricing process. Price limits reduce the probability of over reaction to news. By not allowing prices to move beyond a certain point, they discourage mob psychology and force prices to move slowly. Therefore, by constraining price movements, such mob psychology is reduced (Kim and Rhee (1997)). Moreover, price limits offer the opportunity for normal information transmission in times of market turbulence. During major price changes, a breakdown of information between the trading floor and market participants can occur in which circuit breakers allow time for market participants to be re-informed (Phylaktis, Kavussanos and Manalis (1999)).

In summary, most regulators believe that price limits will reduce stock market volatility. Despite the appealing rationale for price limits, research confirming these beneficial aspects is lacking (Kim and Rhee (1997)). In fact, research has shown that volatility has increased after the implementation of price limits, and this increased volatility may be due to the implementation of price limits. This proposition is discussed below.
2.9.2.2 Con Price Limits

In the literature opposing the use of price limits, critics suggest three main problems with the implementation of price limits. These are the volatility spill-over argument, the delayed price discovery argument, and the trading interference argument.

In the volatility spillover argument, price limit critics argue that they serve no purpose but to slow down or delay price change. That is, even though price limits stop prices falling on the one day when the shock hits, the price will continue to move to equilibrium as new limits are established in subsequent trading days (Phylaktis, Kavussanos and Manalis (1999)). Lehmann (1989), in his study, provides support for the volatility spillover hypothesis. He suggests that supply and demand imbalances for trading actually induce prices to reach their limit. The transactions are then transferred to subsequent trading days. That is, by preventing immediate correction of the order imbalance, price limits cause volatility to spread out over a longer period of time.

In support of the argument that price limits are merely spreading the volatility over a number of days and are, therefore, ineffective, Roll (1989) has stated that:

“Most investors would see little difference between a market that went down 20 percent in one day than a market that hit a 5 percent down limit 4 days in a row”.

In fact, investors may prefer that the market corrected itself immediately in one day. Secondly, the delayed price discovery hypothesis is another costly problem induced by price limits. As price reaches the bounds, trade stops until the limits are revised creating an interference with the price discovery process (see Lehmann (1989) and Lee, Ready and Seguin (1994)). The effect of the price limit is to prevent the price
from moving to its equilibrium level for that day. Stocks then have to wait for the next trading day in order to reach their true price. This is the delayed price discovery process.

Thirdly, price limits prevent trade occurring at the most appropriate time. Traders are forced to advance their trades prior to reaching price limits. However, this may not be the action of the trader had there not been a price limit. It is in this regard that price limits interfere with trading practice, consequently raising price variability (Subrahmanyam (1994)). The next section examines the evidence of the effect of price limits on volatility.

2.9.3 The Evidence

Price limits became a topic of interest in the literature after the 1980s world stock market crash, when it was suggested that price limits could have prevented the market collapse. Despite this interest in price limits, the literature on the effects of price limits is quite small. One of the main reasons for this is related to the problem of measurement of stock price volatility in the presence of price limits. The problem is that price limits have been implemented for the purpose of limiting stock price volatility. Therefore, in a sense, the data is censored, as severe price variations have been restricted through the price limit. Thus, it is possible that extreme price volatility may go undetected. Moreover, it is not possible to measure the true variability of stock prices. As a result, limited research had been conducted in the presence of price limits. However, more recently, Kim (2001) has argued that price limits may actually

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33 For example, studies on the effect of trading restrictions on stock exchanges include Lauterbach and Ben-Zion (1993), Santoni and Liu (1993) and Overdahl and McMillan (1998), while papers focusing on the effects of trading halts on volatility and trading volume include: Amihud and Mendelson (1987), Stoll and Whaley (1990), Gerety and Mulherin (1992) and Lee, Ready and Seguin (1994). The main conclusion from the literature is that trading halts do not reduce volatility or volume.
result in increased volatility in the period where price limits have been implemented. Consequently, the examination of stock price volatility in the presence of price limits is an important research area.

The empirical evidence regarding the role of circuit breakers in moderating volatility and enhancing efficiency is not conclusive. Some researchers have concluded in favour of the over-reaction hypothesis where trading restrictions reduce volatility (Ma, Rao and Sears (1989), and Gerety and Mulherin (1992)). On the other hand, others have found that volatility increases as a result of circuit breakers (Lee, Ready and Seguin (1994)). Most importantly, as suggested by Kim and Rhee (1997), research confirming the beneficial aspects of price limits is lacking.

Ma, Rao and Sears (1989) used Treasury bond future prices to test for the validity of the information hypothesis and the over-reaction hypothesis. The data consisted of the transaction-to-transaction price from January 1, 1980 to December 31, 1983. In their analysis, the information hypothesis implicitly assumes that price levels and their associated variances are driven by the arrival of public and private information. While the over-reaction hypothesis assumes that these factors are affected by noise traders, Ma, Rao and Sears (1989) concluded that the price limit rule has been effective in reducing volatility on the Treasury bond futures market, consistent with the over reaction hypothesis. However, as shown by Brennan (1986), price limits may or may not be stabilising depending on the underlying behavioural assumptions. Thus, these results may not be applicable to other markets or time periods.
Kim and Rhee (1997) examined the effects of price limits on the Tokyo Stock Exchange by dividing stocks into those that reach the price limit and those that do not. Using daily stock price data on the Tokyo Stock Exchange for the period 1989 to 1992, they compare the price behaviour between the stocks that reach the price limit and those that do not. It was found that price limits are ineffective. They contend that price limits do not constrain volatility, but merely cause volatility to be spilled over to subsequent days. This is consistent with the findings of Lee, Ready and Seguin (1994) who found that volatility increases following trading halts in the New York Stock Exchange.

Similarly, Subrahmanyam (1994) showed that if a trading halt is mandated it causes market participants to sub-optimally advance trades and, therefore, circuit breakers will intensify price movements and increase volatility. This is opposite to the intentions of the regulators. Investors also incur costs as they are forced to hold positions that, without the trading halt, they would not hold optimally.

Ackert, Church and Jayaraman (1999) used an experimental method to examine market behaviour under different market structures. The three scenarios were market closure, temporary trading halt, and no interruption. They analysed the impact of circuit breakers on price dynamics, trading volume and profit making ability and found that the expected price did not change significantly across regimes.

Phylaktis, Kavussanos and Manalis (1999) found evidence in support of the information hypothesis on the Athens Stock Exchange. The basis for their analysis was the daily closing price observations for ten stocks, in addition to the general price
index and trading activity data for the period January 1990 to June 1996. For nine out of the ten stocks, in addition to the general price index, the volatility of returns was unaffected by the price limit while the tenth stock’s volatility actually increased as a result of the price limit. They concluded that their results support the information hypothesis, and that price limits have no effect on volatility. That is, price limits did not reduce volatility on the Athens Stock Exchange.

Kim (2001) examined the relationship between price limits and stock market volatility on the Taiwan Stock Exchange using daily return data from 1975 to 1996. He studied the differences in stock market volatility across the six different price limit ranges that the Taiwan Stock Exchange had in this period. The main conclusion from this paper was that volatility on the Taiwan Stock Exchange was generally not lower (higher) when price limits are made narrower (wider). This does not conform with the popular view of regulators that restrictive price limits moderate volatility.

The results are similar for those studies conducted on the effect of price limits on the ESM, where Tooma and Sourial (2004) provided evidence showing volatility still persists after the initial price limit was first imposed on the exchange. They used two of the major daily aggregate indices for the ESM, the HFI and the EFGI. The period of study was the nine year period from January 3, 1993 to December 31, 2001. They empirically tested whether the conditional volatility in the period prior to the introduction of the trading halt is different to the conditional volatility in the period the price limit was functioning. Evidence that the price limits resulted in an increase in unconditional volatility after the implementation of the circuit breakers was found.
Similarly, in another study, Tooma (2005) provided further evidence of price limits increasing volatility on the ESM. In fact, it was found that the circuit breakers had caused volatility spillovers in the ESM and thus price limits may not aid in controlling volatility, as they were set out to do. Moreover, Medhat and Eskandar (2006) found similar results in their study of the effect of price limits on the unconditional volatility of the ESM. They concluded that volatility on the ESM was not lower (higher) when price limits were made narrower (wider). These results were similar to that found by Kim (2001) for the Taiwan Stock Exchange.

In summary, despite the rationale for the introduction of price limits, scant literature actually provides evidence of this. Moreover, evidence has shown that price limits actually increase volatility on the stock exchange. Notably, this is the case for the ESM. This research is significant as it implies that volatility is not necessarily reduced because of the introduction of price limits. Therefore, despite the fact that circuit breakers have been introduced in CASE, it is still valid and important to analyse the volatility of the ESM.

2.10 Summary

The literature on stock market volatility has produced a large amount of theoretical and empirical research, especially since the development of the ARCH/GARCH models of Engle (1982) and Bollerslev (1986). The theoretical research has not been conclusive on how stock market volatility should be modelled and, as such, the development of empirical models to explain and predict stock market volatility remains an active area of research.
This chapter began with an introduction to the theoretical research on stock market volatility. This highlighted the importance of stock market volatility as an active research area. The key characteristics of stock market volatility that have emerged from the literature were discussed. This is important for modelling stock market volatility as it is these characteristics that a volatility model should encompass. Following from this, the chapter then overviewed the concept and measures of volatility. One of the main reasons that makes stock market volatility an important topic of interest is its relationship to the EMH. This section of the chapter thus introduced the concept of market efficiency and showed how evidence of volatility clustering is in contradiction with the EMH.

Furthermore, for the purposes of developing a model for stock market volatility, the factors which cause stock market volatility are an important consideration. Hence, the literature on the causes of stock market volatility was discussed. The next two sections of the chapter described the ARCH/GARCH class of conditional heteroskedasticity models and the SV models where it was shown that the ARCH/GARCH class of models are the more appropriate choice for modelling volatility on the ESM. The empirical evidence of volatility with the ARCH/GARCH models was discussed with context to the region. In particular, the literature was grouped into the developed markets, emerging markets, African & MENA markets and finally, the ESM.

This thesis is innovative in its attempt to model stock market volatility with the ARCH/GARCH class models applied to pooled and panel data. This is a relatively new area of research with limited literature. A close examination of this literature
revealed that a panel fixed effects structure within a GARCH variance equation had not yet been estimated. Such variance equations are vital for testing similarities and differences in volatility structures between stocks. Finally, the last section of this chapter summarised the literature on circuit breakers and their effect on stock market volatility. It was shown that circuit breakers may actually increase stock market volatility, rather than reduce it. This is significant for the analysis in this thesis, as circuit breakers were in place on the ESM for the period of the analysis. The next chapter considers the characteristics of the ESM with a particular focus on factors which are related to stock market volatility, as these are important in the development of volatility models for the ESM.
3. CHAPTER 3: THE EGYPTIAN CAPITAL MARKET: OVERVIEW AND POTENTIAL IMPLICATIONS FOR MARKET VOLATILITY

3.1 Introduction

The previous chapter dealt with the significance of stock market volatility. Further, temporal models of volatility in terms of ARCH/GARCH models were introduced and their application to emerging markets as well as established markets was discussed. Also, volatility was shown to be important in the ESM, particularly in terms of the existence of circuit breakers. Chapter 1 also established the intention of this thesis to examine the nature of volatility in the ESM, but using novel GARCH structures. The objective of this chapter is to discuss the key characteristics of the ECM with particular focus on the ESM to provide a foundation for the analysis of volatility by identifying the implications that these characteristics have for the ESM volatility.

The ESM is one of the oldest stock markets in the Middle East, with a history that dates back to the late 1800s. The Alexandria Stock Exchange was officially established in 1888 followed by the Cairo Stock Exchange in 1903. The two exchanges were both active in this early period, with the ESM being ranked the fifth most active exchange in the world during the 1940s (Cairo and Alexandria Stock Exchanges (2002, p.35)).

By the mid 1950s the Egyptian Government adopted central planning and socialist policies that effectively led to the two exchanges becoming dormant. The following decade of financial policies and other constraints limited the development of the financial sector in Egypt and contributed to keeping the activity on the ESM to a
minimum. During the 1980s, the financial sector was limited to four publicly owned banks, with very few alternative financial intermediaries such as brokers, portfolio managers and mutual funds managers. With little supervision and protection on the ESM, these factors combined to create an environment that disadvantaged the ESM progress (Asal (1997, p.12)).

By the early 1990s the Egyptian Government had embraced the idea of the importance of a market economy for the economic progress of the country. With this acknowledgement of the need for economic reforms, the Egyptian government made the move towards a market economy by implementing an economic reform and restructuring program including deregulation and privatisation (Mecagni and Sourial (1999)).

With the initial success of these market reforms in improving the performance of the ECM, as later demonstrated in this chapter, the current world economic climate and the continued development and improvement of the ECM, CASE aims to be one of the core financial centres in the MENA region. In fact, with the continual adoption of leading-edge technology, the commitment to improving its rules and regulations, the forging of alliances with international markets in addition to the goals of efficiency, transparency and fairness, it is certainly a viable option for Egypt to become the leading market in the MENA region (Cairo and Alexandria Stock Exchanges (2004)).

This chapter begins with an overview of Egypt and the key areas of the Egyptian economy and its importance for the ECM. Market reforms and subsequent economic performance are summarised as they have played such a crucial role in the rapid
development and success of the ECM. Section 3.3 provides an introduction to CASE and the market microstructure that governs the operations of CASE as it provides the foundations for market volatility. The following section presents the market indices available for ECM. Section 3.5 is a vital section since it provides key statistics regarding the performance and the structure of the ESM. The performance of the ESM is examined in terms of four key market variables, namely: activity, size, liquidity, and concentration, as these are important factors that affect market volatility. Likewise, the market structure is overviewed. Section 3.6 analyses the ECM’s performance in comparison to other markets such as the world market and the emerging and Arab markets. Finally, Section 3.7 summarises the key topics discussed in this chapter and their implications for volatility on the ESM.

3.2 Egypt: Country Profile

3.2.1 Country Overview

The Arab Republic of Egypt is located in North Africa and, therefore, forms part of the MENA region. Egypt borders the Mediterranean Sea to the north, Sudan to the south, Libya to the west, and the Gaza Strip to the east. Egypt’s total area covers 1,001,450 square kilometres out of which 995,450 square kilometres is land and 6,000 square kilometres is water.

Over the last three decades Egypt has made considerable improvement in the well being of its people. In terms of social indicators, the education and health services provision for its population has dramatically improved. Moreover, Egypt as a lower
middle-income country\textsuperscript{34} has steadily improved its position in terms of external debt, with a rating of “less indebted”\textsuperscript{35} (World Bank (2003)).

Egypt has also made significant progress in terms of growth and development. Table 3-1 shows the steady growth in population and, as of July 2004, the Egyptian population was estimated at 76,117,421 million. The rate at which the population is increasing remains quite high, although it is slowly decelerating. Egypt has the largest population base amongst the Arab countries. Furthermore, it is shown that the labour force and employment has steadily improved, while unemployment has remained relatively stable. This reflects Egypt’s past ability to turn population growth into a catalyst for development. However, providing sufficient employment for large groups of young people entering the workforce in the future remains a great challenge.

Table 3-1: Selected Indicators of Development from 1996/97 to 2003/04

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<tbody>
<tr>
<td>Population (Millions)</td>
<td>59.4</td>
<td>60.7</td>
<td>62.0</td>
<td>63.3</td>
<td>64.7</td>
<td>66.0</td>
<td>68.0</td>
<td>69.3</td>
</tr>
<tr>
<td>Population Growth Rate (%)</td>
<td>2.05</td>
<td>2.13</td>
<td>2.12</td>
<td>2.12</td>
<td>2.13</td>
<td>2.06</td>
<td>1.95</td>
<td>1.99</td>
</tr>
<tr>
<td>Labour Force (Millions)</td>
<td>17.4</td>
<td>17.9</td>
<td>18.3</td>
<td>18.8</td>
<td>19.2</td>
<td>19.7</td>
<td>20.1</td>
<td>20.7</td>
</tr>
<tr>
<td>Employment (Millions)</td>
<td>15.8</td>
<td>16.3</td>
<td>16.9</td>
<td>17.3</td>
<td>17.6</td>
<td>18.0</td>
<td>18.1</td>
<td>18.6</td>
</tr>
<tr>
<td>Unemployment (Millions)</td>
<td>1.5</td>
<td>1.7</td>
<td>1.5</td>
<td>1.5</td>
<td>1.6</td>
<td>1.8</td>
<td>1.8</td>
<td>1.8</td>
</tr>
<tr>
<td>Labour Force / Population (%)</td>
<td>29.3</td>
<td>29.5</td>
<td>29.5</td>
<td>29.7</td>
<td>29.7</td>
<td>29.9</td>
<td>29.6</td>
<td>29.9</td>
</tr>
<tr>
<td>Unemployment Rate (%)</td>
<td>8.8</td>
<td>8.8</td>
<td>8.1</td>
<td>9.0</td>
<td>9.2</td>
<td>9.0</td>
<td>9.9</td>
<td>9.9</td>
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\textsuperscript{34} The World Bank classifies economies into an income group according to Gross National Income per capita (calculated based on the World Bank Atlas method). As of 2003, Egypt was in the income range of USD 766-3,035.

\textsuperscript{35} The World Bank classifies economies according to the level of external debt. ‘Severely indebted’ requires that three or four key measures of debt are above critical levels. If only a couple of the ratios are above critical levels, they are classified as moderately indebted. Other low-middle income economies are classified as less indebted.
3.2.2 Government

The Egyptian government is a republic. The constitution provides for a legislature, an executive and a judicial authority. The legislative system is two tiered, split into the People’s Assembly and the Consultative Council. The People’s Assembly is made up of 444 elected members and a further 10 members who are appointed by the President, with elections and appointments taking place once every five years. In 2001, for the first time, the elections for both houses of government occurred under the supervision of the judiciary (Ministry of Foreign Trade (2004)). Egypt’s internal stability is anchored by its political prominence in the Middle East, its broad-based popular participation, a stable economy and popular leadership.

3.2.3 Economy

Egypt’s economy has improved dramatically in the 1990s as a result of the Egyptian government launching an Economic Reform and Structural Adjustment Program which was supported by a Standby Agreement with the International Monetary Fund (IMF). Egypt also received a Structural Adjustment Loan from the World Bank, in addition to bilateral debt forgiveness/debt service relief from the Paris Club (Ministry of Foreign Trade (2004)).

This comprehensive reform program was aimed at macroeconomic stability. The program introduced reforms including: financial sector reform, interest rate liberalisation, reduction in subsidies and price controls, exchange rate standardisation, foreign trade liberalisations and public sector reforms. In Egypt’s move towards a market based economy, the main goal of the reform program was to:
“create an open, market-orientated, decentralised economy receptive to foreign direct investment and private sector participation” (Ministry of Foreign Trade (2004, p.8)).

The success of the reform program on the economic performance of Egypt is evidenced in Table 3-2. Foreign debt as a percentage of Gross Domestic Product (GDP) has been reduced from a high of 64.6 percent in 1992-93 to 37.8 percent by 2003-04. Likewise, the current account (as a percentage of GDP) and the total debt (as a percentage of Exports) have been improved. Also, the inflation rate has been rapidly reduced from 11.1 percent in 1992-93, to 4.9 percent in 2003-04. The unemployment rate is also in decline. Each of these variables attests to the success of the economic reforms in Egypt, where the IMF commended Egypt in saying that it is “an achievement that has few parallels” (Ministry of Foreign Trade (2004)).

Figure 3-1 shows the real GDP growth rate over the period 1992-93 to 2003-04. The acceleration of growth in GDP is clear, with an increase from 2.5 percent in 1992-93 to nearly 6 percent in 1999-00 before falling back to 3.1 percent in 2002-03. In 2003-04 GDP growth rate improved to 4.1 percent. The fall in GDP growth rate from 1997-98 can be attributed to the Asian financial crisis and the subsequent drop in international world oil prices affecting Egypt’s exports. In 1997-98 Egypt’s tourism sector was adversely affected by the Luxor attack which also contributed to the declining GDP growth. Tourism was again affected in 2000-01 as a result of terrorism. This decline in tourism was only temporary and withheld by governmental actions (Ministry of Foreign Trade (2004)).
Table 3-2: Selected Macroeconomic Indicators from 1992/93 to 2003/04

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</thead>
<tbody>
<tr>
<td>Real GDP Growth Rate</td>
<td>2.5</td>
<td>3.9</td>
<td>4.7</td>
<td>5.0</td>
<td>5.3</td>
<td>4.1</td>
<td>5.4</td>
<td>5.9</td>
<td>3.4</td>
<td>3.2</td>
<td>3.1</td>
<td>4.1</td>
</tr>
<tr>
<td>Average Annual Inflation (%)</td>
<td>11.1</td>
<td>9.1</td>
<td>9.3</td>
<td>7.3</td>
<td>6.2</td>
<td>3.8</td>
<td>3.8</td>
<td>2.8</td>
<td>2.4</td>
<td>2.4</td>
<td>3.2</td>
<td>4.9</td>
</tr>
<tr>
<td>Unemployment Rate (%)</td>
<td>10.0</td>
<td>9.8</td>
<td>9.6</td>
<td>9.2</td>
<td>8.8</td>
<td>8.8</td>
<td>8.1</td>
<td>9.0</td>
<td>9.2</td>
<td>9</td>
<td>9.9</td>
<td>9.9</td>
</tr>
<tr>
<td>Fiscal Deficit (% of GDP)</td>
<td>3.5</td>
<td>2.1</td>
<td>1.2</td>
<td>0.0</td>
<td>0.9</td>
<td>1.0</td>
<td>2.9</td>
<td>3.9</td>
<td>5.5</td>
<td>5.9</td>
<td>6.1</td>
<td>5.9</td>
</tr>
<tr>
<td>Current Account (% of GDP)</td>
<td>4.9</td>
<td>0.8</td>
<td>0.6</td>
<td>-0.27</td>
<td>0.15</td>
<td>-2.93</td>
<td>-1.90</td>
<td>-1.18</td>
<td>-0.04</td>
<td>0.7</td>
<td>2.80</td>
<td>4.8</td>
</tr>
<tr>
<td>Foreign Debt (% of GDP)</td>
<td>64.6</td>
<td>59.9</td>
<td>54.8</td>
<td>45.9</td>
<td>36.7</td>
<td>33.2</td>
<td>31.2</td>
<td>28.2</td>
<td>28.5</td>
<td>32.6</td>
<td>35.6</td>
<td>37.8</td>
</tr>
<tr>
<td>Total Debt (% Exports)</td>
<td>251.2</td>
<td>257.1</td>
<td>227.1</td>
<td>203.6</td>
<td>173.5</td>
<td>180.2</td>
<td>182.4</td>
<td>156</td>
<td>141.5</td>
<td>171.3</td>
<td>154.1</td>
<td>123.5</td>
</tr>
<tr>
<td>Debt Service Ratio</td>
<td>12.6</td>
<td>11.7</td>
<td>10.5</td>
<td>10.93</td>
<td>8.2</td>
<td>8.5</td>
<td>7.2</td>
<td>8</td>
<td>7.3</td>
<td>9.5</td>
<td>9.8</td>
<td>9.2</td>
</tr>
<tr>
<td>Reserves/Months of Imports</td>
<td>16.1</td>
<td>18.8</td>
<td>16.4</td>
<td>15.7</td>
<td>15.7</td>
<td>14.3</td>
<td>12.7</td>
<td>10.2</td>
<td>10.4</td>
<td>11.6</td>
<td>12</td>
<td>9.9</td>
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</table>

These figures show evidence of the success that the economic reforms had on the Egyptian economic performance in the immediate period following their implementation.

Since the economic reforms of the mid 1990s there has been a lack of continued economic reforms and this has limited foreign direct investment into Egypt and kept the annual GDP growth rate around 2-3 percent over the period 2001 and 2003. The Egyptian government proposed new privatisation and customs measures at the end of 2003 and early 2004 to sustain its economic performance. Monetary pressures on an overvalued Egyptian pound led the government to float the currency in January 2003. The float resulted in the currency depreciating and concomitant increased inflationary pressures. To reduce the public’s frustration, the Egyptian government increased subsidies on basic commodities in September 2003, increasing the budget

|------|------|------|------|------|------|------|------|------|------|------|

Source: Standard and Poor's Corporation (2005)
deficit. Due to tourism and Suez Canal revenues not being affected badly, Egypt’s balance of payments has remained steady despite the war in Iraq during 2003. The export market for natural gas remains a “bright spot” for the future growth prospects of the Egyptian economy (U.S. Central Intelligence Agency (2004)).

3.2.4 Major Economic Sectors

Egypt’s economy is the second largest in the Arab world (behind Saudi Arabia) and its economic sectors reflect its size. The Egyptian economy is reasonably well diversified, with no single sector accounting for more than 20 percent of GDP. A solid economic base reduced the vulnerability to external shocks, and has enabled Egypt to attract foreign investments in a number of sectors. Figure 3-2 shows the GDP composition by industry during 2003/04.

![Figure 3-2: GDP Composition during 2003/2004](image)


Given the diverse nature of industry in Egypt, it is useful to examine the industry level data in terms of three key economic sectors. These are the services sector, the industry
sector, and the agriculture sector. Services accounts for approximately 47 percent of GDP, industry accounts for approximately 37 percent of GDP while agriculture accounts for 16 percent of GDP. The following provides a short summary of these key sectors and their contributions to economic activity.

3.2.4.1 Services

Tourism, trade, banking and shipping services on the Suez Canal are the main contributors to the service sector revenues. As a result of the 1997 Luxor attack in Egypt and the September 11, 2001 terrorist attacks in the U.S., the tourism sector and Suez Canal were badly affected. It is estimated that these combined events caused tourism to fall by more than 50 percent. The Egyptian government responded quickly to these events by financing many tourism projects and heavily promoting tourism whilst cutting tariffs on air travel by 40 percent. As a result, tourism figures were back on track and started to show signs of recovery in early 2002. This sector’s performance has since been improving, although the Suez Canal sector has been less promising (Cairo and Alexandria Stock Exchanges (2002, p.47)).

3.2.4.2 Industry

The Industry sector is dominated by energy, comprising petroleum and petroleum products, natural gas, and electricity and is one of the most important sectors in the Egyptian economy contributing to foreign currency reserves and accounting for almost 7 percent of GDP for the fiscal year 2000-01 (Cairo and Alexandria Stock Exchanges (2002, p.41)). This sector is largely affected by exogenous factors such as the performance of the world’s oil markets. There has been a downturn in revenues for this sector because of the increased growth and demand from the domestic market.
The construction sector is a promising sector of the Egyptian economy. This is due to the government’s infrastructure and modernisation program. This sector has continued to thrive on the governments efforts at privatisation (Nuseibeh (2002)).

3.2.4.3 Agriculture

Arable land only accounts for 2.87 percent of overall land, but agriculture remains an important sector of the economy. Its significance has declined from 25.6 percent of GDP in 1985-1986 to only 16 percent of GDP in 2004. Cotton has been the country’s largest export for many years. With the removal of subsidies in this sector, high production costs have forced the number of cotton exports to fall (Nuseibeh (2002, p.141)). Wheat and rice exports also make up a considerable part of the agriculture sector, becoming increasingly important over the 1990s.

3.2.5 Market Liberalisation

The key components of the economic reform program included a combination of stabilising economic policies, privatisation, deregulation, an improved regulatory framework and trade liberalisations. These economic reforms remain an important component in reaching the joint goals of improving the growth rate of the Egyptian economy and the creation of a strong stock market that has the potential to attract foreign and local investors (Omran and Pointon (2004)).

Since the economic reforms and the macroeconomic adjustment program have played such a significant role in Egypt’s development over the last 15 years, the following two subsections will provide a summary of the two key components of the reforms that have allowed the Egyptian economy to face the challenge of the global
integration of production, trade and financial markets. That is, the financial and economic deregulation, and privatisation programs.

This is significant since a wide debate in the literature has focused on the effect that liberalisation measures have for emerging equity markets’ volatility. The consensus is clear that volatility is higher in emerging markets; however, the proposal that liberalisation increases volatility is debatable. One argument is that the integration into world capital markets would make the process to market equilibrium efficient and thus decrease volatility. On the other hand, foreign investors may be quick to react to changes in the short term economic outlook in emerging economies, causing unrestricted capital flows to be more volatile. This volatility of capital flows may increase the volatility of the stock market (Kim and Singal (2000)).

Empirical evidence has tended not to support these arguments (see Aggarwal, Inclan and Leal (1999), De Santis and Imrohoroglu (1997)), although Stiglitz (2004) suggests that the economic crises of the 1990s were at least partly attributable to capital market liberalisations. Thus, it is possible that the liberalisation process of the Egyptian economy in general, and the ECM in particular, contributed to the increased stock market volatility evidenced on the ESM. Therefore, this is discussed in the next two subsections.

3.2.5.1 Financial and Economic Deregulation

Financial sector reforms began in 1991 with the removal of interest rate controls on the Egyptian pound deposits and loans. Treasury bill auctions were later introduced. In 1992 and 1993 lending limits to the private and public sector were removed
respectively. These changes were made in conjunction with other reforms in an attempt to strengthen the efficiency of banks and security markets and to enhance their viability in a less regulated environment (Samak and Helmy (1999, p.22)).

Currency regulations have also been relaxed. The unified exchange rate system became fully convertible in 1991. The Central Bank of Egypt controlled foreign exchange risk through heavy intervention, namely keeping the Egyptian pound relatively constant to the American dollar. The introduction of the Foreign Exchange Law No. 38 in 1994 removed the restrictions on capital transactions in the Balance of Payments. Foreign and local banks were granted authorisation to trade in either local or foreign currency. Further, allowing banks to make currency transfers effectively resulted in complete international capital mobility in Egypt (Samak and Helmy (1999, p.23)).

To obtain a more flexible exchange rate, the Central Bank of Egypt introduced a new managed peg exchange rate system in early 2001. This allowed the exchange rate to move within a one percent band around a central parity (Cairo and Alexandria Stock Exchanges (2002, p.14)).

However, with improving macroeconomic fundamentals, reflected by strong balance of payments, providing a favourable environment for the implementation of a new exchange rate system and the commitment to establishing the credibility of economic policy, the Central Bank of Egypt announced full domestic convertibility of the Egyptian pound in January 2003. That is, the exchange rate was floated and it is now
determined by market forces. This is a major and positive step forward that will help attract foreign direct investment (Ministry of Foreign Trade (2004)).

The regulations on international trade have also been liberalised. The majority of non-tariff protection measures have been removed, while import tariffs have been reduced to a range of 40-50 percent. Also, the majority of tariffs on capital goods have been removed (Samak and Helmy (1999, p.23)).

3.2.5.2 Privatisation

Privatisation became a worldwide phenomenon after its successful implementation in the United Kingdom in the 1980s. Privatisation, a key component of the economic reform program adopted by Egypt in the early 1990s, has been successful in improving economic performance as well as re-activating the ECM.

In the beginning, the government earmarked 314 publicly owned enterprises from a diverse range of sectors, to be offered for sale to the private sector. From the advent of the program in 1994 until the end of June 2002, 190 companies representing almost 60 percent of the original portfolio were privatised. Although only 28 percent of privatised companies were sold through initial public offerings (IPO), this accounted for 47 percent of the proceeds of the program. The remaining 72 percent of companies were sold through other methods such as anchor investor sales, employee shareholders associations, liquidations and long term leases (Cairo and Alexandria Stock Exchanges (2002, p.56)).
Also worth noting is the fact that the Egyptian privatisation program proceeded in a
cautious and rational manner, when compared with other emerging markets. Such
prudence has helped Egypt to avoid the financial adversities that have accompanied
privatisation programs in other parts of the world (Cairo and Alexandria Stock
Exchanges (2003)).

The privatisation program was priced so that stock market activity would be
encouraged with initial success. However, due to unfavourable market conditions and
loss of interest in emerging market securities, the pace of privatisation has been
somewhat slow in the recent past. Other factors that have contributed to this situation
include: the overvaluation of companies, lack of bank financing, lack of information
and liquidity issues. Consequently, to keep the privatisation program viable, a number
of measures had to be introduced to encourage investors. These included tax
exemptions for privatised companies that are in financial trouble, minimisation of
overvaluing companies and allowing firms to lease the land from the holding
company rather than having to pay the full value of the land (Cairo and Alexandria

To summarise, this section has examined the key foundations of the environment in
which the ESM operates. It is important to understand the key features and
developments of the Egyptian economy, since these factors are directly reflected in
the performance of the ESM. In particular, the behaviour of the ESM and,
consequently, the volatility of the ESM, is a direct mirror of the economy.
This section has introduced the basic structure of the Egyptian government and the Egyptian economy. This was followed by an overview of the key sectors of the Egyptian economy. Finally, and most importantly, the market liberalisation program including the deregulation of the economy and the financial market as well as the implementation of the privatisation program, was described since they represented the turning point for the performance of the ESM and they have a vital role in affecting the volatility of the ESM.

The next section examines the key characteristics and developments of CASE, with a focus on the features that are most likely to affect stock market volatility. This is an expansion to the previous discussion on the Egyptian economy by specifically examining the structural foundations of the exchange itself and the environment under which it operates. This includes an examination of the structure, regulations, listing requirements, trading system and the clearing, settlement and depository system. This is important as each of these factors affects the price discovery process and, hence, the volatility on the stock exchange.

3.3 Cairo and Alexandria Stock Exchange (CASE)

This section details the market microstructure that underpins the legal, institutional, and structural framework that governs the operations of CASE. This is important since it affects market volatility. In fact, dating back to Black's (1986) seminal paper, it is well documented that transaction data occurring in financial markets are contaminated by market microstructure effects such as bid-ask spreads, liquidity ratios, turnover and asymmetric information (see also Hasbrouck (1993), Hasbrouck and Seppi (2001) and O'Hara (2003)). Moreover, Awartani, Corradi and Distaso
(2004) tested for the presence of market microstructure effects on measures of volatility for high frequency data and found that microstructure induces severe bias in the Dow Jones Industrial Average.

Similarly, O'Hara (2003) examined the implications of market microstructure for asset pricing. He argued that the current asset pricing models ignore the fact that market microstructure focuses on the idea that asset prices evolve in markets. Markets provide liquidity and price discovery, where liquidity is defined as the matching of buyers and sellers. Firstly, the transaction cost of liquidity results from the mismatch between buyers and sellers. This cost is borne by the investor and thus affects asset returns. Consequently, changes to asset returns filter through to asset prices and thereby the asset’s volatility. Secondly, price discovery involves the incorporation of new information into asset prices. According to microstructure analyses, the uninformed investor (or noise trader) is always uninformed and, therefore, always loses. In other words, uninformed traders are always subject to an undiversified risk which is the risk of price discovery. This consequently has an effect on required return and asset prices. O'Hara (2003) developed an asset pricing model with asymmetric information which shows how asset prices are influenced by both the transaction costs of liquidity and the risks of price discovery.

In summary, the market microstructure literature suggests that market microstructure has a direct impact on the four fundamental market characteristics: liquidity, efficiency, trading costs, and, consequently, volatility. The type of trading system, the way transactions are processed and how information is transferred to market participants, all influence market operations. Liquid and efficient markets will be less
volatile than illiquid and inefficient markets; thus, market microstructure should be developed to maximise benefits to the market (Raafat (1998)).

### 3.3.1 Structure

Egypt’s stock exchange has two locations: Cairo and Alexandria. The same Chairman and Board of Directors manage both locations. The Chairman is appointed by the Government whilst the Board of Directors is made up of Directors elected from market participants, nominated representatives from the Capital Market Authority (CMA), the Central Bank of Egypt and the banking sector (Cairo and Alexandria Stock Exchanges (2001)).

Apart from CASE itself monitoring the operations of the exchange, the CMA is the key regulatory agency of CASE. CASE is responsible for online surveillance of the stock exchange while the CMA is responsible for offline surveillance. Particular attention is applied to the detection of market manipulation or insider trading. Both organisations have the ability to halt trading and/or place ceilings or floors on trading prices based on the closing price of the preceding day. CASE has taken serious steps in order to enhance investors’ protection in the market. This includes the development of an advanced surveillance system that allows the exchange to monitor online transactions on a real time basis (Cairo and Alexandria Stock Exchanges (2002, p.39)).

The CMA was established in the late seventies with the aim of organising, developing and monitoring the good practices of the capital market. The CMA aims to create an environment that increases investor confidence in the ECM and make sure market
participants adhere to their responsibilities. At the time of the introduction of economic reforms, a new law was introduced to give the CMA greater integrity and control of the capital market. Items of control include: information dissemination, inspection of securities’ companies, and supervision over market participants’ training and law enforcement (Capital Market Authority (2004)).

The market participants include brokers, underwriters, portfolio managers, mutual funds, venture capital firms, and primary dealers. By the end of 2004, the ECM market participants consisted of 122 brokerage firms, 35 underwriters, 37 portfolio investment management companies, 21 mutual funds, 15 venture capital firms, 14 primary dealers and one clearing, settlement and central depository (Ministry of Foreign Trade and Industry (2004)).

3.3.2 Regulations

A June 1998 study by the Economist on financial centres indicated that having a strong regulatory framework, that focuses on the protection of retail and wholesale investors, is one of the primary reasons why some cities have succeeded in becoming financial centres. For Egypt, regulations must move toward increasing the standards of disclosure, insider dealing measures, corporate governance, shareholder minority rights and takeover regulations (Raafat (1998, p.26)).

It is in this regard that the most important law introduced as part of the reform process of CASE was the enactment of the Capital Market Law No. 95 in 1992. This law restructured the securities and bonds market, providing the framework in which
market participants operate. The legislation also included changes to facilitate the issuing of corporate bonds and encourage the growth of the debt market.

After the strong performance of the ESM in the mid 1990s, the CMA became concerned that there may be a stock market bubble (Sourial (2002)). As a precautionary measure, the CMA introduced circuit breakers on the 2\textsuperscript{nd} of February 1997. The circuit breakers imposed a symmetric price limit. Individual stock price fluctuations were confined to a range of 5 percent in either direction per day, and to a maximum of a 20 percent change in price weekly. Sourial (2002) has suggested that this attempt to dampen volatility may have failed. In fact, the circuit breakers may have extended the impact of shocks on market volatility for longer, thus causing a slow decay in prices. For example, Subrahmanyam (1994) showed that circuit breakers increased price variability when prices are close to the break limit. With the need to increase the efficiency of the price discovery process on the ESM, changes were made to the circuit breakers in 2002. As of the 21\textsuperscript{st} of July 2002, a new price ceiling system was set in place and applied to the most active stocks that fulfilled certain criteria.

To ensure fairness in the new price ceiling system, it stipulated the halting of trade on any of the 12 stocks for a period of thirty minutes, forty-five minutes or till the end of the trading session if its prevailing weighted average price exceeded 10 percent, 15 percent or 20 percent respectively, when compared to the opening price (Cairo and Alexandria Stock Exchanges (2002, p.37)).
In 2003, further measures were adopted with the intention of completing the legislative structure of the ECM. Amendments were made to the Capital Market law, Depository and Central Filing laws. Entities that were licensed to practice custodian activities and to purchase on margin were specified. Adjustments were also made to the methodology applied in the calculation of trading and closing prices (Central Bank of Egypt (2003)).

All restrictions on foreign trading on CASE have been removed. For instance, there is no ceiling on foreign ownership of companies, taxes on capital gains and dividends were eliminated, and foreigners are not restricted in terms of the repatriation of profits. Foreign securities companies are allowed to operate in Egypt and face the same licensing procedures as domestic firms (Cairo and Alexandria Stock Exchanges (2004)).

3.3.3 Listing Requirements
Due to CASE and the CMA’s commitment to increasing the transparency and disclosure on the ESM, the listing rules are continually being improved and adjusted. These adjustments focus on information disclosure, corporate governance, penalising insider trading and encouraging firms to adhere to internationally accepted accounting standards (Cairo and Alexandria Stock Exchanges (2002, p.53)).

The CMA’s Board of Directors approved the new listing rules for CASE and these came into effect on the 1st of August, 2002. The prior listing rules consisted of three categories: official, unofficial (1), and unofficial (2). The new listing rules introduced a fourth category, thus the four separate schedules are the official (1), official (2),
unofficial (1), and unofficial (2). Due to the time required for companies to adjust to the new listing rules, a fifth category exists for the companies that have yet to meet these listing rules, and this category is known as the temporary or transitional category. Companies were given a one-year period to meet the requirements of any of the four categories (Cairo and Alexandria Stock Exchanges (2002, p.37)). Table 3-3 summarises the key listing requirements on CASE.

Table 3-3: Key Listing Requirements on CASE as of 2002

<table>
<thead>
<tr>
<th>Requirements</th>
<th>Official Schedule (1)</th>
<th>Official Schedule (2)</th>
<th>Unofficial Schedule (1)</th>
<th>Unofficial Schedule (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum shareholding or ownership for public offerings (%)</td>
<td>30</td>
<td>-</td>
<td>10</td>
<td>-</td>
</tr>
<tr>
<td>Minimum number shareholders</td>
<td>150</td>
<td>-</td>
<td>50</td>
<td>-</td>
</tr>
<tr>
<td>Minimum years of operation</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Minimum issued and paid up capital (L.E.* millions)</td>
<td>20</td>
<td>20</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>Minimum net profit before taxes as percent of issued capital (%)</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>Shareholders equity must not be less than total issued or paid up capital</td>
<td>Required</td>
<td>Required</td>
<td>Required</td>
<td>Required</td>
</tr>
<tr>
<td>Minimum number of issued shares (millions)</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>0.5</td>
</tr>
<tr>
<td>Prior years Audited Financial Accounts</td>
<td>3</td>
<td>3</td>
<td>At least 1</td>
<td>At least 1</td>
</tr>
</tbody>
</table>

* The Egyptian pound is the current legal currency of the Arab Republic of Egypt. The local abbreviation for the Egyptian pound is L.E., which stands for the Livre Égyptien (French for Egyptian Pound).

Source: Cairo and Alexandria Stock Exchanges (2002)

In addition, the new rules stipulate that some fines are to be levied on companies that do not meet the listing and disclosure requirements. These fines vary between imposing money charges and the delisting of companies (Cairo and Alexandria Stock Exchanges (2002, p.38)).
Table 3-4 shows the number of companies listed on the official, unofficial and temporary schedules of the CASE over the period 1998 to 2004. The majority of the companies listed on the CASE are in the unofficial schedules. That is, the majority of the companies listed on the ESM are only subject to the minimum listing requirements. They are not subject to requirements such as the number of shares issued or number of shareholders and the minimum profitability of the company.

<table>
<thead>
<tr>
<th></th>
<th>1998</th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
</tr>
</thead>
<tbody>
<tr>
<td>Official (1)</td>
<td>132</td>
<td>139</td>
<td>141</td>
<td>147</td>
<td>8</td>
<td>68</td>
<td>85</td>
</tr>
<tr>
<td>Official (2)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>4</td>
<td>33</td>
<td>44</td>
<td></td>
</tr>
<tr>
<td>Unofficial (1)</td>
<td>633</td>
<td>660</td>
<td>696</td>
<td>738</td>
<td>752</td>
<td>30</td>
<td>39</td>
</tr>
<tr>
<td>Unofficial (2)</td>
<td>105</td>
<td>234</td>
<td>239</td>
<td>225</td>
<td>239</td>
<td>344</td>
<td>552</td>
</tr>
<tr>
<td>Temporary*</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>148</td>
<td>503</td>
<td>75</td>
</tr>
<tr>
<td>Total</td>
<td>870</td>
<td>1,033</td>
<td>1,076</td>
<td>1,110</td>
<td>1,151</td>
<td>978</td>
<td>795</td>
</tr>
</tbody>
</table>

*Firms yet to satisfy the 2002 listing requirements


In 2004, 552 out of the 798 companies listed on the stock exchange were listed in the unofficial (2) schedule and thus subject to the minimum requirements. Since the market microstructure has been shown to affect asset prices and volatility (see O'Hara (2003)), the fact that the majority of the listed firms are not required to make their information available to investors contributes to information asymmetries in the ECM. Information asymmetries can be treated as a transaction cost and, therefore, it can be argued that the market microstructure (through information asymmetries) creates a transaction cost which affects asset prices and, consequently, volatility.
3.3.4 Trading System

There is a vast amount of literature that has been concerned with stock market microstructure and its effect on market efficiency. One particular area of interest is the effect of changes to trading mechanisms.

The literature proposes a number of reasons as to why automated trading systems influence aspects of trading, such as market efficiency and volatility. Firstly, it has been suggested that automation improves market efficiency by reducing transaction costs. This leads to improved trading, liquidity, price discovery and, consequently, market efficiency and volatility (see Pirrong (1996) and Domowitz (1993)). On the other hand, it is argued that electronic trading reduces market efficiency by increasing transaction costs. That is, automated trading diminishes price efficiency since the judgemental aspects of trade execution are removed (see, for example, Aitken (2004), Theissen (1999), Jefferis and Smith (2004), and Maghyereh (2005)). It is clear in the literature that trading systems have implications for the volatility on stock exchanges. Therefore, it is important to have an understanding of the key characteristics of the trading system in Egypt.

The original trading system used by CASE was based on the open outcry system. This is where buyers and sellers match themselves up directly by calling out bid and offer prices in the trading ‘pit’. Since 1992 the automated order-driven system has been in place. For the first phase of transition to the automated system, the CMA developed the automated trading system which was in use until May 2001. The second phase was the introduction of a new state-of-the-art trading system that conforms to international standards. The signing of the contract with the Canadian Software
Company, EFA Software Ltd., in 1998 provided the exchange with a new trading, clearing and settlement system. The trading component of the new system was operational on the 14th of May 2001.

One of the important features of this new trading system is the pre-opening session that allows for price discovery. This system positions the ESM on equal footing with international and regional markets and enhances liquidity and transparency (Cairo and Alexandria Stock Exchanges (2002, p.36)). In summary, the implementation of the automated trading system in 1992, and the continual improvements to the trading system in recent years, may have implications for the volatility on the ESM.

### 3.3.5 Clearing, Settlement and Central Depository

Misr for Clearing, Settlement and Central Depository (MCSD) is a private company, established in October, 1996 which handles the clearing and settlement operations and acts as the central depository for all securities in Egypt. The company’s main shareholders and their share is as follows: CASE 35 percent, banks 50 percent and brokers 15 percent (Cairo and Alexandria Stock Exchanges (2004)).

In January 2000, a Settlement Guarantee Fund was established by the CMA and is operated and maintained by the MCSD. The role of the Settlement Guarantee fund is to buy shares on behalf of the defaulting party or to pay cash and, therefore, acts to reduce the number of unsettled transactions by reducing settlement risk associated with these transactions. The guarantee fund has resulted in the number of unsettled transactions on the exchange to fall significantly (Cairo and Alexandria Stock Exchanges (2003, p.38)).
JP Morgan Chase Investor Services evaluates depositories around the world using its Depository Safekeeping Assessment methodology. In June 2001, the MCSD had a rating of 1.25 which places it near the top of “best practices” based on the following scale where 1 is best practice, 2 is mid range practice and 3 is worst practice. MCSD managed to achieve this ranking after 5 years of operation and this is remarkable for an emerging market (Ministry of Foreign Trade and Industry (2004)).

Since the establishment of the MCSD, Egypt has been moving towards a complete dematerialised environment. The process of dematerialisation refers to the conversion of shares from a physical form into an electronic form, and is one of the most important changes to the operation of stock markets in recent years. In a dematerialised environment there are no physical stocks, the stocks are in electronic form (scripless) and are transferred directly between accounts of member firms of the depository. As of the 18th of June 2002, the CMA made dematerialisation a mandatory requirement for all new companies listed on the exchange (Cairo and Alexandria Stock Exchanges (2002, p.38)).

The significance of dematerialisation for stock market volatility is clear since dematerialised environment changes the way that stocks are held and traded and, therefore, has an effect on every other function of the market (see Goldfinger (2000)). That is, by allowing the electronic transfer of stocks, the cost of conducting transactions is affected and, therefore, has an impact on stock returns and, consequently, stock volatility (Maghyereh (2005)).
Shares traded in the ESM can either be physical or in scripless form with a rolling settlement system where trades are scheduled for settlement a certain number of days after the transaction (T). The settlement cycle is T+2 days for the most active stocks that have no 5 percent price limit, T+3 days for dematerialised securities that constitute 90 percent of trading, and T+4 days for the physical securities (Cairo and Alexandria Stock Exchanges (2004)). The next section describes the recent developments of CASE.

3.3.6 Developments

As suggested earlier, a number of recent developments have occurred on CASE which may have influenced the volatility of the ESM. This section describes some of these major developments.

One important development of CASE which occurred in 1997 was the appointment of a new board of directors with a mission to modernise the exchange. By 2005, the ESM had made significant progress in its movement to become a modern stock exchange operating under international standards.

In December 1998, CASE created its own web site to increase the availability of information on the ESM. This website has been continuously improved to ensure accurate coverage of the exchanges activities, trading information and rules. Likewise, the disclosure department at CASE has succeeded in building closer links with the investment relation officers of listed companies, to provide timely and useful information on material events to market participants. The disclosure system is currently designed to provide information about listed companies. Moreover,
subscribers are to be linked to the system so that they can obtain information about issuers on a real time basis (Cairo and Alexandria Stock Exchanges (2002, p.21)).

Other achievements that demonstrate CASE commitment to information dissemination include the establishment of the Egypt Information Dissemination Company in June 1999. As a fully owned subsidiary of CASE, the Egypt Information Dissemination Company began transmitting CASE financial data to all market participants, both locally and internationally, starting from the 1st of January 2002.

Other significant initiatives of CASE have included efforts to increase the awareness of the general public to capital market investment in Egypt through awareness campaigns involving the implementation of the Stock Riders Game, Stock Riders Sports Clubs and a series of publications to educate investors about the basics of investing in capital markets. CASE has also prioritised the development of its human resources through offering a number of training programs, with each of the programs concentrating in capital market related topics (Cairo and Alexandria Stock Exchanges (2002, p.22)).

Currently the global financial environment is changing rapidly as a result of advances in technology, institutionalisation, globalisation, and deregulation. Each of these factors threatens the existence of the “classical” stock exchange. To ensure the survival of the Egyptian Stock Exchange, CASE has entered a number of international associations to form strategic alliances with other stock exchanges. The increased collaboration between stock exchanges in the areas of financial instruments includes issuing and trading, organising and facilitating clearing and settlement mechanisms,
and the exchange of information. This collaboration also aims at developing cooperation between intermediation institutions in those markets and encourages joint/cross listings. Some of these collaborations between CASE and other financial markets are described below.

On the 16th of April 2003, the U.S. Securities and Exchange Commission officially recognised CASE as a “Designated Offshore Securities Market” as defined in Section 902(b) of the Regulation ‘S’ of the Securities Exchange Act 1933. Under this section, the U.S. Securities and Exchange Commission designates any foreign securities exchange or non-exchange market as a “designated offshore securities market” if that exchange satisfies certain criteria. This includes:

“Organisation under foreign law, association with a generally recognised community of brokers, dealers, banks, or other professional intermediaries with an established operating history; oversight by a governmental or self-regulatory body; and an organised clearance and settlement system”.

In addition, on the 1st of November 2005, the World Federation of Stock Exchanges (WFE) made the decision to include Egypt as a full member, making it the first Arab country to become a full WFE member. Egypt was a correspondent member from 1999 and became an affiliate member in 2001. This achievement is in recognition of the fact that the Egyptian Stock Exchange has complied with the:

“International standards recognised by financial institutions and regulatory bodies in different markets” (Cairo and Alexandria Stock Exchanges (2006)).

37 http://www.sec.gov/divisions/corpfin/33act/index1933.shtml
38 http://www.law.uc.edu/CCL/33ActRls/rule902.html
The WFE is a private international organisation which currently consists of 57 member exchanges, representing approximately 97 percent of the market capitalisation. The purpose of this federation is to facilitate cooperation between member exchanges, and direct them to the “best technical and administrative practices” (Cairo and Alexandria Stock Exchanges (2006)). Thus it was an important achievement that will help CASE to maintain the best practices and contribute to a more efficient environment conducive to reducing market volatility.

In late 2005, an agreement was signed by a number of Arab countries and institutions to establish the Arab Stock Exchange. This was a major initiative put forward by Egypt and was designed to support an integrated Arab economic system and facilitate the movements of Arab funds among the Arab countries, rather than investing them abroad. It was also expected to boost multilateral investments in the region. The ESM has been chosen to take responsibility of executing the Arab Stock Exchange project.

Finally, CASE is a member of the Federation of Euro-Asian Stock Exchanges, the African Stock Exchanges Association and the union of Arab Stock Exchanges. Agreements also exist with the Bahrain, Amman, Kuwait, Beirut and Tunis Stock Exchanges in terms of allowing the exchange of information of jointly listed companies. Further, CASE has signed a ‘Memorandum of Understanding’ with various global exchanges such as Korea, London, Madrid, Kuala Lumpur and the Hong Kong Stock Exchanges (Ministry of Foreign Trade and Industry (2004)).

In summary, CASE has made significant efforts to modernise the exchange, and increase the awareness and availability of information on the market. The efforts and
success of CASE have been recognised with the achievement of being classified as a designated offshore securities market, achieving full membership with the WFE, and signing agreements with different financial markets. These collaborations and agreements are important for the efficient operation of CASE and need to be considered as a vital factor affecting the volatility of the ESM.

To recapitulate, this section has outlined the market microstructure framework that governs the operations of CASE, focusing on those factors that have implications for volatility on the ESM. That is, the structure, regulations, listing requirements, trading system, clearing, settlement and depository and lastly, the recent developments occurring on the exchange. The next section describes the main stock market indices adopted in the ESM. The market indices represent an indicator of market performance and, therefore, can be used to gain an understanding of the nature of volatility on the ESM.

3.4 Stock Market Indices

The previous section provided a summary of the market microstructure framework under which CASE operates and which influences the degree of volatility in the ESM. Such volatility can be measured by changes in the various stock market indices adopted in the ESM. There are a number of indices that serve as benchmarks for the Egyptian market. These market indices can be classified as international or local. This section will provide an overview of the major stock market indices available for the ESM.

39 The most common and well-known world wide indices include S&P, Financial Times, Dow Jones, MSCI. etc. These indices are calculated by private companies and not the stock exchanges. In addition, stock exchanges calculate their own indices and the most famous include: New York Stock Exchange, DAX, Nikkei, Hang Seng etc.
Stock market indices measure the performance of general stock price movements and thus act as indicators of business conditions. The importance of stock market indices is demonstrated by the variety of market indices that are produced for the ESM. These market indices can be classified as international or local. The ESM performance has been monitored by a number of well known international and local indices. The international indices include the S&P Emerging Market Indices and MSCI, and the local indices include the CMAI, the CASE 30 Index, HFI, EFGI, and the PIPO.

3.4.1 International Indices

3.4.1.1 S&P Emerging Markets Indices

The S&P Emerging Market Indices are widely recognised as the most comprehensive and reliable measures of the world’s emerging markets. The indices, and the underlying database, which S&P acquired from the IFC in 2000, have been maintained since 1975. Since their inception, the indices have grown to cover more than 2,000 companies in 53 markets (Standard and Poor's Corporation (2006)).

The indices are broken down into two main categories, namely, the S&P/IFCG (global) indices and the S&P/IFCI (investable) indices. The S&P/IFCG (global) indices are designed to represent the performance of the most active stocks in their respective markets. This index is constructed to reflect the broad market movements for each of the emerging markets, representing the widest possible opportunity set of active stocks. The S&P/IFCG indices target 70-80 percent of the total market capitalisation for exchange listed stocks. On the other hand, the S&P/IFCI indices are a subset of the S&P/IFCG indices and reflect only the returns of stocks that are legally
and practically available to foreign investors. Egypt was included in the IFC global and investable indices in January 1996 and November 1997 respectively.

3.4.1.2 MSCI Indices

MSCI is the second major provider of global equity indices. The MSCI global equity indices have become the most widely used equity benchmarks by international investors in the last 30 years. Like all market indices, the purpose of the MSCI standard index series is to provide “benchmark indices” of equity performance. This is done comprehensively, not only by benchmarking performance at the global, regional and country level, but also by the sector and industry levels for all countries. This wide range of indices makes it possible to aggregate individual country, sector and industry indices to create meaningful regional, country and sector benchmarks (Morgan Stanley Capital International (2006)). For that reason, along with the comprehensive availability and coverage of the MSCI indices, they are an ideal source on which to base the analysis in this thesis. Chapter 5 will provide further details on the MSCI indices.

In 1997 Egypt was included on a stand-alone basis in the MSCI index. In May, 2001, MSCI started calculating MSCI Egypt as part of its emerging markets free index (EMFI) which included 26 emerging markets and the All Country World Index (ACWI) which included 49 developed and developing markets. There were initially fourteen Egyptian companies in the index with a total capitalisation of USD 2.53 billion, representing 0.28 percent of the EMFI capitalisation and 0.015 percent of the ACWI (Cairo and Alexandria Stock Exchanges (2002)).

See http://www2.standardandpoors.com for more details.
By the end of July 2004, seventeen Egyptian companies were included in the MSCI Egypt Index. The total market capitalisation of the index is USD 1,396 million, representing 0.2 percent of the EMFI capitalisation and 0.01 percent of the ACWI (Ministry of Foreign Trade (2004)). In 2005, according to the MSCI index, Egypt was the best performing emerging market.

3.4.2 Local Indices

3.4.2.1 CASE and CMA Indices

Cairo and Alexandria Stock Exchanges 30 (CASE 30)

From the 1st of January 2000 the exchange started calculating its own in-house index, the Cairo and Alexandria Stock Exchanges 50 (CASE 50), which includes the top 50 companies in terms of liquidity and activity. This index was calculated until the 31st of January, 2003. CASE replaced this with a new index, the CASE 30 Price Index, which has a start date of 1st January 1998 and a base value of 1,000 points. The CASE 30 Price index measures the return on an investment based solely on changes in the market value of stocks (Cairo and Alexandria Stock Exchanges (2006)).

The CASE 30 index consists of the top 30 companies in terms of liquidity and activity. To be consistent with international standards, the CASE 30 index takes account of the free float for the companies included in the index. The free float is defined as the “share capital of a company, which is freely available for trading in the market”. It therefore represents the investable opportunities of investors by taking into account market restrictions on share ownership. The CASE 30 index is a market capitalisation index where stocks are included in the index proportional to their

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41 For example, specific companies may limit share ownership after a certain percentage.
market share and adjusted for the free float. Currently, for a company to be included in the CASE 30 index, it must have at least 15 percent free float (Cairo and Alexandria Stock Exchanges (2006)).

*Capital Market Authority Index (CMAI)*

The CMA calculates a daily price weighted market capitalisation index that includes all companies listed on CASE, which is considered as a truly overall market indicator. The CMAI was set to 100 on the 2nd of January, 1992 (Cairo and Alexandria Stock Exchanges (2002, p.76)).

### 3.4.2.2 Financial Institutions Indices

Some financial institutions in Egypt have also developed their own in-house indices, tracking the most actively traded companies on the market. Of these indices, the most prominent ones in use include the HFI, EFGI, and PIPO.

*Hermes Financial Index (HFI)*

On the 2nd of January 1993, Egyptian Financial Group (EFG)-Hermes Corporation developed the HFI which tracks the movement of the most active Egyptian stocks on the CASE. By 2005, the HFI consisted of 28 stocks (EFG-Hermes (2005)).

The HFI is a broad based index, which limits its constituents to those that are generally liquid in the market. The index includes stocks that have been actively traded during a quarter with a minimum trading value of L.E. 7 million, a minimum of 200 transactions and a minimum of 20 days traded. Also, HFI is calculated on a total
returns basis, thus taking into account the reinvestment of dividends, and it is rebalanced quarterly (EFG-Hermes (2005)).

**Egyptian Financial Group Index (EFGI)**

The EFGI is a subset of the HFI which tracks the movement of large capitalisation Egyptian companies that are most actively traded during a quarter. It is an investable large capitalisation index that began on the 2\textsuperscript{nd} January, 1993 and currently includes 22 stocks, each having a total market capitalisation over L.E. 650 million. Like the HFI, the EFGI is also calculated on a total return basis taking into consideration the reinvestment of dividends and it is rebalanced quarterly (EFG-Hermes (2005)).

**Prime Initial Public Offerings Index (PIPO)**

The Prime Initial Public Offering (PIPO) index was developed in 1994 by Prime Group to track the performance of the initial public offering (IPO) companies. This was in response to the market liberalisation policies implemented by the Egyptian government in the early 1990s.

As discussed earlier, the government aggressively privatised numerous state owned companies in order to improve the performance of the Egyptian economy and the ESM. The privatisation process was conducted mostly through IPO, and as such, the purpose of the index was to provide a definitive standard for measuring IPO stock performance on a general basis. As of December 2005, the PIPO index consisted of 64 companies (Prime Group (2005)).
3.5 The Egyptian Capital Market (ECM) Statistics

The previous section briefly introduced some important stock indices used in the ESM. Some of these indices will be used in this section, providing an overview of the ESM performance from 1991 to 2004. Particular emphasis will be placed on measures of market activity, market size, market liquidity and market concentration. This is due to their vital role in affecting the volatility of the ESM. Furthermore, the market structure, in terms of the securities profile and the market participants is discussed. Each of these factors has been shown in the literature to affect stock market volatility.

3.5.1 Performance

This subsection provides an overview of the performance of the ESM for the period 1991 to 2004. This period was selected to show that, since the early 1990s when the Egyptian government began market reforms, interest in the market had significantly improved. This subsection attempts to show evidence of change in the performance and volatility of the ESM using some major indices for the Egyptian market (described in the previous section). It also identifies the general market factors which may have contributed to the volatility experienced on the ESM. Specific key indicators of the ESM performance, namely, activity, size, liquidity and concentration, are then described in detail. These specific indicators have been identified in the literature as potential factors affecting stock market volatility. This is important for understanding and examining stock market volatility since these factors provide an indicator of the level of volatility on the ESM.

With the revitalisation of the ESM in the early 1990s to promote the market as a venue for savings and investment, the ESM has experienced rapid growth and
development. This is evidenced by the increase in the value of three major ESM indices, CMAI, HFI and PIPO over the period January, 1995 to December, 2004 (with January 1995 as the base year) as shown in Figure 3-3 (Panel A). Figure 3-3 (Panels B, C, and D) shows the change in the indices prices calculated as the absolute returns for each index, which highlights volatility fluctuations. The CMAI index (Panel B), which included all stocks in the markets, exhibits moderate volatility in general, and reached its highest volatility level in 1997. However, since most of the stocks listed on CASE and included in the CMAI are inactive, it will be better to look into the volatility of the HFI index, shown in Figure 3-3 (Panel C), which includes active stocks only. The HFI index exhibited periods of high volatility in 1997, 2000-2001, and 2003-2004. The IPO companies, represented by the PIPO index, showed periods of high volatility in 1997, 2000-2001, and 2003-2004. For all three performance indices, clustering exists within the periods of high volatility, with temporal groupings of the logged differences returns by absolute values. That is, large differences seem to be followed by large absolute differences and small differences seem to be followed by small absolute differences.

The ESM was relatively sluggish over the period 1995-1996. But, as the privatisation program began to speed up at the end of 1996, with the government selling major stakes in public companies as IPO to the private sector, the market began to pick up. Furthermore, the issuance of the Global Depository Receipts (GDRs) also contributed to the rising market and increased volatility. Capital inflows picked up as a result of the GDRs, causing the ESM to experience a strong level of volatility. The market

\[ r_t = \ln \left( \frac{p_t}{p_{t-1}} \right) = \ln(p_t) - \ln(p_{t-1}) \]

42 The return of the index is calculated as: }
peaked to new highs in early 1997, before exogenous events such as the South East Asia emerging market crisis, falls in oil prices and the Luxor attack caused the market to fall.

From this point, the market picked up again to reach new highs in early 2000 due to the sale of four major cement companies to encourage investors. However, as monetary conditions worsened and there was tension in the foreign exchange market, this high market performance was short-lived.

Towards the end of 2003 and early 2004, the ESM saw great improvements in performance, reflecting current economic conditions and developments in the capital market. The prevailing conditions in other emerging markets and in the MENA region have contributed to the ESM performance. For example, the latest increases in capital flows in the emerging markets are a consequence of the market liberalisation and globalisation policies that have been implemented (Central Bank of Egypt (2003)).

Moreover, the government’s new foreign exchange policy of floating the Egyptian pound was another contributor to this movement, after the market was quiet for some time. The overall expectations of better corporate results and improvement in some leading economic indicators paved the way for optimism towards the stock market (Ministry of Foreign Trade (2004)).
Figure 3-3: General Market Performance and Absolute Value of Returns for the Daily Closing Prices of the CMAI, HFI and PIPO Indices (1995-2004)

Panel A: Volatility CMAI, HFI & PIPO

Panel B: CMAI Volatility (Absolute Value of Returns)

Panel C: HFI Volatility (Absolute Value of Returns)

Panel D: PIPO Volatility (Absolute Value of Returns)

Source: Securities Industry Research Centre of Asia-Pacific (SIRCA) (2005)
3.5.1.1 Market Activity

Market activity is often used as a proxy for the level of stock market development. There are numerous measures that can be used to proxy market activity, the most common measure being stock market trading volume. Trading volume is an important variable to consider when examining stock market volatility, and a substantial amount of literature has attempted to explain stock market volatility by documenting a relationship between trading volume and price volatility.

Tauchen and Pitts (1983) showed that price variability rises with the growth in trading volume. After adding trading volume to the GARCH (1,1) specification of returns, the estimated persistence of volatility was diminished (see also Clark (1973) and Karpoff (1987)). This indicates that market expansions may be reflected in increased volume traded and its concomitant effect on volatility. That is, a major fact emerging from this literature is that the level of trading volume is positively correlated with contemporaneous price volatility (Mixon (2001)). Therefore, it is important to examine these activity measures on the ESM, as they provide an indicator of stock market volatility. This is described below.

During the period 1991 to 2004 the ESM experienced exponential growth in activity reflected by large increases in volume traded, value traded and the number of transactions. In fact, volume and value traded increased approximately 10,000 percent, where volume of trading recorded 2.4 billion securities with a value of L.E. 42 billion in 2004 compared to a volume of 22.7 million securities with a value of L.E. 430 million in 1991. In addition, the number of transactions increased from
10,305 million in 1991 to 1,743,564 million in 2004. This represents an increase in the number of transactions of approximately 16,000 percent (see Figure 3-4).

Figure 3-4: Percentage Change in Volume Traded, Value Traded, and Number of Transactions between 1991 and 2004

![Graph showing percentage change in volume traded, value traded, and number of transactions.

Source: Cairo and Alexandria Stock Exchanges (2005)]

The ESM witnessed a dramatic change in activity over a relatively short period of time and, therefore, is likely to have contributed to the appearance of increased volatility on the ESM over this period. The inactivity prior to the early 1990s is indicative of low price volatility in this period. This, followed by the large increases in activity over this relatively small time frame, provides the pre-condition for an environment of increased market volatility.

### 3.5.1.2 Market Size

Similar to the literature on market activity, market size has been used as an explanatory variable in stock market volatility. In fact, the literature has specifically examined thinness of speculative markets and its affect on market volatility (see
Cohen, Ness, Okuda, Schwartz and Whitcomb (1976), and Tauchen and Pitts (1983)).

The general finding has been that, *ceteris paribus*, thin markets are more volatile than deep ones. A plausible explanation, given by Pagano (1989), is that thin markets are generally characterised by a small number of transactions per unit of time and thus their prices are more sensitive to the impact of individual traders’ demand shocks. This suggests a rationale for the observed relationship between market size and price volatility. For this reason, it is essential to examine the size of the ESM to understand the past volatility experience and its implications for modelling volatility on the ESM.

Following Beck, Demirgüç-Kunt and Levine (1999), stock market size is measured via total market capitalisation and market capitalisation as a percentage of GDP. Consistent with the large increases in market activity, the ESM has grown relatively continuously in size over the period 1991-2004. In fact, market capitalisation has multiplied more than twenty seven times to reach L.E. 233.9 billion in 2004, representing 53 percent of GDP, compared to L.E. 8.8 billion, representing only 6.3 percent of GDP in 1991. This consistent growth in market capitalisation is shown in Figure 3-5. Moreover, other market indicators of size show similar trends.

*Figure 3-5: Market Capitalisation and Market Capitalisation as Percentage of GDP (1991-2004)*

![Figure 3-5: Market Capitalisation and Market Capitalisation as Percentage of GDP (1991-2004)](image)

Source: Cairo and Alexandria Stock Exchanges (2005)
The number of listed companies increased to 795 at the end of 2004, compared with the 627 companies in 1991. Furthermore, the number of traded companies increased from 218 in 1991 to 503 in 2004, while the average monthly traded companies increased from 79 in 1991 to 200 in 2004 (see Figure 3-6).

![Figure 3-6: Market Size Indicators (1991-2004)](image)

All of these measures are indicative of the significant increase in market size over this period. Since the literature has shown a relationship between market size and stock market volatility, the increase in market size may have an implication for the volatility on the ESM.

### 3.5.1.3 Market Liquidity

Market liquidity is a concept that is not clearly defined in the literature, although it is closely related to market activity and market size. In general, liquidity is seen as the degree to which large transactions can occur in a timely fashion with minimal impact on prices. As suggested by Fernandez (1999, p.9) in his study of liquidity risk, liquidity:
“is not defined or measured as an absolute standard but a scale, which incorporates key elements of volume, time and transactions. Liquidity then may be defined by three dimensions which incorporate these elements: depth, breadth (or tightness) and resiliency”.

That is, there is no clear and consistent proxy for market liquidity. Asset pricing theory has suggested that any factor that influences stock returns should be priced in the asset. Thus, if liquidity affects stock returns, then liquidity should be included as a factor determining stock price and, consequently, anything that affects stock prices will have an impact on stock price volatility (Porter (2003)). For example, market liquidity is of critical importance to an investor’s decision to invest in a particular market. Foreign investors and institutional investors are attracted to larger and more liquid stock markets as this ensures easy entry and exit from the market. The liquidity of a stock market has implications for the profitability of that market and, therefore, the volatility of that market (O'Hara (2003)).

Investors usually use liquidity and market capitalisation to ensure that they invest in companies that are large enough that they will have an impact on the performance of their portfolios. There are a number of indicators that can be used as a measure of liquidity including: volume and value traded, average monthly value traded, number of transactions, number of traded companies, turnover ratios, and bid-ask spreads (see, for example, O'Hara (2003), and Sarr and Lybek (2002)).

Volume and value traded were used in a previous section as measures for the activity of the market. It was established that there has been a substantial rise in the level of volume and transactions occurring on the ESM. Figure 3-7 reports two market liquidity indicators, namely the average monthly value traded and the turnover ratio for the ESM over the period 1991 to 2004. The average monthly value traded has
grown considerably over the period, from L.E. 35.6 million in 1991 to L.E. 3,531.2 million in 2004.

The stock market turnover ratio also measures liquidity, as well as providing an indicator for the efficiency of a stock market. It is defined as the ratio of the value of total shares traded to market capitalisation. It measures the activity or liquidity of a stock market relative to its size. A small but active stock market will have a high turnover ratio whereas a large, but less liquid stock market will have a low turnover ratio (Beck, Demirgüç-Kunt and Levine (1999, p.17)). Similar to the average monthly value traded, the turnover ratio has improved considerably over the same period, although it remains quite low at only 15.45 percent in 2004. The improvement in the turnover ratio from 2.64 percent in 1991 to 15.45 percent in 2004 represents an improvement in the liquidity of the ESM and thus the efficiency of the stock exchange (O'Hara (2003)).
Moreover, other market indicators of liquidity show similar trends. The number of transactions has increased from 10,305 million in 1991 to 1,743,564 million in 2004, while the number of traded companies has increased from 218 in 1991 to 503 in 2004.

### 3.5.1.4 Market Concentration

Similar to the market performance measures of activity, size and liquidity, another important indicator of the ESM performance is that of market concentration. Market concentration can be defined as the proportion of market activity or size (measured by market capitalisation) that is accounted for by a small percentage of the companies that comprise the market. This is usually calculated as the proportion of the largest stocks share of either value traded or market capitalisation (see Omran and Pointon (2004)). This is an important measure, not only as an indicator of the development of a stock market but also because of its direct link with market volatility ((Gupta (2002)).

Market concentration can be used as a proxy for the development of the stock market. In general, the higher the concentration of the market, the less diversified the market is. This suggests a lower level of stock market development and vice versa. In fact, Bekaert and Harvey (1997) suggested that asset concentration is one of the reasons for emerging markets exhibiting higher levels of volatility when compared to developed markets (see also Gupta (2002)). Furthermore, Yiu-Wah Ho, Strange and Piesse (2004) detailed the fact that the concentration of market activities and equity ownership into a relatively small group of individual stocks or market sectors has important implications for the structure and, consequently, the volatility of the market.
In summary, the literature has drawn a link between market concentration and volatility, suggesting that the level of market concentration has significant implications for market volatility. It is, therefore, important to examine the experience of market concentration on the ESM. Since there is no clear measure for stock market concentration, this examination focuses on three key proxies, namely, the concentration of the 30 most heavily traded stocks in terms of value traded, the concentration the 30 largest companies in terms of market capitalisation, and the concentration of certain sector(s) in terms of market capitalisation.

Table 3-5 summarises both, the concentration ratio of the 30 most heavily traded stocks in terms of value traded as a proportion of the total value traded of the market over the period 1998 to 2004, and the concentration ratio of the 30 largest companies in terms of market capitalisation as a percentage of the total market capitalisation over the period 1998 to 2004. Also, Table 3-5 reports the percentage of 30 companies as a proportion of the total companies listed on CASE over the period 1998 to 2004.

<table>
<thead>
<tr>
<th></th>
<th>1998</th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value traded concentration ratio for the 30 most heavily traded companies (%)</td>
<td>49.04</td>
<td>73.30</td>
<td>73.87</td>
<td>59.45</td>
<td>51.39</td>
<td>81.14</td>
<td>83.57</td>
</tr>
<tr>
<td>Equity ownership concentration ratio for the 30 largest companies (%)</td>
<td>45.40</td>
<td>52.13</td>
<td>53.89</td>
<td>48.00</td>
<td>48.34</td>
<td>29.36</td>
<td>50.94</td>
</tr>
<tr>
<td>30 companies as percentage of total listed Companies (%)</td>
<td>3.40</td>
<td>2.90</td>
<td>2.80</td>
<td>2.70</td>
<td>2.60</td>
<td>3.10</td>
<td>3.80</td>
</tr>
</tbody>
</table>


It is clear that the majority of the ESM activity is concentrated in a small percentage of the listed companies. The concentration ratio in terms of the value traded for the 30
most heavily traded stocks kept increasing over the period with a slight reduction in 2001 and 2002 reaching its peak in 2004 where 83.57 percent of the total value traded on the ESM is accounted for by 3.8 percent of the companies listed on CASE. This indicates that the majority of the companies that are listed on the exchange are infrequently traded and thus significantly reducing the liquidity of the market. This high proportion of non-actively traded shares on the ESM is largely due to the tax advantages of being listed on the stock exchange. This brings into question the effectiveness of the current listing requirements.

Similarly, the equity ownership concentration ratio for the 30 largest companies was relatively stable over the period from 1998 to 2004 with a big drop in 2003 due to the delisting of 173 companies owing to non-adherence to the more rigorous new listing rules of CASE. In 2004, 50.94 percent of the total market capitalisation of the ESM was accounted for by 3.8 percent of the companies listed on CASE.

Finally, Table 3-6 presents the capitalisation per market sector(s) as a percentage of the total market capitalisation. It is clear that the equity ownership in the ESM is dominated by a certain sector or a group of sectors with Utilities, Entertainment, Information Technology, Mining and Gas sectors having the biggest share starting from 2000, followed by Building Materials and Construction, Housing and Real Estate, Electrical Equipment and Engineering sectors. Most interesting is that the Financial Services sector (one of 20 sectors) accounted for 22.5 percent of the total market capitalisation in 1998, but decreased to 12 percent by 2004.
Table 3-6: Market Capitalisation by Sector(s) as Percentage of Total Market Capitalisation on CASE (1998-2004)

<table>
<thead>
<tr>
<th>Sector</th>
<th>1998</th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utilities, Entertainment, Information Technology</td>
<td>13</td>
<td>24</td>
<td>40</td>
<td>33</td>
<td>33</td>
<td>43</td>
<td>43</td>
</tr>
<tr>
<td>Mining and Gas</td>
<td>1.5</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Holding Companies</td>
<td>5</td>
<td>6</td>
<td>6.5</td>
<td>6</td>
<td>6</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>Trade, Retailers, Textiles and Clothing, Customer and Household Goods</td>
<td>13</td>
<td>11</td>
<td>6.5</td>
<td>8</td>
<td>7.5</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>Health and Pharmaceuticals, Chemicals, Paper and Packaging and Plastics, Miscellaneous Services</td>
<td>12</td>
<td>9</td>
<td>8</td>
<td>8</td>
<td>9</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>Food and Beverage, Agricultural and Fishing, Mills and Storage</td>
<td>22.5</td>
<td>19</td>
<td>15</td>
<td>17</td>
<td>17.5</td>
<td>14</td>
<td>12</td>
</tr>
<tr>
<td>Financial Services</td>
<td>33</td>
<td>29</td>
<td>23</td>
<td>26</td>
<td>25</td>
<td>21</td>
<td>28</td>
</tr>
<tr>
<td>Building Materials and Construction, Housing and Real Estate, Electrical Equipment and Engineering</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>


From the previous analysis, it becomes clear that the ESM activity and size is concentrated in a small proportion of listed companies and sector(s). This evidence of strong market concentration on the ESM may have been a contributing factor to volatility in the market.

In summary, this section has examined four different performance measures for the ECM, namely, market activity, size, liquidity and concentration. The reason for the focus on these measures is due to their defining effects on the volatility of the ESM. It was shown that market activity and size has increased significantly over the period 1991 to 2004 which may have influenced the ESM experience of volatility. Secondly, market liquidity was shown to improve dramatically over this period. Higher levels of liquidity indicate that more transactions are taking place, thus providing more opportunities for prices to change in response to new information and, therefore,
allowing for the increasing volatility in the market (Jefferis and Smith (2004, p.17)). Lastly, the level of market concentration was examined in terms of the concentration of the 30 most heavily traded stocks in terms of value traded, the concentration of the 30 largest companies in terms of market capitalisation, and the concentration of certain sector(s) in terms of market capitalisation. Market concentration was shown to be extremely high over the period 1998 to 2004. Again, each of these performance measures affects the ESM volatility.

The performance of the ECM showed rapid development over a relatively short period of time. Market activity, size and liquidity have improved significantly. These factors are important because of their implications for the volatility of the ESM. The next section describes the ECM structure, in terms of the securities traded and the participants in the market.

3.5.2 Structure
With the ECM only recently being reactivated, the growth of each of the sectors of the securities market is a long-term process. To become a strong, deep and diverse market, it is important that the financial market offers a variety of investment products and avenues for investment to satisfy the needs of all potential market participants. This, in turn, will provide greater stability for the financial market in general.

One of the important developments in the ECM since its resurrection has been the continued decline in financial assets that is accounted for by the banking sector. Market evidence shows that over the period 1992 to 2004, the percentage of financial assets accounted for by the four state owned banks has fallen from 65-70 percent in
the early 1990s to nearly 50 percent of total assets at the end of February 2004. This reflects the growing significance of the ECM and other non-bank financial institutions (U.S. Department of Commerce (2004, p.77)).

The Egyptian government has been encouraging the development of alternative financial intermediaries such as factoring companies, securitisation companies, lease financing companies, venture capital funds, turn-around funds, direct investment funds and funds that invest in mortgage backed securities. These benefit the Egyptian economy by diversifying the types of financial instruments. This allows investors to maintain, balance, and minimise investment risks. It also encourages growth in the ECM as well as rationalising financing costs and contributing to the growth of GDP (Capital Market Authority (2000)).

The main markets that make up the ECM include the organised market (CASE) and the over the counter (OTC) market. Figure 3-8 presents the total value traded for securities traded on both markets. Although the value of unlisted securities traded on the OTC market doubled from 1997 to 2004, the majority of activity in the ECM is concentrated in CASE. That is why it is important to understand the various types of securities listed and traded on CASE as well as the market participants who are involved in trading on the market.
3.5.2.1 Securities Profile

Securities listed and traded on CASE are: equity (Common stocks and Preferred stocks), the fixed income securities (Governmental bonds and Corporate bonds) and mutual funds. To gain an understanding of the significance of the bonds and mutual funds in relation to the stock market, Figure 3-9 shows the market capitalisation (size) break down in terms of equity, bonds and mutual funds. In 2004, as a proportion of total market capitalisation, equity had the largest share of the market size accounting for 86 percent of the total market capitalisation followed by Bonds which accounted for 12 percent of the total market capitalisation while mutual funds had the smallest share of the market with only 2 percent of the total market capitalisation.

In terms of activity, the total value traded of listed securities in 2004 amounted to L.E. 36.139 million (USD 6.23 million), of which shares, bonds, and mutual funds represented 92.13 percent, 7.86 percent, and 0.01 percent respectively (Cairo and Alexandria Stock Exchanges, 2004).
Alexandria Stock Exchanges (2004)). The significant size and activity of equity securities confirms the importance of the stock market as a mode of analysis for market volatility.

Figure 3-9: Securities traded on CASE as a percentage of the Total Market Capitalisation (December 2004)

![Pie chart showing percentages of different types of securities traded on CASE](chart.png)


Although bonds and mutual funds are not the main focus of this thesis, they may have implications for volatility on the ESM. The key features of bonds and mutual funds listed and traded on CASE are briefly described below.

**Bonds**

Bonds are generally long-term debt instruments and have been found to have differing characteristics to other financial instruments such as stocks (see Reilly, Wright and Chan (2000)). As such, the literature on stocks and bonds has developed separately. However, more recently, the literature has began to examine equity and bond market
volatility, to determine whether there is a relationship between the performances of these two types of securities.

In general, the literature shows some evidence to suggest that stocks and bonds markets are affected by similar factors, such that volatility in the bonds market has implications for volatility in the stock market (see, for example, Campbell and Ammer (1993), and Chordia, Sarkar and Subrahmanyan (2003)). Therefore, it is important to have an understanding of the bonds market in Egypt as it may have implications for the volatility in the stock market.

Bonds are generally considered among the most important instruments in financial markets worldwide since they foster a balance in the market by diversifying the range of available securities and, therefore, minimise investment risks. For this reason, the encouragement of the bonds market in Egypt is seen as vital, particularly since, in comparison to other emerging and developing markets, the Egyptian fixed income securities market is small (Cairo and Alexandria Stock Exchanges (2004)).

The Egyptian government has taken the primary initiative in activating the long-term securities markets through the issue of governmental securities since 1998. In 2001, the government succeeded in floating its first USD 1.5 billion Eurobond issue in both Europe and the US markets. Furthermore, private companies from different sectors of the economy have started to raise funds through the issuance of bonds rather than relying on banks. The Ministry of Finance and several other corporations have announced their bond issues (Cairo and Alexandria Stock Exchanges (2002)).
A recent measure to increase activity in the bonds market has been the establishment of the primary dealers system in November 2004. The system aims to make the local bonds market more competitive by enhancing its liquidity in the primary and secondary markets. It is the role of the primary dealers in the system to underwrite the initial offering of government securities in the primary market as well as to act as the market maker in the secondary market (Cairo and Alexandria Stock Exchanges (2002, p.18).

The launch of the primary dealers system has increased the liquidity of the primary market. However, the secondary market remains relatively small and less active. In December 2004, the total market capitalisation for the bonds market amounted to L.E. 31 billion which accounted for 12 percent of the total market capitalisation, where 10 percent are government bonds and 2 percent are corporate bonds (Cairo and Alexandria Stock Exchanges (2004)). Figure 3-10 shows the bonds value traded for the period 1998 to 2004. In general, there is evidence that the bonds market has implications for the volatility of the ESM.

Volatility on the ESM tends to decrease with the increase in the activity of the bonds market (see Figure 3-3, panels B and C). Starting from 1998, the volatility of the ESM decreased along with the steady increase in the activity of the bonds market which reached its maximum in 2002 when many investors reallocated their funds from stocks to bonds and mutual funds. In 2003 and 2004, investors increased their investment in stocks and reduced their investments in bonds. This is apparent in the reduction of the value of bonds traded and the increase in volatility in the ESM during that period.
Mutual Funds

Mutual funds have been growing in importance as an investment vehicle on the world’s stock exchanges. This increasing growth in the mutual fund industry has great importance in influencing stock prices around the world. As such, the literature on mutual funds and their effect on stock markets has rapidly expanded. One area of interest has been the attempt to link flows into and out of mutual funds with stock market volatility (see Litan (1998), Warther (1998), and Edelen and Warner (2001)).

Chang and Wang (2002) examined the relationship between the flow of funds into the U.S. equity mutual funds and market volatility. An asymmetric negative relationship between fund flow and market volatility was found where increases in funds inflow are accompanied by a less volatile market, and increases in funds outflow are accompanied by a more volatile market. Similarly, Alexakis, Niarchos, Patra and Poshakwale (2005) examined the effect of mutual fund flows on the Greece stock market for the period 1994 to 2003 using cointegration analysis. The results showed a
two way directional relationship between mutual fund flows and stock returns. That is, mutual fund flows in the Greece stock market caused stock returns to rise or fall and vice versa.

In summary, the literature suggests a correlation between mutual funds flows and price changes in the equity market. Therefore, it is important to understand the experience of the Egyptian mutual funds industry and its performance because of its implications on the volatility of the ESM.

Egypt’s mutual fund industry began its operations in 1994 with three local funds. By the end of 2004, there were 22 local mutual funds operating in Egypt (20 are open-ended and 2 are closed-ended) with a total size of LE 3.89 billion. Nine fund management firms manage the 22 local mutual funds. There are also eight offshore funds (with a size of USD 509.3 million) investing in Egyptian securities.

Table 3-7 shows the activity of the mutual funds traded in the ECM represented by the total volume and value of mutual funds traded on CASE and the OTC for the period from 1999 to 2004. It is clear that the mutual funds industry in Egypt has become increasingly important as suggested by the continuous increase in the volume and value of mutual funds traded on CASE.

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43 An open-ended mutual fund constantly offers new shares and redeems outstanding shares and there is no limit to the number of shares that can be issued. Open-ended fund shares are bought and sold directly through the fund itself and are thus not traded on the exchange or the OTC market. On the other hand, a closed-end mutual fund offers a limited numbers of shares. The outstanding shares are not redeemed by the fund. Thus an investor who no longer wants to hold shares with the mutual fund may sell them on the market. Therefore, closed-end mutual funds are traded on the stock exchange. (Madlem and Sykes (2000))
Moreover, even though the mutual funds industry is still considered relatively small in size compared to other securities traded in the Egyptian market, there is evidence of a relationship between the activity of mutual funds and stock market volatility. ESM volatility tends to decrease with the increase in mutual funds activity. For example, in 2002, when the mutual funds activity hit the ceiling, the volatility of the stock market was very low (see Figure 3-3, panels B and C).

In general, the volatility of the ESM may indeed be affected by the activity of both, the bonds and Mutual funds markets, even though they constitute a small portion of the total ECM size and activity. The next section describes the market participants which make up the ECM.

### 3.5.2.2 Market Participants

**Individuals versus Institutions**

Institutional investors consist of investment funds, savings and pension funds and other financial institutions. The increasing dominance of institutional investors in stock markets worldwide since the 1980s has stimulated interest in financial economics in terms of the effect of institutions’ trading on stock prices. The literature suggests that the existence of institutional investors either increases or reduces market

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</thead>
<tbody>
<tr>
<td><strong>Volume</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CASE</td>
<td>3,745</td>
<td>24,093</td>
<td>2,101</td>
<td>68,891</td>
<td>3,3598</td>
<td>0</td>
</tr>
<tr>
<td>OTC</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>3,745</td>
<td>24,093</td>
<td>2,101</td>
<td>68,891</td>
<td>3,3598</td>
<td>0</td>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Value</strong></td>
<td>3,554</td>
<td>4,235</td>
<td>1,244</td>
<td>24,825</td>
<td>1,1342</td>
<td>0</td>
</tr>
<tr>
<td>CASE</td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>OTC</td>
<td>0</td>
<td>0</td>
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<td>0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>3,554</td>
<td>4,235</td>
<td>1,244</td>
<td>24,825</td>
<td>1,1342</td>
<td>0</td>
</tr>
</tbody>
</table>

**Note:** *Volume traded is measured in units  **Value traded is measured in L.E. (000’s)*

Source: Capital Market Authority (2004)
volatility (see, for example, Badrinath, Gay and Kale (1989), Bohl and Brzeszczynski (2005), and Bohl, Gottschalk, Henke and Pál (2006)).

The Egyptian market has long been characterised by the dominance of individual investors. In 2000, The Egyptian CMA attempted to boost the role of institutional investors in the ECM. Institutional investors in this case are regarded as informed traders, who speed up the adjustment of stock prices to new information. Since institutional investors have better access to information at lower marginal cost, and are less concerned with the daily movement in stock markets, they may be less active in the short term, eventually reducing market volatility (Capital Market Authority (2000)).

Table 3-8 shows the percentage breakdown of individuals versus institutional market participants in terms of total value of stocks traded from 2000 to 2004. Although both types of participants generally account for an even amount of the market, the effect of the institutional investors on market volatility is noticeable. In 2000, the volatility of the ESM reached high levels due to the existence of more individual investors (see Figure 3-3, panels B and C). This volatility began to fall until it reached a low level in 2002, where the institutional investors accounted for 62 percent of the total value traded on the ESM. This big increase in institutional activity in the market managed to reduce the volatility of the ESM during that year. The market volatility started to rise again in 2003 and 2004 with the reduction in the institutional investors’ activity on the ESM.
Table 3-8: Individuals versus Institutions in Terms of Total Value Traded from 2000 to 2004 (excluding Bonds and Mutual funds)

<table>
<thead>
<tr>
<th></th>
<th>2000</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
</tr>
</thead>
<tbody>
<tr>
<td>Institutions</td>
<td>46</td>
<td>49</td>
<td>62</td>
<td>57</td>
<td>47</td>
</tr>
<tr>
<td>Individuals</td>
<td>54</td>
<td>51</td>
<td>38</td>
<td>43</td>
<td>53</td>
</tr>
</tbody>
</table>

Source: Cairo and Alexandria Stock Exchanges (2005)

In general, it is clear that the type of market participant in the ESM may have an impact on stock market prices and, hence, stock market volatility.

**Foreigners versus Locals**

Domestic and foreign investors have differing characteristics such as endowments, risk tolerance, and portfolio constraints and may differ in their reaction to the same information. Thus, it is suggested in the literature that, because of these differing characteristics, local or foreign investors have differing impacts on stock volatility (Wang, J. (2003)).

Brennan and Cao (1997) found that foreign investors are momentum traders and exhibit significant herding. This type of trading behaviour negatively affects stock market volatility. On the other hand, Karolyi (1999) found that the momentum trading of foreign investors did not have a destabilising effect on stock market prices and volatility. Also, Tesar and Werner (1995) found evidence of an information disadvantage for foreign investors. The effect of this information disadvantage is to cause momentum trading and thus contribute to stock market volatility. In contrast, Bailey, Mao and Sirodom (1999) found that foreign investors have an information advantage over domestic investors and thus are better informed investors. In this case, it is argued that foreigners decrease the volatility on the stock market.
Foreigners versus locals as a proportion of total trading on the ESM have an important role in determining market prices. It is usually the case in emerging markets that foreign investors are more experienced than local investors and thus have an important role in directing market prices. However, foreign participation on the ESM has generally only represented a small proportion of total trade. Figure 3-11 shows the Egyptian versus the foreign share of the total value of securities traded on the ECM over the period 1998-2004.

**Figure 3-11: Foreign Participation as a Percentage of Total Value Traded (1998-2004)**

![Chart showing foreign participation as a percentage of total value traded from 1998 to 2004.](chart)

Source: Cairo and Alexandria Stock Exchanges (2005)

Foreigners represented around 40 percent of total value traded in 1998; this increased to a high of 60 percent in 1999 before dropping back to around 30 percent in 2004. This major drop in foreign investment was mainly attributed to the overseas investors’ concern about the Egyptian macroeconomic climate as well as the pace of the structural reform, privatisation, fiscal and monetary policies, and regional concerns.
In general, foreign investors’ share of activity in the ECM is very small, leading to the conclusion that the observed volatility on the ESM may be attributed to the local market participants’ activities rather than to the foreign investors’ activities.

To summarise, this section has outlined the two main securities listed on CASE beside stocks; that is, bonds and mutual funds. It appears that the size and activity of these two securities are small compared to the equity market, yet they may have an implication for the volatility on the ESM. This section further discussed the two major groups of market participants, that is, individual investors against institutional investors, and foreign investors against local investors. The literature has shown that each of these types of market participants, because they are affected by different characteristics in their decision making, will have differing impacts on the volatility in the market. It was, therefore, essential to consider the market participant breakdown on the ECM to gain a thorough understanding of the factors leading to volatility on the ESM. The next section compares the Egyptian market performance and characteristics with the world, emerging and Arab markets. This is another area of important consideration for market volatility as there are clear linkages between different markets as a result of globalisation.

### 3.6 Egypt Compared to Other Markets

The recent financial crises\(^{44}\) have brought about a renewed interest in theoretical and empirical investigations into international links between asset market volatilities. It has been suggested that the origins of financial crises are in emerging markets, where

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\(^{44}\) This includes the Mexican crisis of 1995, the Asian crisis in 1997-1998, the default of the Russian government in 1998 and the significant depreciation of the Brazilian currency in 1999 (Kodres and Prisker (2002)).
financial assets are traded in the context of exchange rate and bank instability. These characteristics are incorporated in the growing literature on the ‘contagion effect’ of asset market volatility (see Kodres and Pritsker (2002), Cifarelli and Paladino (2005) and Masson (1999)).

The financial market contagion effect refers to the notion that markets move more closely together during periods of crises. That is, countries may experience increases in volatility and co-movement of their financial asset markets. Various explanations have been put forward in the literature to explain this market contagion effect. However, this section examines the nature and the trend of the ECM performance in comparison with other local and foreign markets since this can have important implications for the volatility of the ESM. The first section examines the world and emerging markets compared to the Egyptian market, and the following section examines the Arab markets compared to the Egyptian market.

3.6.1 Egypt Compared to World and Emerging Markets

To begin with, the recent experience in the global economy provides a general indicator of the performance of the global stock markets. Mirroring the activity in the global stock markets, the world economies began to pick up in 2003 after two years of recession. This global recovery has extended beyond the major developed markets to China and Japan, and has led to rising equity markets, lower taxes and greater spending (Cairo and Alexandria Stock Exchanges (2004)). Global growth has continued to be led by the U.S., with Asia showing some of the strongest growth rates. Activity in Latin America and other emerging markets has also picked up strongly,
while the recovery in Europe remains relatively weak (International Monetary Fund (2004b, p.3)).

Moreover, the recent evidence of capital flows in the world’s markets has shown the increasing significance of emerging markets. With the dominance of the U.S. markets diminishing of late, capital flows have spread to other parts of the world. The major recipients of these capital flows have been the emerging markets, and this highlights the growing interdependence between different markets. Specifically, portfolio investment has contributed to increasing the volatility of capital flows since investors can easily sell their assets on different securities markets. Sudden withdrawals of foreign investment can cause major disruptions to domestic financial systems not only through drastic changes to liquidity, but also through wide fluctuations in asset prices, which rapidly transmit the shockwaves of financial turmoil from one market to another (Cairo and Alexandria Stock Exchanges (2002, p.23)).

Figure 3-12 shows the performance of the MSCI Egypt index compared to the ACWI and the EMFI. It provides a general comparison of the ECM performance with the world capital market performance in general and other emerging capital markets in particular.

It can be seen in Figure 3-12 that the ECM has performed better than the emerging markets (EMFI) for the period December 1994 to 2004. Moreover, the Egyptian experience, comparable to the world (ACWI) follows a similar trend except for the period 2000 to 2003 after which the ECM starts to pick up again increasing more than the world and emerging markets.
In general, from Figure 3-12, it appears that all the major market indices have exhibited a similar trend over the period, indicative of the linkages between the various markets. This suggests the possibility that the performance of each market is not independent, and that volatility in one market may be transferred from one market to another.

To gain a greater understanding of the international linkages between the Egyptian market and the other major markets, Figure 3-13 depicts the monthly volatility (measured by the standard deviation) of the ACWI, the EMFI, and the MSCI Egypt index. It can be seen that although the performance of the Egyptian market was good compared to the world and the emerging markets as shown in Figure 3-12, there appear to be some key similarities and differences in performance. The volatility of returns tends to be high within the same periods of high performance compared to the
world and the emerging markets. Moreover, the volatility of the Egyptian market tends to be negatively correlated with the world and the emerging markets in some periods; for example, in mid 2000 where the volatility of the Egyptian market was increasing while the world and the emerging markets’ volatility was decreasing. This is an indication that, although the ECM was performing better than other markets at certain periods, the risk of the Egyptian market was higher as well.

3.6.2 Egypt Compared to Arab Countries

Given the previous discussion that the world’s capital markets are inter-related, it is likely that the Arab countries, since they are in close physical proximity to Egypt, may have a greater influence on the volatility of the ESM. Therefore, the following is

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45 The Arab markets consist of those countries in the MENA region. The key Arab markets comprise twelve different stock markets namely: Abu Dhabi; Amman; Bahrain; Saudi; Kuwait; Casablanca; Tunis; Dubai; Muscat; Doha; Beirut; and Egypt.
a discussion of the key characteristics which affect market volatility for the Arab markets.

It should be noted that the majority of countries in the Arab region have made significant progress in developing and reforming their financial markets. This has resulted in an increased share of foreign direct investment being directed to this region, reflecting the increasing importance of the Arab markets (Kamaly (2002)).

As suggested earlier in this chapter, the size and activity of the capital market are important determinants of volatility. Comparing the ECM with the other Arab markets, it was found that the ECM was relatively small in size and activity in comparison to other Arab markets. In 2004, companies listed on the ESM accounted for approximately 50 percent of the total listed companies on the Arab markets. However, in terms of market capitalisation, Egypt only comprises 6.12 percent of the total Arab market capitalisation. Similarly, in terms of value and volume traded on the Arab markets, Egypt accounts for only 1.2 and 4.27 percent of the total value and volume of securities traded respectively. The relatively small size and activity of the ECM in comparison to the other Arab markets may imply that most of the companies listed on the ESM are relatively small and inactive. This characteristic of the ESM compared to the other Arab markets, may have implications on the foreign direct investment into the ESM. This, in turn, may have implications for volatility on the ECM (Arab Monetary Fund (2005)).
3.7 Summary

This chapter has provided an overview of the ECM. The focus has been to describe the key characteristics of the ECM, and linking these characteristics to stock market volatility. The first section briefly provided a general overview of Egypt, the structure of its government and the Egyptian economy. Since the performance of the Egyptian economy mirrors the activity in the ECM, the Egyptian economy significantly improved after the implementation of the market liberalisation policies.

Continuing, the market microstructure literature identified was shown to have important implications for market volatility. As such, the next section described the market microstructure of CASE. The discussion focused on the structure of CASE, the regulations governing practices of the exchange, listing requirements, the trading system and the recent developments of the exchange.

The next section moved on to the actual performance and characteristics of the ECM. First, the major market indices that are used to benchmark the performance of the ECM were described. These included the S&P emerging market indices, the MSCI indices and the local indices such as the CASE 30, EFG, HFI, CMAI and PIPO. As benchmarks of market performance, these indices are important for identifying volatility on the ESM.

Following on from this, the ECM characteristics and recent market performance were described. The overall market performance was shown to have rapidly improved in recent years, and that there is some suggestion of volatility clustering on the ESM. The literature has shown that market activity, size, liquidity and concentration may
have implications for market volatility and, therefore, each of these factors were described for the ECM. Similarly, the types of securities traded in the market and the type of market participant, also affect stock market volatility. The breakdown for each of these factors was shown for the ECM.

Finally, since world markets are moving towards globalisation, there is increasing evidence of the inter-linkage between different markets and the fact that volatility in one market is being transferred to other markets. Therefore, it is important to describe the performance of these different markets because of the implication this may have for the volatility of the ESM. The performance of the ECM was compared with world markets, the emerging markets and other Arab markets. Egypt rates comparably well with other emerging and Arab markets. The next chapter examines the methodology for modelling stock market volatility on the ESM.
CHAPTER FOUR

4. CHAPTER 4: RESEARCH METHODS AND MODELS

4.1 Introduction

The previous three chapters established the research objective and the theoretical framework on single time series and panel GARCH modelling, as well as the key characteristics of the ECM with an emphasis on the ESM. Building on that work, this chapter will develop the general framework in modelling volatility on the ESM in a panel data context and specifying the testable research hypotheses which, in turn, will be used in attempting to identify the similarities and differences in the temporal volatility structures of different industries and stocks on the ESM.

To recapitulate, the first three chapters of this thesis have provided the foundations to the analysis of stock market volatility on the ESM, which is a significant motive of this thesis. Firstly, Chapter 1 identified the key areas of interest in the literature regarding stock market volatility, which has formed the motivation of this thesis. The objectives and the significance of this research were identified. This highlighted the gap in the existing research that has not considered modelling stock market volatility through GARCH techniques applied to panel data sets.

Chapter 2 examined the extant literature that has attempted to provide answers to various issues relating to stock market volatility. The main topics covered included the EMH, causes of stock market volatility and an examination of the relationship between stock market volatility and circuit breakers. A significant portion of the chapter was devoted to the literature regarding temporal volatility models with ARCH/GARCH structures in a single time series and panel contexts. Evidence from
the application of these models to developed and emerging markets as well as the ESM was clear.

Chapter 3 presented an overview of the key characteristics of the ECM and linked these directly with its potential implications for the ESM volatility. The main areas covered included the Egyptian economy and the rules and regulations governing CASE (market microstructure). The stock market indices used to measure the performance of the ESM were also detailed. In addition, the performance of the ECM was discussed in terms of market activity, size, liquidity and concentration.

This chapter expands on previous discussions by detailing the methods and models employed in the analysis of this thesis. It explores the methods and techniques that will be used in this thesis to model the volatility on the ESM. Modelling volatility, however, will be conducted in a panel data context instead of a single time series.

The remainder of the chapter is structured as follows. Section 4.2 provides a detailed description of the general volatility modelling framework which will be followed using the general to specific methodology to develop hypotheses and pooled-panel volatility models with GARCH (1,1) structures. These volatility models will identify the similarities and differences in the temporal volatility patterns of different industries and stocks listed on the ESM. This is followed by Sections 4.3 and 4.4 which discuss in detail the estimation procedure for each of the models identified in Section 4.2 and the hypothesis testing procedure used in this thesis. Section 4.5 deals with the analysis of persistency in volatility. Sections 4.6 and 4.7 describe the panel unit root and stationarity tests used in this thesis to determine the stationarity
properties of the data. Since panel unit root and panel stationarity tests are developed from single time series unit root and stationarity tests, the single time series unit root and stationarity tests are also discussed. Finally, Section 4.8 provides a general summary for the chapter.

4.2 GARCH Modelling

The main advantage of panel data, over time-series and cross-sectional data, is that it allows the researcher a greater flexibility in modelling differences in behaviour across individuals. A new development in financial econometrics is the more frequent use of panel methods. Most financial time series data are conditionally heteroskedastic and many studies in the literature have addressed this issue but none have analysed conditional heteroskedasticity in financial time series from a full panel data perspective. Another reason for using panel data instead of a single time series is that the asymptotic distributions of test statistics in panel data are asymptotically normally distributed, instead of following non-conventional distributions and are approximately normally distributed for samples with sizes generally encountered in financial data.

This study, within a general to specific framework of test specification, uses panel methods in conditional heteroskedastic variance equations. The methodology adopted in this general to specific approach is subject to the idea of falsification, which gets plenty of attention in the methodology literature, largely due to the work of Karl Popper (see Caldwell (1991)). That is, hypotheses are subject to the test of disproof. The general to specific methodology sets up a general model which nests within it alternative competing specifications and these competing alternatives can be discriminated by test of disproof. In fact, it was mentioned that:
“The modern world has influenced the approach to empirical modelling and consequently the approach to methodology in general. The question of whether to base a model on an economic theory is easier when several models can be constructed, but an empirical evaluation analysis is required. Starting with a widely specified model and using a reduction procedure is currently a popular process” (Granger (2005)).

The general to specific modelling, based on the theory of reduction, is attributable to, amongst others, Professor David Hendry (see, for example, Hendry (1995), Hendry and Krolzig (2003), Campos, Ericsson, and Hendry (2005) and Hendry and Krolzig (2005)). Usually, general to specific modelling is used to distinguish between different dynamic structures. In this thesis the general to specific methodology will be used to distinguish the similarities and differences between models of return for various time series with conditional heteroskedastic variance.

In terms of testing from the general model to the more restricted model, numerous specification tests have been developed for this purpose\textsuperscript{46}. This thesis employs the LRT procedure, which was first proposed by Neyman and Scott (1948) (see also Neyman and Pearson (1928a, 1928b, 1993)). The LRT is used where the restricted model is nested within a more complex model (Verbeek (2000)) and basically tests a function of the difference between the two model estimates (Aldrich (1997) and Cameron and Trivedi (2005)).

For an individual time series, the time varying volatility model of returns is:

\[
y_t = \mu_t + \varepsilon_t, \tag{4.2.1}
\]

\[
\varepsilon_t | \Omega_{t-1} \sim N(0, h_t),
\]

\textsuperscript{46} The most popular methods include the LRT, the Wald test and the Lagrange multiplier test (Hausman (1978)).
\[ h_t = \alpha_0 + \sum_{m=1}^{q} \alpha_m \varepsilon_{t-m}^2 + \sum_{n=1}^{p} \delta_n h_{t-n} + \nu_t, \]  
\[ \nu_t \sim \text{IIN}(0, h_t), \]  

(4.2.2)

where:

\( y_t \) is the continuously compounded rate of return at time \( t \);

\( \Omega_{t-1} \) is the information set conditioning the disturbance;

\( \alpha_0 \) is a constant term;

\( h_t \) is the conditional variance;

\( \varepsilon_{t-m}^2 \) (The ARCH term), is news about volatility from the previous periods, and is measured as the lag of the squared residual from the mean equation; and

\( h_{t-n} \) (The GARCH term), is the conditional variance lagged by \( n \) periods.

In terms of a panel of series, a general model would allow all parameters \( \mu, \alpha_0, \alpha_1, \ldots, \alpha_m, \) and \( \delta_1, \delta_2, \ldots, \delta_n, \) to vary over all the series included in the panel. This model will be referred to as “Model A: The General Model: The Varying Parameters Model”.

Nested within this general model are a large variety of models based on restrictions associated with different combinations of common and varying parameters for individual series in each panel. It is through a series of nested tests based on this general model that the similarities and differences in volatility structures between stocks in the same sector and different sectors will be examined.

Prior to examining some important potential nested specification in depth, it is important to deal with several issues which arise because of the complexity in
estimating some models such as a pooled mean with panel fixed effects in GARCH model with a large number of parameters.

Firstly, whilst all the conditional variance equations in this chapter are generalised to GARCH \((p,q)\), it must be remembered that the models estimated were restricted to GARCH \((1,1)\). Higher order GARCH lead to a large number of parameters to be estimated in the panel model. For the same reason, the number of stocks in each panel is restricted to ten or less. Fortunately, this restriction fits within the general to specific framework adopted here. The hypothesis tested is that stocks within the same sector or industry will exhibit the same volatility structure, whereas different sectors or industries will exhibit different volatility structures. The first part is tested using six panels of stocks of varying size representing different sectors on the ESM. The indices for these sectors were then used in a sectoral panel to test the second part of the hypothesis.

Secondly, cross-sectional independence was assumed throughout the analysis. That is, the covariance between the individual stocks in a panel was assumed to be zero. This restriction considerably reduces the number of parameters to be estimated in the variance equation with panel structure (see Cermeno and Grier (2001)).

Finally, in terms of restrictions to identify specifications within the general model, joint restrictions were always placed on the GARCH \((1,1)\) parameters. This prevented the generation of a large number of sub-models. Further, this reflects the nature of the hypothesis to be tested here; that is, the similarities and differences in temporal patterns of volatility between units in each panel.
The remainder of this section provides a detailed examination of the general model, accompanied by a diagrammatic exposition of all of the potential sub-models. Further, this section examines in depth the path of general to specific models that was determined through tests on restrictions and which was eventually followed in this thesis.

### 4.2.1 Model A: The General Model (Varying Parameters Model)

The general varying parameters model, Model A:

\[ y_{it} = \mu_i + \varepsilon_{it}, \quad i = 1, 2, ..., N \quad t = 1, 2, ..., T \quad (4.2.3) \]

\[ \varepsilon_{it} \sim N(0, h_{it}) \]

where:

- \( y_{it} \) = dependent variable;
- \( \mu_i \) = intercept coefficient for each \( i \);
- \( \varepsilon_{it} \) = is an error term;
- \( N \) = number of cross sections; and
- \( T \) = time periods in the panel.

Following Bollerslev's (1986) model for single time series, the conditional variance process in a panel context is:

\[ h_{it} = \alpha_{0i} + \sum_{m=1}^{q} \alpha_{mi} \varepsilon_{i,t-m}^2 + \sum_{n=1}^{p} \delta_{ni} h_{i,t-n} + \nu_{it}, \quad \text{for} \ i = 1, 2, ..., N \quad (4.2.4) \]
where $\alpha_0$ is the constant term which constitutes the time independent component of volatility and reflects the volatility if no ARCH (last period’s shock, $\alpha_m$) or GARCH (previous period’s variance, $\delta_n$) effect is significant.

To estimate the unknown parameters of Model A, the method of ML first suggested by Fisher (1922) is employed. ML is regarded as the most efficient estimation among consistently asymptotically normal estimators. However, it does suffer from a few practical problems. The main issue being that the ML problem is not tractable using analytical methods. As a result, numerical methods are needed to estimate the unknown parameters. There are numerous optimisation methods\(^{47}\), the most popular being the algorithm suggested by BHHH (1974). According to Bollerslev (1986) the BHHH (1974) algorithm facilitates convergence and is used in this thesis\(^{48}\).

To estimate Model A, the following log likelihood function needs to be maximised, assuming that the disturbances are cross-sectionally independent:

\[
I(\mu, \phi) = -\left(\frac{NT}{2}\right) \ln(2\pi) - \left(\frac{1}{2}\right) \sum_{t=1}^{N} \sum_{r=1}^{T} \ln\left(h_t(\phi_r)\right) - \frac{1}{2} \sum_{t=1}^{N} \sum_{r=1}^{T} \left(\frac{y_{it} - \mu_t}{h_t(\phi_r)}\right)^2, \quad (4.2.5)
\]

where $\phi_r$ is a vector of all the parameters of the variance process given in $\left(h_t(\phi_r)\right)$ and $\left(y_{it} - \mu_t\right)^2$. The full parameter vector to be estimated for this model has

\(^{47}\) Alternative optimisation techniques include iterative and gradient methods (Greene (2003)), Newton-Raphson (NR) method (Cajori (1911)), method of scoring (MS), method of steepest ascent and the Gauss-Newton (GN) method among others.

\(^{48}\) BHHH (1974) is one generalisation of a Quasi Newton estimation where the asymptotic variance-covariance matrix of a maximum likelihood estimator is equal to the variance covariance matrix of the gradient of the likelihood function. This is an improvement to Newton’s method, where the Hessian of the function is calculated at each iteration.
The key feature of this general model (Model A) is that all estimated coefficients are free to vary, hence the name, the ‘varying parameter model’. There are no restrictions placed on the parameters and they are therefore non-constant. An issue with this model is the large number of parameters associated with it. Hsiao (2003, p.15) identifies a similar linear panel model, but without time varying variance and notes the potential for a large number of parameters. As a general model, it is most likely that this model is not the most efficient model representing the underlying data generating process. For this reason restrictions will be imposed on the estimated coefficients. This not only simplifies the estimated model by reducing the estimated parameters but also results in a model that more accurately defines the data. The efficiency and appropriateness of the restrictions imposed will be determined using hypothesis tests based on the LRT statistic which will be discussed later in Section 4.3. Importantly, this process of reduction will reveal the underlying structure of similarities and differences in volatility for entities in a panel.

Figure 4-1 presents the general volatility modelling framework which displays all the possible volatility models with a GARCH (1,1) structure⁴⁹ nested within the general model by imposing specific restrictions on the mean and conditional variance equations parameters. A first restriction to be imposed is that the constant in the mean equation is fixed for all cross-sectional units in the panel, that is, Model B in Figure 4-1. If the null hypothesis cannot be rejected then the restriction is retained and further

⁴⁹ It should be noted that the modelling in this thesis begins with the GARCH model. The ARCH model is not considered because, as discussed in Chapter 2, Bollerslev (1986) generalised the ARCH model, such that the GARCH model is simply an infinite number of ARCH processes. Therefore, only the GARCH model is estimated in this thesis.
restrictions are imposed. That is, the left hand branch of Figure 4-1 is followed. Alternatively, if the null hypothesis is rejected then the varying parameters model must be retained and restrictions on the conditional variance equation parameters must be tested. That is, the right hand branch of Figure 4-1 is followed. Figure 4-1 is symmetrical, the only difference being the fixity of the parameter $\mu$ for all units in the panel, which constitutes the left half of the figure and the variability of the parameter $\mu$ across individual units in the panel which constitutes the right half of the figure. The process of placing restrictions on the variance equation is the same for both sides of Figure 4-1.

Concentrating on the left hand side, the process of restrictions is as follows. Firstly, restrictions on the slope parameters of the variance equation are tested; that is, the null hypothesis that $\alpha_1$ and $\delta_1$ are common for all units in the panel against the alternative hypothesis that $\alpha_1$ and $\delta_1$ are different across units in the panel. This is equivalent to testing the null hypothesis that different entities in the panel will have different mean volatility and will display a common temporal pattern around those means against the alternative hypothesis that different entities in the panel will have different mean volatility but will display different temporal patterns around those means. If the null hypothesis cannot be rejected, then the specific model is now Model C and further restrictions are imposed on the variance equation of this model. That is, the left hand branch following Model B. Alternatively, if the null hypothesis can be rejected then Model B is retained and further restrictions are imposed on the variance equation of this model. That is, the right hand branch following Model B. Again following the whole figure, the left and right hand branches of Model B are symmetric as further restrictions placed on the variance parameters.
Figure 4-1: General Volatility Modelling Framework: Testing from General to Specific Volatility Models with a GARCH (1,1) Structure

$H_0: \mu_1 = \mu_2 = \ldots = \mu_N = \mu$

$H_1: \mu_1 \neq \mu_2 \neq \ldots \neq \mu_N$

The General Model
Model A
$\mu_i, \alpha_{0i}, \alpha_{1i}, \delta_{1i}$

Model B
$\mu, \alpha_0, \alpha_1, \delta_{1i}$

Model C
$\mu, \alpha_0, \alpha_1, \delta_1$

Model D
$\mu, \alpha_0, \alpha_1, \delta_1$

Model A
$\mu_i, \alpha_{0i}, \alpha_{1i}, \delta_{1i}$

Model A
$\mu, \alpha_0, \alpha_1, \delta_{1i}$

Model F
$\mu_i, \alpha_{0i}, \alpha_{1i}, \delta_1$

Model F
$\mu_i, \alpha_{0i}, \alpha_{1i}, \delta_{1i}$

Model G
$\mu_i, \alpha_{0i}, \alpha_{1i}, \delta_{1i}$

Model H
$\mu_i, \alpha_{0i}, \alpha_{1i}, \delta_{1i}$

Model A
$\mu_i, \alpha_{0i}, \alpha_{1i}, \delta_{1i}$

$H_0$: Null hypothesis, $H_1$: Alternative hypothesis, Models C, D, F and G are equivalent to Models 3, 1, 4, and 2 in Cermeno and Grier (2001), respectively.
Concentrating on the left branch from Model B, namely Model C, the further restriction that can be placed on this model is that the parameter $\alpha_0$ is the same for all units in the panel; that is, the null hypothesis of a pooled model, Model D against the alternative hypothesis of a panel fixed effects in GARCH, Model C. A close examination of the path following the right hand side of Model B in Figure 4-1 will reveal the symmetry between the right and left branches of that model. Similarly, a close examination of the right hand branch stemming from the general model, Model A, will reveal the symmetry of the right hand and the left hand branches to that model. As a generalisation of Figure 4-1, the further one goes down each left branch, the higher the level of commonality of parameters in the remaining model. Alternatively, the further down each right hand branch, the greater is the level of difference in parameters between individual units in the panel. The two extreme models therefore are on the bottom line of Figure 4-1. On the right is Model A, the general model, where all parameters vary between units in the panel, and on the left is Model D, the pooled model, where all parameters are identical for all units in the panel.

Figure 4-1 constitutes a general exposition of a series of nested tests designed to ascertain the level of difference and commonality in models of returns for cross-sectional units in a panel, where those returns can be on individual stocks from different sectors or industries or indices representing sectors or industries. The actual tests on restrictions in this thesis followed the left branch stemming from Model A at the top of the diagram because it was not possible to dismiss the null hypothesis of a common mean parameter, $\mu$, for all panels included in the analysis. The rest of this section is given over to a more detailed exposition of the various specific models identified on this path, which are Models B, C, D, and E.


4.2.2 Model B: Pooled Mean with Varying Parameters in GARCH

Nested within the general model is Model B, with parameter homogeneity in the mean equation and full parameter heterogeneity in the conditional variance equation. That is, the parameter in the mean equation is a common constant for all \( N \) individuals in the sample:

\[
(i) \quad \mu_1 = \mu_2 = \ldots = \mu_N = \mu,
\]

while the parameters in the variance equation are unrestricted. This assumption is based on the classical tradition of the ‘Theory of Industrial Organisation’, which was first proposed by Bain (1956). Following Bain (1956) industrial economists treated the industry or the market as the unit of study. Differences among firms were assumed to be transitory or unimportant unless based on scale economies, which were generally found to be important.

As suggested by Porter (1979), the theory of industrial organisation has viewed the industry as a homogeneous unit. Firms in an industry are assumed to be alike in all economically important dimensions except for their size. In this situation, market power is an asset shared by all firms in the industry in proportion to their sales, and above normal profits is the manifestation of this market power. The profit rate of the firms in an industry should then be equal except for random uninteresting disturbances (Porter (1979)). This theory of industry wide or “shared asset” profit determination has proven versatile in the literature and, for this reason, forms the basis
for the structure of the mean equation in Model B.\footnote{See also Cubbin and Geroski (1987), Schmalensee (1985), and Porter (1979) for further details on the industrial economics literature.}

Specifically, Model B can be written as equations (4.2.3) and (4.2.4) but now with the cross-sectional unit index $i$ dropped from the mean equation; that is:

\begin{align*}
y_{it} &= \mu + \varepsilon_{it}, \quad i = 1, 2, \ldots, N \quad t = 1, 2, \ldots, T \\
h_{it} &= \alpha_{0i} + \sum_{m=1}^{q} \alpha_{mi} \varepsilon_{ij-m} + \sum_{n=1}^{p} \delta_{ni} h_{ij-n} + \nu_{it}, \quad \text{for } i = 1, 2, \ldots, N. \tag{4.2.6, 4.2.7}
\end{align*}

To estimate the unknown parameters of Model B, the following log likelihood function needs to be maximised, assuming that the disturbances are cross-sectionally independent:

\begin{align*}
l(\mu, \phi) &= -\left(\frac{NT}{2}\right) \ln(2\pi) - \left(\frac{1}{2}\right) \sum_{i=1}^{N} \sum_{t=1}^{T} \ln\left(h_{it}(\phi)\right) - \frac{1}{2} \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{(y_{it} - \mu)^2}{h_{it}(\phi)}, \tag{4.2.8}
\end{align*}

where $\phi_{i}$ is a vector of all the parameters of the variance process given in $\left(h_{it}(\phi)\right)$ and $(y_{it} - \mu)^2$. The full parameter vector to be estimated for this model has $(1 + N + N(q + p))$ elements.

Summarising Model B, there is homogeneity in the mean equation while the parameters in the conditional variance equation are heterogeneous (unrestricted). In terms of general to specific modelling, hypothesis testing using the LRT will be
employed to determine whether the imposition of the constraint can be accepted or rejected. The LRT statistic follows a $\chi^2$ distribution with $N-1$ degrees of freedom in this case. If the constraint can be rejected then testing down from a general to a specific model halts in this direction. Varying parameters in the mean equation would be retained and restrictions imposed on the variance equation would be tested. Alternatively, if the restriction cannot be rejected, a common constant in the mean model would be retained and further restrictions can be imposed on the conditional variance equation to produce even more specific models. This is the case of Model C.

4.2.3 Model C: Pooled Mean with Panel Fixed Effects in GARCH Model

If the restriction (i) in Model B cannot be rejected, then it is maintained and further restrictions can be imposed. In this case, in addition to the constant in the mean equation being restricted, the ARCH (1) and GARCH (1) terms are constant across units in the panel, namely,

(ii) $\alpha_{i1} = \alpha_{i2} = \ldots = \alpha_{iN} = \alpha_1,$
(iii) $\delta_{i1} = \delta_{i2} = \ldots = \delta_{iN} = \delta_1.$

With these restrictions in place, Model C is a pooled mean with panel fixed effects in GARCH model. Specifically, there is a common effect in the mean equation, which is the mean average of all the individual specific effects for each of the series included in the panel, and individual specific effects in the variance equation with fixed ARCH and GARCH terms; that is:

$$y_{it} = \mu + \varepsilon_{it}, \quad i = 1,2,\ldots,N \quad t = 1,2,\ldots,T \tag{4.2.9}$$
The conditional variance equation now reflects the fixed effects panel model which should be familiar from static linear panel mean models. This restriction is very interesting and the variance model has a sensible financial interpretation. The conditional variance or risk of a specific sector or industry consists of:

- the mean variance, $\alpha_{0i}$, which is a time independent component, is different for each stock recognising the potential for different firm specific risk (unsystematic risk) associated with different stocks in the same sector or industry; and
- the temporal volatility, which is time varying components, and compromises previous shocks or news for a certain sector or industry that affects all stocks included in that sector or industry, $\alpha_{1}$, and the previous variance or risk of that sector or industry, $\delta_{1}$.

Although the restrictions on the GARCH parameters in this model may justify the volatility structure for a panel of stocks that constitute a sector or an industry, it may explain little of the volatility structure on the aggregate level where a panel of sectors or industries constituting a market is used. The reason for that is that a shock or news related to a certain industry will equally affect all stocks included in that industry. However, market shocks or news may have a different effect on one sector or industry compared to another. That is, on the aggregate level, assuming that market shocks or news will affect all sectors or industries equally may not be true.
Once again, to estimate the parameters of Model C, a log likelihood function needs to be maximised. Assuming that the disturbances are cross-sectionally independent, this likelihood function will have exactly the same notation as (4.2.8). However, it should be noted that the parameter set $\varphi_i$ now reflects the restrictions of (ii) and (iii). In this case the parameter vector to be estimated has $(1 + N + q + p)$ elements.

Again, following standard general to specific methodology if the restrictions of (ii) and (iii) can be rejected then testing down in this direction is halted. The restrictions are abandoned and alternative restrictions would then be imposed on Model B. If restrictions (ii) and (iii) cannot be rejected then they will be retained and further restrictions will be imposed on this model for a more parsimonious form.

### 4.2.4 Model D: Pooled Model

If the additional restrictions in Model C are not rejected, then a more parsimonious specification can be identified by the restriction that the constant in the variance equation (4.2.10), $\alpha_{i0}$, is also common to all cross-sectional units. That is:

$$(iv) \alpha_{01} = \alpha_{02} = \ldots = \alpha_{0N} = \alpha_0.$$\]

Moreover, combining restrictions (i) to (iv), gives the nested model, Model D, which is referred to as the pooled model. Specifically, the pooled model consists of complete parameter homogeneity in the mean and variance equations. That is, all estimated coefficients of the model are restricted to be constant across all cross-sectional units. Expressly, Model D can be written as:
\[ y_{it} = \mu + u_{it}, \quad i = 1, 2, \ldots, N \quad t = 1, 2, \ldots, T \]  \hspace{1cm} (4.2.11)

\[ h_t = \alpha_0 + \sum_{m=1}^{q} \alpha_m e_{t-m}^2 + \sum_{n=1}^{p} \delta_n h_{t-n} + \nu_t. \]  \hspace{1cm} (4.2.12)

In financial terms, the conditional variance of a sector or industry consists of:

- the time independent mean variance of stocks included in that sector, \( \alpha_0 \); and
- the time varying temporal volatility which compromises previous shocks or news for a certain sector or industry that equally affects all stocks included in that sector or industry, \( \alpha_1 \), and the lagged variance or risk of that sector or industry, \( \delta_1 \).

The restriction (iv), which distinguishes Model D from C, seems fairly severe because assuming that stocks in the same industry will have the same average risk may not be true since, although these stocks operate under the same market risk, each stock is still subject to its own firm specific risk. The distinction is still very important because, if these restrictions apply, then the practice of examining stock market volatility by market indices and generalising those patterns to stocks in the index can be justified. Alternatively, if these restrictions are rejected, then the degree of volatility will vary between stocks.

In this model the full parameter vector has \((1+1+q+p)\) elements. To estimate the parameters of Model D, a log likelihood function similar to that of Model C needs to be maximised. Assuming that the disturbances are cross-sectionally independent, the
likelihood function has exactly the same notation as (4.2.8), but with the parameter vector $\phi$ reflecting restrictions (ii), (iii) and (iv).

### 4.2.5 Model E: Pooled Mean and Variance with Varying GARCH Parameters Model

Recalling from Section 4.2.3 and following standard general to specific methodology, if the restrictions of (ii) and (iii) can be rejected then testing down in this direction is halted. The restrictions are abandoned and alternative restrictions would then be imposed on Model B. From this model a more parsimonious specification can be identified by imposing the restriction that the constant in the conditional variance equation (4.2.7), $\alpha_{0i}$, is common for all cross-sectional units included in the panel; that is, restriction (iv) in Section 4.2.4.

Combining restrictions (i) and (iv), gives the nested model, Model E, which is referred to as the pooled mean and variance with varying GARCH parameters model. Expressly, Model E can be written as:

$$
\begin{align*}
    y_{it} &= \mu + \epsilon_{it}, \quad i = 1, \ldots, N \quad t = 1, 2, \ldots, T \\
    h_{it} &= \alpha_0 + \sum_{m=1}^{Q} \alpha_m \epsilon_{i,t-m}^2 + \sum_{n=1}^{p} \delta n h_{i,t-n} + \nu_{it}, \quad \text{for } i = 1, 2, \ldots, N.
\end{align*}
$$

In this model, the mean variance in the conditional variance equation, $\alpha_0$, is common for all units included in the panel as in Model D. However, the temporal volatility pattern is allowed to be different for each unit in the panel and constitutes each series’ own innovation spillovers, $\alpha_i$, and lagged volatility spillovers, $\delta_i$. 
In this model the full parameter vector has \((1 + 1 + N(q + p))\) elements. Once again to estimate the parameters of Model E, a log likelihood function similar to that of models C and D needs to be maximised. Assuming that the disturbances are cross-sectionally independent, the likelihood function will have exactly the same notation as (4.2.8), but with the parameter vector \( \varphi \), reflecting restriction (iv).

Thus far, this chapter has concentrated on the exposition of the general to specific methodology that will be used to identify the similarities and differences in the conditional variance structure between the different stocks that will constitute a panel of data. However, the general to specific methodology can be used to test the hypothesis that stocks in the same market will have similar volatility structures and that stocks in different markets will have different volatility structures. In this thesis, data from the ESM will be used at two levels of aggregation. Firstly, at a completely disaggregated level, several panels of individual stocks will be used, where each panel comprises a specific sector or industry on the ESM. Secondly, and at a higher level of aggregation, a panel of sector indices will be used where each unit in the panel will be the index from the sectors in the disaggregated data. Recalling Figure 4-1, if stocks within the same sector or industry are expected to display homogeneity in conditional variance structures compared to stocks from different sectors or industries, then one would expect the test to a more parsimonious model to go further down the left hand branches of this figure for those panels comprising sectors of individuals stocks, in comparison to the panel of indices from these sectors. In this way testing down to the most parsimonious model will ascertain whether there are important differences in volatility structures between different stocks that are not from the same sectors or industries.
The next section of this chapter will deal with the procedures used in the estimation of the different models. It will deal with the likelihood function for each of the important models identified in this section. The emphasis will be on the practicalities of estimating the models under different regimes of restrictions.

4.3 Estimation Procedure

4.3.1 Background

The purpose of this section is to first deal with the practical issue of estimation, what software was used and drawing the distinction between estimation of the five different models identified. The second purpose is to briefly outline the BHHH (1974) algorithm used in the numerical optimisation to identify the parameter vector of each model.

Because of the large number of parameters to be estimated, especially in Model C, the order of lags in the variance model was restricted to GARCH (1,1). At first glance this might be seen as being overly restrictive. However, it must be borne in mind that the majority of volatility studies in stock markets apply the GARCH (1,1). Further, Bollerslev (1986) argues that the GARCH model is one that is valued for its parsimony in lag order. In Chapter 2, Section 2.1.5.2 it was demonstrated that a GARCH (1,1) captures an infinite ARCH model so that higher order lags may be redundant. The important issue in this thesis is not the order of lags, but to use general to specific modelling to identify similarities and differences in the temporal structure of the returns on different stocks in the same industry.
4.3.2 Maximum Likelihood (ML) Estimation

All estimates were undertaken with routines written in the GAUSS 5.0 matrix language (Aptech Systems Inc. (2003)). Wherever possible, estimates were validated using pre-programmed software, notably STATA 8.0 (StataCorp (2003)) and SHAZAM 9.0 (Northwest Econometrics Ltd. (2003)). At the core of each GAUSS routine is the estimation of the likelihood for an individual time series. The numerical algorithm used in all cases was BHHH (1974). Variations on this single series estimation were used for the estimation of the different parameter sets associated with multi-series Models A, B, C, and D.

4.3.2.1 Model A: The General Model (Varying Parameters Model)

Recalling the likelihood function of (4.2.5):

\[ I(\mu_i, \varphi) = -\left(\frac{NT}{2}\right)\ln(2\pi) - \left(\frac{1}{2}\right)\sum_{i=1}^{N} \sum_{t=1}^{T} \ln\left(h_{it}(\varphi_i)\right) - \frac{1}{2} \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{(y_{it} - \mu_i)^2}{h_{it}(\varphi_i)}. \]

It should be noted that the likelihood function for all \(i\) stocks or sector indices in the pooled sample is simply the sum of the individual likelihoods over \(T\) for all individual units in the sample. Given that \(T\) is large for each unit and following Hsiao (2003, p.15)\(^{51}\), it was therefore possible to find the parameters for each individual stock or index, \(i\), by maximising its own likelihood over the sample \(T\). The outcomes for each individual series using GAUSS software were then validated with re-estimation using STATA and SHAZAM softwares. Fortunately, the GAUSS algorithm worked well.

\(^{51}\) Hsiao (2003, p.15) specified a general static linear panel model with constant variance. He stated that such a model is estimated as the regression of each individual time series.
In order to compute LRT statistics to undertake the required tests for restrictions, the overall likelihood for all stocks and indices in the sample was simply estimated as the sum of the individual maximum likelihoods for all \( i \) series in the sample. It should be emphasised that this was possible, simply because each stock in the sample was a long time series.

### 4.3.2.2 Model B: Pooled Mean with Varying Parameters in GARCH Model

A similar procedure was adopted in the estimation of the joint likelihood of all \( i \) units in the sample. Again, an examination of the likelihood function reveals that this is simply the summation of the likelihoods of individual series, \( i \), in the sample. This leads to two possibilities:

i) If the common value of \( \mu \) is known in the mean equation, the parameters in the variance equation can be estimated for individual series, \( i \), in the sample by maximising the individual likelihoods.

ii) If the common value of \( \mu \) is unknown then it has to be estimated along with all of the other parameters. However, because it is a common parameter, the likelihoods for individual series, \( i \), now have to be maximised jointly.

In this thesis, optimisation method i) has been used. Reasonable estimates of \( \mu \) could be obtained from the mean of the \( \mu \)'s estimated in the general model. This \( \mu \) was then fixed for the free estimation of all other parameters for the individual likelihoods. For purposes of the LRT of this restricted model, against the general model, the joint ML was estimated as the sum of the individual maximum likelihoods.
4.3.2.3 Model C: Pooled Mean with Panel Fixed Effects in GARCH Model

Similar arguments can be applied to the parameter estimation in this model as those made in Model B. The restrictions result in the parameters of the conditional variance equation associated with the lagged terms in $e_i^2$ and $h_t$ being common across all units, $i$, in the panel. If these parameters, $\alpha_1, \alpha_2, \ldots, \alpha_q$ and $\delta_1, \delta_2, \ldots, \delta_q$, are all known then estimation of the remaining unknown parameters can be done by maximising the individual likelihood functions. Alternatively, where these parameters are unknown, they have to be estimated by maximising the joint likelihood functions across all units, $i$.

There is no justification for imposing arbitrarily pre-determined values for these important slope parameters and to test the important hypothesis that cross-sectional units in the panel had the same or different inter-temporal volatility pattern. It was, therefore, necessary to use the joint estimation method where all unknown parameters are freely estimated.

Whilst fixed panel effects in an ARCH model have previously been estimated, they have not been estimated in a GARCH model. This, therefore, necessitated the development of the GAUSS code to maximise the joint likelihood over all units in the panel.

4.3.2.4 Model D: Pooled Model

The pooled model was estimated using the likelihood routine written for the estimation of a single series. This is because all parameters are identical across all
units, \(i\), in the panel. Again, estimates in GAUSS were validated with the same estimates in STATA and SHAZAM.

4.3.2.5 Model E: Pooled Mean and Variance with Varying GARCH Parameters Model

As in the estimation of Model B, there are two possibilities for estimating Model E:

i) If the common value of \(\alpha_0\) is known in the variance equation, the parameters in the variance equation can be estimated for individual series, \(i\), in the sample by maximising the individual likelihoods.

ii) If the common value of \(\alpha_0\) is unknown then it has to be estimated along with all of the other parameters. However, because it is a common parameter, the likelihoods for individual series, \(i\), have to now be maximised jointly.

Optimisation method i) was used. A reasonable estimate of the common parameter \(\alpha_0\) could be obtained from the mean of the \(\alpha_0\)’s estimated in the general model. This \(\alpha_0\) was then fixed for the free estimation of all other parameters for the individual likelihoods. For purposes of the LRT of this restricted model, against the Model B, the joint ML was estimated as the sum of the individual maximum likelihoods.

4.4 Numerical Optimisation: BHHH

The likelihood function in GARCH models cannot be maximised using analytical methods. Thus, a numerical method is needed to obtain the optimal parameter estimates (Cameron and Trivedi (2005)). Whilst there are several optimisation algorithms, Bollerslev (1986, 1988) used the BHHH (1974) algorithm. The BHHH
algorithm, following Bollerslev, will be used in all estimation in this thesis. Given its importance to the thesis, a brief description of the algorithm is given here.

Assume the log of the likelihood function is:

\[
L(\theta; y_i) = \sum_{i=1}^{i=N} \ln \left[ f_{y_i}(y_i, \theta) \right], \tag{4.4.1}
\]

where:

- \(f\) is the probability density function governing the random variable \(Y\);
- \(y\) is a realisation of the random variable \(Y\);
- \(\theta\) is a vector of unknown parameters; and
- \(i\) is an index of observations \(i = 1, 2, \ldots, N\).

Given the function \(f\) and the observations \(y\), the problem is to choose that vector \(\theta\) which maximises \(L\).

The generic quasi Newton algorithm for the solution to this problem is:

\[
\theta^{u+1} = \theta^u - H^{-1}w \tag{4.4.2}
\]

where:

- \(w\) is the gradient vector of \(L\) with respect to \(\theta\) evaluated at the parameter vector \(\theta^u\);
- \(H\) is the Hessian matrix of \(L\) with respect to \(\theta\) evaluated at the parameter vector \(\theta^u\); and
\( a \) and \( a+1 \) are superscripts referring to the current parameter vector and the updated parameter vector.

The iterative procedure requires placing the current parameter vector with the updated parameter vector and estimating a new updated parameter vector. This process continues until some sensible convergence criterion is reached.

The BHHH estimator replaces the Hessian with:

\[
H = \sum_{i=1}^{i=N} G_i
\]

where, abstracting from panel data, \( i \) is a subscript denoting an individual observation from the whole sample with sample size \( N \). Further, the matrix \( G_i \) is the outer product:

\[
G_i = g_i g_i'
\]

and the column vector \( g_i \) is the vector of first derivatives of the log likelihood for an individual observation for all parameters \( \theta \). That is:

\[
g_i = \frac{\partial L_i}{\partial \theta}
\]

A clear distinction must be made here between \( g_i \) and the gradient vector of the log of the likelihood function given in (4.4.2):
\[ w = \frac{\partial L}{\partial \theta}. \]

Not only does the BHHH algorithm have the virtuous property that it does not require estimation of the second order partial derivatives but, according to Bollerslev, it also leads to tractable estimation of the parameters of the GARCH models. Further, the negative of the inverse Hessian estimated in this way was used as the estimate of the parameter covariance matrix. This algorithm was used in all of the GAUSS routines coded to estimate the different parameter vectors associated with the general model and the nested specific alternatives. However, it should be pointed out that in all cases, numeric first derivatives were used and not the analytical derivatives. The use of numeric derivatives was tested by validating estimates wherever possible with estimates using the alternative pre-programmed software, STATA 8.0 and SHAZAM 9.0. In all cases the GAUSS estimates were replicated by the comparative estimates.

### 4.5 Persistence Tests

Following from the previous discussion of the various panel volatility models with different GARCH structures, once a model is specified as the best model describing the data generating process (DGP) of a certain data panel, a useful and further analysis in this general GARCH framework is the level of volatility persistence.

Persistence in volatility, referring to the property of momentum in conditional variance, is defined as how permanent a shock is to volatility (Lamoureux and Lastrapes (1990b)). According to GARCH models, shocks to variance persist according to an Autoregressive Moving Average (ARMA) structure of the squared residuals of the process and volatility is said to persist if yesterday’s innovation has a
great impact on future variance forecast many periods in the future (Engle and Patton (2001)). Therefore, the measurement of volatility persistence is an important aspect of volatility modelling and forms the basis for an interpretation of the GARCH modelling results.

Volatility persistence can be measured by the persistence parameter which is directly measured as part of the GARCH modelling estimation process. It is the sum of the GARCH parameters in the conditional variance equation (see Chapter 2, equation 2.4.3). As a general rule, the closer the persistence parameter is to unity, the longer the shocks to volatility influence the returns; that is, the greater the persistence of volatility shocks. If the persistence parameter is one, volatility shocks persist forever and the conditional variance is not determined by the model (Chou (1988)). If the persistence parameter is less than one, then there is mean reversion of the returns process.

As mentioned in Chapter 2, Section 2.5.2, a related aspect to the concept of volatility persistence is the concept of the HL. The HL, as discussed by Lamoureux and Lastrapes (1990b) measures the period of time (number of days) that it takes for volatility shocks to fall back to half their original size. Calculating the HL depends on the persistence parameters discussed earlier and is given in equation 2.4.4. The HL is calculated for the panel indices and all panel sectors and can be used as evidence for the volatility clustering hypothesis.
In this thesis the persistence parameters and the HL of volatility for each selected model will be computed and analysed. The next two sections examine the procedure used to test for stationarity in the data sample.

4.6 Testing for Stationarity

Prior to modelling the volatility of asset returns in a panel data context, it is necessary to determine the stationarity properties of each panel. In particular, are logarithmic prices stationary in levels or first differences (continuous compounded returns). It will be necessary to undertake these tests in their panel format because volatility modelling on the ESM will be done as panel estimates.

The significance of panel unit root and stationarity tests is that modelling time series in levels or differences may lead to very different predictions. Deciding which model to use is therefore very important. Panel unit root and stationarity tests can be used as a diagnostic tool to guide the decision. In fact, one of the early motivations for unit root tests was to help determine whether to use forecasting models in differences or levels (see Dickey, Bell and Miller (1986)).

4.6.1 Unit Root versus Stationary Stochastic Process

A stochastic process is a “statistical phenomenon that evolves over time according to probabilistic laws” (Box, Jenkins and Reinsel (1994)), which governs the joint distribution of the random variables over time. A strictly stationary stochastic process is where the random variables $Y_{t-k}, Y_t, Y_{t+k}$, have identical and independent distributions. Frequently, a process is defined as a weak stationary stochastic process, where such a definition relies on the first and second moments of the distributions of
the random variables of the stochastic process. This is sometimes known as covariance stationary. Such a process has the following characteristics:

\[
E(Y_t) = \mu; \\
\text{var}(Y_t) = \left[ E(Y_t - \mu)^2 \right] = \sigma^2 = Y_0; \text{ and} \\
\text{cov}(Y_t, Y_{t-k}) = E \left[ (Y_t - \mu)(Y_{t-k} - \mu) \right] = \gamma_k, \\
\]

for all \( t \). That is, the unconditional mean, variance and covariance are independent of time (see, for example, Franses (1998), Fuller (1996), and Hendry (1995)).

A stationary process is defined as a weak white noise process when it has the following characteristics:

\[
\{ \varepsilon_t \} \text{ is a sequence of uncorrelated random variables and:} \\
E(\varepsilon_t) = 0; \\
\text{var}(\varepsilon_t^2) = \sigma^2; \text{ and} \\
\text{cov}(\varepsilon_t, \varepsilon_s) = \gamma_k = 0, \\
\]

for all \( t \) (see, for example, Hamilton (1994), and Hendry (1995)).

An independent white noise process has the first and second unconditional moment’s characteristics of (weak) white noise but:

\[
\{ \varepsilon_t \} \text{is a sequence of independent and identical distributed random variables} \\
\text{and in this case } \varepsilon_t \sim \text{i.i.d } (0, \sigma^2). \]
A white noise process is sometimes referred to as a Gaussian white noise process. This has the first and the second unconditional moments characteristics of (weak) white noise but:

\[ \{\varepsilon_t\} \text{ is a sequence of independent and normally distributed random variables} \]

\[ \text{and in this case } \varepsilon_t \sim \text{IN}(0, \sigma^2). \]

A non-stationary process has a mean, variance, and covariance that are independent of time. Non-stationary processes are not convergent, and they cannot be modelled using traditional estimation methods. Alternatively, stationary processes are stable and they can be modelled using regression methods.

If a non-stationary process is stationary in first differences, it is said to be integrated order 1, denoted as I(1). If a non-stationary process is second difference stationary it is said to be integrated order 2, that is I(2). Generally an I(d) process is d order difference stationary if it has to be differenced a minimum of d times in order to become a stationary, I(0) process\(^{52}\).

### 4.6.2 Non-Stationary Processes and Unit Roots

Consider a first order autoregressive, AR (1), process:

\[ y_t = \alpha y_{t-1} + \varepsilon_t, \quad \{\varepsilon_t \sim \text{N}(0, \sigma^2)\}. \quad (4.6.1) \]

\(^{52}\)Over differencing is a common error. If \( \Delta^d Y \) is stationary then so to is \( \Delta^{d+1} Y \). The minimum number of differences required to reach stationary determines the order of integration.
That is, the value of variable $y$ in period $t$ is determined by the value of $y$ in the previous period plus some stochastic component, which is distributed as a Gaussian white noise.

Setting the start period $t=0$ and a start value for $y$ as $y_0$, iteration from period zero to period $t$ gives (see Enders (2004) and Franses (1998)):

$$y_t = \alpha y_0 + \sum_{i=1}^{t} \phi_i \epsilon_{t-i}.$$ (4.6.2)

The asymptotic properties of (4.6.2) are:

1. if $\lim_{t \to \infty}$ and $|\alpha| < 1$, then the process converges; but

2. if $\lim_{t \to \infty}$ and $|\alpha| > 1$, then the process is explosive.

The special case of $|\alpha| = 1$ or $|\alpha| = 1$, so that (4.6.1) becomes:

$$y_t = y_{t-1} + \epsilon_t.$$ (4.6.3)

is interesting. Using (4.6.2) and (4.6.3), gives (Franses (1998)):

$$y_t = y_0 + \sum_{i=0}^{t} \alpha^i \epsilon_{t-i}.$$ (4.6.4)

The time series described by (4.6.3) and (4.6.4) has the following properties (Enders (2004)): 


a. Any $\varepsilon$ is non-decaying, so that any $y_t$ is permanently influenced by previous shocks or innovations. That is, any $\varepsilon$ produces a permanent echo in $y$, which never dissipates over time. This contrasts with (4.6.2) when $|\alpha| < 1$, where the influence of any $\varepsilon$ reduces over time. The closer the parameter $\alpha$ is to 1 in (4.6.2), the longer is the memory of $\varepsilon$ in the series $y$.

b. Recalling that $y_0$ is constant and $E(\varepsilon) = 0$, at any $t$, the *ex post* expectation of $y$ in (4.6.4) is:

$$E(y_t) = y_0 + E\left(\sum_{i=0}^{t-1} \varepsilon_{t-i}\right) = y_0.$$ 

c. However the *ex ante*, one period ahead, expectation at any time $t$ is:

$$E(y_{t+1}) = E(y_t + \varepsilon_{t+1}) = y_t,$$

and for $s$ leading periods at time $t$ the expectation is:

$$E(y_{t+s}) = E\left(y_t + \sum_{i=1}^{s} \varepsilon_{t+s}\right) = y_t.$$ 

d. Recall that in (4.6.4) the $\varepsilon$’s are identically distributed with variance $\sigma^2$, so that at any time $T$:
\[ \text{var}(y_T) = \text{var} \left( \sum_{i=1}^{T} \varepsilon_i \right) = \sum_{i=1}^{T} \sigma^2 = T \sigma^2. \]

Thus, the variance of \( y \) increases without limit over time.

e. The covariance of \( y_t \) with any realisation lagged \( s \) times is:

\[ \text{Cov}(y_t, y_{t-s}) = (t-s)\sigma^2. \]

f. Because \( \varepsilon \) is white noise, the time series described by (4.6.3) is stationary in differences. Subtracting \( y_{t-1} \) from both sides of (4.6.3) gives

\[ y_t - y_{t-1} = \varepsilon_t \Rightarrow \Delta y_t = \varepsilon_t. \]

Thus, \( y_t \) in (4.6.4) is a non-stationary time series because the characteristics of points c, d and e breach the conditions for a weak stationary process. That is, \( y_t \) is non-stationary because the mean, variance and covariance with lagged terms are time dependent. Further, because \( y_t \) is stationary in first difference but non-stationary in levels, the time series is I(1). The series (4.6.4) has a unit root and it is non-stationary. While (4.6.4) has only one root, an AR(\( p \)) process will have multiple roots and can have more than one unit root.
4.7 Unit Root and Stationarity Tests

The previous section shows that, prior to analysing data from the ESM for time varying volatility, it is important to test for unit root processes. Since the seminal work of Nelson and Plosser (1982), where a number of U.S. time series were tested for stationarity, unit root tests have exploded in the econometrics literature. This section will explore the development of unit root tests and their use in this analysis. Whilst the tests used in this thesis are panel unit root and panel stationarity tests, these tests are developed from tests of single series. Therefore, the next two subsections will examine tests based on single series beginning with the augmented Dickey Fuller (ADF) unit root tests and then the KPSS stationarity test. The rest of the chapter will deal with the related panel unit root and panel stationarity tests and how they are used in the thesis.

4.7.1 Single Time Series Unit Root and Stationarity Tests

4.7.1.1 Augmented Dickey Fuller Unit Root Tests

The most popular tests for a unit root in time series are those conducted by Dickey and Fuller (1979, 1981). This subsection describes these tests in some detail. Begin by considering a test for a unit coefficient in the regression model:

\[ y_t = \alpha y_{t-1} + \epsilon_t, \quad t = 1, 2, ..., T \]  \hspace{1cm} (4.7.1)

where \( \alpha \) is a real number, and \( \epsilon_t \) is a sequence of independent normal random variables with mean zero and variance \( \sigma^2 \). It would seem natural to estimate (4.7.1) by Ordinary Least Squares (OLS) and use a t-statistic to test the null hypothesis that
\( \alpha = 1 \). However, under the null hypothesis, the series \( y_t \) is a non-stationary process with a variance increasing as time, \( t \), increases; that is, \( \text{var}(y_t) = t\sigma^2 \). Under this condition the t-statistic for testing the null that \( \alpha = 1 \) is not asymptotically normally distributed. The Dickey Fuller test overcomes this problem by using the fact that if \( \alpha = 1 \) then (4.7.1) is difference stationary.

Subtracting \( y_{t-1} \) from (4.7.1) gives:

\[
\Delta y_t = \rho y_{t-1} + \varepsilon_t \quad \{ \rho = \alpha - 1 \} \quad \{ \rho = 0 \leftrightarrow \alpha = 1 \}.
\] (4.7.2)

The DF test estimates (4.7.2) by OLS and then tests the following hypothesis:

\[
H_0 : \rho = 0,
\]
\[
H_1 : \rho < 0.
\]

The distribution of the test statistic under the null hypothesis of \( \rho = 0 \) is obtained by Monte Carlo simulations. The critical values from such simulations can be found in Fuller (1976) and Dickey and Fuller (1979, 1981) who list the tabulated critical values for testing the null hypothesis of a unit root. Equation (4.7.2) assumes a DGP of a random walk with no drift or trend. However, there are two more tests that can be considered, especially when dealing with financial data. The two tests are:

\[
\Delta y_t = \mu + \rho y_{t-1} + \varepsilon_t, \quad (4.7.3)
\]
\[
\Delta y_t = \mu + \beta t + \rho y_{t-1} + \varepsilon_t, \quad (4.7.4)
\]
where, in each case, the null hypothesis that \( \rho = 0 \) can be tested using the t-statistics from the estimated coefficients in equations (4.7.2), (4.7.3) and (4.7.4). The critical values depend on which test is estimated and recalling that these critical values will be non-standard. Following Dickey and Fuller (1979), the statistics analogous for testing the null hypothesis that \( \rho = 0 \) in equations (4.7.2), (4.7.3) and (4.7.4) are termed the \( \hat{\tau}, \hat{\mu}, \hat{\tau} \) statistics respectively. In a later paper, Dickey and Fuller (1981), describe three further test statistics, \( \Phi_1, \Phi_2 \) and \( \Phi_3 \). These are joint restriction tests on the parameters of equations (4.7.3) and (4.7.4), and they are constructed as F tests. Again, they do not have the usual F distribution. \( \Phi_1 \) tests the null hypothesis of \( (\mu, \rho) = (0,1) \) in equation (4.7.3), \( \Phi_2 \) tests the null hypothesis of \( (\mu, \beta, \rho) = (0,0,1) \) in equation (4.7.4) and \( \Phi_3 \) tests the null hypothesis of \( (\mu, \beta, \rho) = (\mu,0,1) \) in equation (4.7.4) and the critical values can be found in Dickey and Fuller (1981).

A problem with the DF test is the possible presence of serial correlation in the residuals, which will affect the distributions of the test statistics and, therefore, invalidate the tests. The solution favoured by Dickey and Fuller (1981) is to add distributed lags in the first difference of the series and these constitute the ADF tests. ADF1, ADF2 and ADF3 equations augmented with lags in first differences from lag 1 to lag \( p \) are respectively:

\[
\Delta y_1 = \rho y_{t-1} + \sum_{i=1}^{p} \theta_i \Delta y_{t-i} + \varepsilon_i, \quad (4.7.5)
\]

\[
\Delta y_{11} = \mu + \rho y_{t-1} + \sum_{i=1}^{p} \theta_i \Delta y_{t-i} + \varepsilon_i, \quad (4.7.6)
\]
The idea behind these models is to use lagged changes in the dependent variable to correct for residual autocorrelation and make sure that $\varepsilon_i$ is white noise. The validity of this procedure follows from noting that the $AR(p)$ process:

$$y_t = \mu + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \alpha_3 y_{t-3} + \ldots + \alpha_p y_{t-p} + \varepsilon_t$$

can be written as:

$$\Delta y_t = \mu + \rho y_{t-1} + \sum_{i=2}^{p} \theta_i \Delta y_{i-1} + \varepsilon_t,$$

where

$$\rho = -\left(1 - \sum_{i=1}^{p} \alpha_i \right) \quad \text{and} \quad \theta_i = \sum_{j=1}^{i} \alpha_j.$$

Test outcomes are sensitive to the number of lags included in the test equations. It is important that the optimal number of lags, $p$, is determined transparently. Campbell and Perron (1991) suggested a method for determining the optimal lag, where an upper bound to the ADF order is chosen. Testing then proceeds from general to specific using either the lags that minimise SIC or simply testing the significance of

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53 Phillips and Perron (1988) suggested a non-parametric method to correct for autocorrelation, which modifies the test statistic after estimation to correct for estimated residual autocorrelation rather than allowing for residual correlation in the regression equation.
the last included lag (stopping when the coefficient on the last included lag is significant). Once the lag order required in the ADF test is established, the testing sequence moves to a consideration of which regression model to apply.

While the ADF test is extremely popular in applied research, due largely to its relative simplicity and the fact that most econometric packages carry routines which perform the calculations, it does have its drawbacks. One of the most frequently quoted of these is its low power. There are two broad reasons for this. The first is that the tests use the criteria of classical statistical inference in judging the null hypothesis of a unit root and, unless there is strong evidence to the contrary, the null hypothesis will not be overturned. The second is a more general problem. The hypothesis being tested is that the root is exactly equal to one. This defines the presence of a unit root in the time series and its non-stationarity. If the root is close to, but not quite, one, say 0.99, then the series will in fact be stationary and, obviously, does not have a unit root. Clearly, distinguishing between roots of one and roots close to one is likely to lead to low power in such tests.

4.7.1.2 KPSS Stationarity Test

An alternative is to test the null hypothesis of a stationary process. The most common test here is attributable to Kwiatkowski, Phillips, Schmidt and Shin (1992), denoted by KPSS. Unfortunately, switching the null and alternative hypotheses has not really solved the power problem. Nevertheless, the KPSS can be considered an alternative to the ADF tests.
Kwiatkowski, Phillips, Schmidt and Shin (1992) considered a time series, which is generated as the sum of a deterministic trend, a random walk and a stationary error term:

\[ y_t = \xi t + r_t + \varepsilon_t. \]  

(4.7.9)

The random walk component \( r_t \) is:

\[ r_t = r_{t-1} + u_t, \]  

(4.7.10)

where \( \varepsilon_t \) and \( u_t \) are i.i.d \( N(0, \sigma^2_{\varepsilon}) \) and i.i.d \( (0, \sigma^2_u) \) terms. The initial value \( r_0 \) is treated as a fixed intercept. Harvey (1989), in dealing with models of this form, notes that the random walk component will become deterministic as the term \( \sigma^2_u \) gets smaller. Thus, the KPSS test for stationarity is based on the null hypothesis that \( \sigma^2_u = 0 \) and, hence, \( \Delta r_t = 0 \), so that the process \( y_t \) will be trend stationary. Drawing on the model of Nabeya and Tanaka (1988), they derived an LM test statistic to test this null hypothesis.

To test the null hypothesis of trend stationarity using the method suggested by Nabeya and Tanaka (1988), the series, \( y_t \), is regressed on a constant and trend, and the residuals, \( e_t \), for this regression are retrieved. If \( \sigma^2_{\varepsilon} \) is the estimated error variance of the regression then the test statistic is given by:
\[ LM = \frac{\sum_{t=1}^{T} S_t^2}{\sigma^2}, \]

where \( S_t \) is defined as the partial sum process of residuals and is given by:

\[ S_t = \sum_{i=1}^{t} \hat{e}_i, \quad t = 1, 2, \ldots, T. \]

The assumption about the error term \( e_t \) can be relaxed to allow for serial correlation using the results of Phillips (1987), Phillips and Perron (1988), and Newey and West (1987). This method corrects the derived test statistic for autocorrelation, not by including extra regressors in the regression model, as in the ADF test, but rather by accounting for the autocorrelation, by correction to the test statistic after estimation.

Define the estimator, \( s^2(l) \) of the long-run variance \( \sigma^2 \) to be:

\[ s^2(l) = T^{-1} \sum_{i=1}^{T} \hat{e}_i^2 + 2T^{-1} \sum_{i=1}^{l} w(s,l) \sum_{i=s}^{T} \hat{e}_i \hat{e}_{i-s}, \]

where the Barlett window \( w(s,l) \) is a weighting function which guarantees the non-negativity of \( s^2(l) \) (see Newey and West (1987)), and is given by \( w(s,l) = 1 - s/(l+1) \). Using this estimate of the long-run variance in place of \( \sigma^2 \), Kwiatkowski, Phillips, Schmidt and Shin (1992) derived two test statistics, denoted \( \hat{\eta}_u \) and \( \hat{\eta}_t \). The first is based on the regression of \( y_t \) on a constant only, and the second is based on the regression of \( y_t \) on a constant and trend. Thus, the respective
null hypotheses for the two test statistics are level stationary and trend stationary and the tests are given by

\[ \hat{\eta}_u = \eta_u / s^2(l) = T^{-2} \sum S_t^2 / s^2(l), \]  \hspace{1cm} (4.7.13) 

and

\[ \hat{\eta}_r = \eta_r / s^2(l) = T^{-2} \sum S_t^2 / s^2(l). \]  \hspace{1cm} (4.7.14) 

Kwiatkowski, Phillips, Schmidt and Shin (1992) derived the asymptotic distributions and critical values for the test statistics (see Kwiatkowski, Phillips, Schmidt and Shin (1992), Table 1, p. 166) and carried out an extensive set of Monte Carlo simulations to test the size and power characteristics of the test statistic. The simulations showed a clear trade off between size and power. In the presence of autocorrelated errors, small sample size and low values of \( l \) lead to considerable size distortions in the test statistic. On the other hand, higher values of \( l \) lead to lower power.

To summarise, Section 4.7.1 discussed two of the most widely used single time series unit root and stationarity tests including the ADF unit root and the KPSS stationarity tests. As mentioned before, although panel unit root and stationarity tests are used in this thesis, they mainly developed from the ADF and KPSS tests. Since volatility modelling on the ESM will be done as panel estimates, the next section will discuss the panel unit root and stationarity tests that were used as preliminary tests for determining the stationarity properties of each of the data panels used for this analysis.
4.7.2 Panel Unit Root and Panel Stationarity Tests

Recalling from Section 4.6, the main reason for conducting panel unit root and stationarity tests is to establish the time series properties of the data panels of logarithmic prices. This is because the volatility analysis requires panel methods.

Several approaches have been developed to test for a unit root or stationarity in panel data including Quah (1992, 1994), Levin and Lin (1992, 1993), Hadri (2000) and Im, Pesaran and Shin (2003). However, only Quah (1992, 1994), Levin and Lin (1992, 1993), Hadri (2000) are of interest in this thesis because of the complete panel nature of the null and alternative hypotheses. Since volatility will be modelled in a panel context, the stationarity of each data panel needs to be determined as a whole. That is, an appropriate unit root (stationary) test is one that tests if all the series in a panel are unit root (stationary) as the null hypothesis versus the alternative hypothesis that all series in a panel are stationary (unit root). The Quah (1994) and Levin and Lin (1992) panel unit root tests and the Hadri (2000) stationarity test satisfy these conditions and, therefore, will be used in this thesis. The Im, Pesaran and Shin (2003) panel unit root tests, however, have the null hypothesis that all series in the panel contain a unit root versus the alternative hypothesis that at least one of the individual series in the panel is stationary, which is not useful in this thesis since the null of unit root could be rejected if only one series in the panel was found to be stationary.

Quah (1992, 1994) initiated research in this area and proposed asymptotically normal tests for unit roots. Quah (1992, 1994) utilised random field methods to derive the asymptotic standard normality of unit root t-statistics for a model with independent

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54 See also Im, Pesaran and Shin (1995) and Im, Pesaran and Shin (1997) for their early papers.
and identically distributed disturbances and no individual specific fixed effects. Using the Summers-Heston dataset on world income containing 25 annual observations for 100 different counties, Quah used Monte Carlo simulations to determine that the standard normal distribution is a good approximation for certain panel sizes. Although the null hypothesis that all series have a unit root versus the alternative that all series are stationary seems attractive for panel modelling, the random field methodology is difficult to apply to more general model specifications while allowing for individual specific fixed effects or serial correlation in disturbances.

Following Quah (1992) other panel unit root and stationarity tests emerged including the Levin and Lin (1992, 1993) and Hadri (2000) tests. The following two subsections are devoted to discussing these two tests in detail and their relevance to this thesis.

4.7.2.1 Levin Lin Panel Unit Root Test

Levin and Lin (1992)\textsuperscript{55}, denoted by LL (1992), developed a panel unit root test that has close correspondence to the existing literature on individual time series unit root tests, particularly the DF tests, and can be applied in a straightforward manner to a large variety of test specifications. LL (1992) assumed that the stochastic process \( y_{it} \) is generated according to the standard dynamic model for panel data:

\[
y'_{it} = \alpha_i y_{it-1} + z'_i \nu + \varepsilon_{it}, \quad i = 1, 2, \ldots, N \quad t = 1, 2, \ldots, T \tag{4.7.15}
\]

where \( \varepsilon_{it} \) is i.i.d \((0, \sigma^2)\) and, therefore, individual processes for each \( i \) are cross-sectionally independent and there is no serial correlation, \( \alpha_i = \alpha \) for all \( i \) and, therefore,

\textsuperscript{55} This article was ultimately published as Levin, Lin and Chu (2002).
homogeneity is imposed across all cross-sectional units in the panel, and $z_{i}^{'}$ is the deterministic component which can take many forms. Table 4-1 summarises all the possible forms that $z_{i}^{'}$ can take forming seven different tests. This taxonomy is similar to that of Harris and Sollis (2003, p.194). However, Table 4-1 has some variations on that taxonomy. The first and the simplest, LL_1, sets $z_{i} = 0$. Tests LL_2 and LL_3 are standard pooling of cross-sectional, time series data with a common intercept ($\mu$) or an intercept and time trend ($\mu, \beta t$). Tests LL_4 to LL6 take into account the panel aspect of the data by allowing for heterogeneity across units of the panel in terms of fixed effects ($\mu_{i}$), or shocks over time that have equal effect on all units in the panel ($\nu_{i}$), or finally both fixed effects and individual effects that may vary with time ($\mu_{i} + \beta_{i}t$). In all tests, the null hypothesis is $H_{0}: \alpha = 1$ against the alternative $H_{1}: \alpha < 1$. That is, under the null all $i$ series in the panel contain a unit root, while the alternative is that all individual series are stationary. Levin and Lin (1992) showed that, as $N \to \infty$ and $T \to \infty$, the limiting distributions of the corresponding t-statistic for testing the null hypothesis under each test is a standard normal distribution $N(0,1)$.

The Levin and Lin (1992) tests had problems with autocorrelation and heteroskedasticity resulting in the development of the Levin and Lin (1993), denoted LL (1993), extended tests. Their model comprised:

$$\Delta y_{it} = \rho y_{i,t-1} + \sum_{L=1}^{P_{i}} \theta_{L} \Delta y_{i,t-L} + z_{it}^{'} \nu_{i} + \varepsilon_{it},$$  \hspace{1cm} (4.7.16)
<table>
<thead>
<tr>
<th>Test</th>
<th>Assumptions</th>
<th>Model</th>
<th>Hypothesis</th>
</tr>
</thead>
<tbody>
<tr>
<td>LL_1</td>
<td>( z_a = 0 )</td>
<td>( y_a = \alpha y_{a,t-1} + \varepsilon_a )</td>
<td>( H_0: \alpha = 1; H_1: \alpha &lt; 1 )</td>
</tr>
<tr>
<td>LL_2</td>
<td>( z_a = \text{intercept} = \mu )</td>
<td>( y_a = \alpha y_{a,t-1} + \mu + \varepsilon_a )</td>
<td>( H_0: \alpha = 1; H_1: \alpha &lt; 1 )</td>
</tr>
<tr>
<td>LL_3</td>
<td>( z_a = \text{intercept and time trend} = (\mu, \beta t)' )</td>
<td>( y_a = \alpha y_{a,t-1} + \mu + \beta t + \varepsilon_a )</td>
<td>( H_0: \alpha = 1 ) and ( \mu = 0 ); ( H_1: \alpha &lt; 1; \mu \neq 0 )</td>
</tr>
<tr>
<td>LL_4</td>
<td>( z_a = \text{time-specific fixed effect} = v_i )</td>
<td>( y_a = \alpha y_{a,t-1} + v_i + \varepsilon_a )</td>
<td>( H_0: \alpha = 1; H_1: \alpha &lt; 1 )</td>
</tr>
<tr>
<td>LL_5</td>
<td>( z_a = \text{individual-specific fixed effects} = \mu_i )</td>
<td>( y_a = \alpha y_{a,t-1} + \mu_i + \varepsilon_a )</td>
<td>( H_0: \alpha = 1 ) and ( \mu_i = 0 ); ( H_1: \alpha &lt; 1; \mu_i \neq 0 ) for all ( i )</td>
</tr>
<tr>
<td>LL_6</td>
<td>( z_a = \text{individual-specific fixed effects with a trend} = (\mu_i, \beta_i t)' )</td>
<td>( y_a = \alpha y_{a,t-1} + \mu_i + \beta_i t + \varepsilon_a )</td>
<td>( H_0: \alpha = 1 ) and ( \beta_i = 0 ); ( H_1: \rho &lt; 0; \beta_i \neq 0 ) for all ( i )</td>
</tr>
<tr>
<td>LL_7</td>
<td>( z_a = 0 ) ( \text{but allowing for serial correlation in the disturbances} )</td>
<td>( y_a = \alpha y_{a,t-1} + \varepsilon_a ) with serial correlation</td>
<td>( H_0: \alpha = 1; H_1: \alpha &lt; 1 )</td>
</tr>
</tbody>
</table>
where:

i) equation (4.7.15) is now transformed, by subtracting $y_{t-1}$, into a first-difference equivalent version such that the null hypothesis becomes

$$H_0 = \rho = \alpha - 1 = 0 \{ \rho = 0 \Leftrightarrow \alpha = 1 \} ;$$

ii) different lags are allowed across the $i$ cross-sections; and

iii) the serial correlation and heterogeneity in the disturbances are allowed by specifying $\epsilon$ to follow the stationary invertible process for each individual expressed as:

$$\epsilon = e_{t} = \sum_{i=1}^{\infty} \phi_y e_{t-i} + e_{t},$$

where $e_{it}$ are white noise processes with heterogeneous variances $\sigma_i^2$ for $i = 1, 2, ..., N$.

LL (1993) considered three different tests where $z_\mu = 0$, $z_\mu = \mu$, and $z_\mu = (\mu + \beta_t)^\prime$.

Table 4-2 summarises the LL (1993) tests.

To implement these models, LL (1993) advanced a testing procedure that can be summarised in three steps:
First, a separation of ADF regressions for each individual $i$ in the panel is carried out to generate orthogonalised residuals. This is obtained by regressing $\Delta y_{it}$ and $y_{i,t-1}$ in (4.7.16) against $\Delta y_{i,t-L}$ ($L=1,...,p_i$) and the deterministic variables, $z_{it}'\nu$. The generated residuals are:

$$\hat{e}_{it} = \Delta y_{it} - \sum_{L=1}^{p_i} \hat{\theta}_{it,L} \Delta y_{i,t-L} - z_{it}'\nu,$$

and

$$\hat{v}_{it} = y_{i,t-1} - \sum_{L=1}^{p_i} \hat{\theta}_{it,L} \Delta y_{i,t-L} - z_{it}'\nu,$$

where $\hat{e}_{it}$ and $\hat{v}_{it}$ are then corrected for heterogeneity across individuals in the panel as follows:

$$\bar{e}_{it} = \frac{\hat{e}_{it}}{\hat{\sigma}_{\hat{e}_i}} \quad \text{and} \quad \bar{v}_{it} = \frac{\hat{v}_{i,t-1}}{\hat{\sigma}_{\hat{v}_i}},$$

$\hat{\sigma}_{\hat{e}_i}$ and $\hat{\sigma}_{\hat{v}_i}$ are estimated from the sample.
where $\hat{\sigma}_{\epsilon i}$ is the ADF regression standard error.

Secondly, LL (1993) calculated the average of the estimates ratio of long-run to short-run (innovation) standard deviation which is given as:

$$\hat{S}_N = (1/N) \sum_{i=1}^{N} \hat{\sigma}_{yi} / \hat{\sigma}_{\epsilon i},$$

where $\hat{\sigma}_{yi}$ is the estimator of the long-run standard deviation, obtained for LL_8 test as $^{56}$:

$$\hat{\sigma}_{yi} = \sqrt{\frac{1}{T-1} \sum_{t=2}^{T} \Delta y_{it}^2 + 2 \sum_{L=1}^{L} w_{KL} \left[ \frac{1}{T-1} \sum_{t=2+L}^{T} \Delta y_{it} \Delta y_{it-L} \right]}, \quad (4.7.17)$$

where $K$ is the lag truncation parameter which can be determined using an automatic truncation data dependent method and $w_{KL}$ is the sample covariance weight proposed by Newey and West (1987) and which is based on the lag windows such as the Bartlett Kernel window $^{57}$ under which:

$$w_{KL} = \frac{L}{K-1}.$$

$^{56}$ For LL_9 $\Delta y_{it}$ in (4.7.17) is replaced with $\Delta y_{it} - \overline{\Delta y_{it}}$, where $\overline{\Delta y_{it}} = \frac{1}{T} \sum_{t=1}^{T} \Delta y_{it}$. Also, if the data include a time trend, i.e. LL_10, then the trend should be removed before estimating the long-run variance.

$^{57}$ More details on the Bartlett weight or window can be found in Hamilton (1994).
The third and final step is to pool all cross-sectional and time series observations to estimate:

\[ \tilde{e}_t = \rho \tilde{v}_{i,t-1} + \tilde{e}_t, \]  

(4.7.18)

with \( N\tilde{T} \) the total number of observations, where \( \tilde{T} = T - \bar{p} - 1 \) is the average number of observations per units in the panel, and \( \bar{p} = \frac{1}{N} \sum_{i=1}^{N} p_i \) is the average lag order in the individual ADF regressions.

The t-statistic for testing \( \rho = 0 \) in (4.7.18) is obtained by:

\[ t_\rho = \frac{\hat{\rho}}{\text{STD}(\hat{\rho})}, \]

where \( \hat{\rho} \) is the OLS of \( \rho \) in (4.7.18) computed as:

\[ \hat{\rho} = \frac{\sum_{i=1}^{N} \sum_{t=2+\bar{p}_i}^{T} \tilde{v}_{i,t-1} \tilde{e}_t}{\sum_{i=1}^{N} \sum_{t=2+\bar{p}_i}^{T} \tilde{v}_{i,t-1}^2}, \]

\( \text{STD}(\hat{\rho}) \) is the standard error of \( \hat{\rho} \) given by:

\[ \text{STD}(\hat{\rho}) = \hat{\sigma}_\tilde{e} \left[ \sum_{i=1}^{N} \sum_{t=2+\bar{p}_i}^{T} \tilde{v}_{i,t-1}^2 \right]^{-1/2} \]
\( \hat{\sigma}_e \) is the standard error of the regression in (4.7.18) calculated as:

\[
\hat{\sigma}_e = \sqrt{\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=2}^{T} (\hat{\epsilon}_{it} - \hat{\rho} \hat{\nu}_{it-1})^2}.
\]

Under the null hypothesis \( (H_0: \rho = 0) \), LL (1993) found that, as \( N \to \infty \), the t-statistic \( (t_\rho) \) has a standard normal limiting distribution in the LL_8 test, but diverges to negative infinity for the LL_9 and LL_10 tests. Therefore, LL (1993) considered the following adjusted t-statistic:

\[
t^*_\rho = \frac{t_\rho - NT\bar{S}_N \hat{\sigma}_e^2 STD(\hat{\rho}) \bar{\lambda}_{z_t}^{*}}{\bar{\sigma}_{z_t}^{*}}, \tag{4.7.19}
\]

where \( \lambda_{z_t}^{*} \) and \( \sigma_{z_t}^{*} \) are adjustment factors used to adjust the mean and the standard deviation of the panel unit root test statistics given in equation (4.7.19) and which were estimated using Monte Carlo simulations for different \( N \) and \( T \) values and under different regression models, \( z'_{it} \) (see Levin and Lin (1993, Table 2, p.33)). LL (1993) proved that under the null hypothesis, the \( t^*_\rho \) statistic converges to a standard normal distribution (for all Models) as long as \( N / T \to 0 \) when \( N \to \infty \) and \( T \to \infty \).

In this thesis, the LL_9 and LL_10 panel unit root tests were applied\(^58\) using EViews 5.0 (Quantitative Micro Software (2004)) to test the null hypothesis that all units in the panel are unit root against the alternative hypothesis that all units in the panel are unit root.

\(^58\) Since it is unlikely that financial data do not have an individual specific mean or an individual specific mean and time trend, LL_8 test was not considered.
stationary. The optimal number of lags used in each cross-sectional unit’s ADF regression, \( p_i \), was based on the lag number that minimises the SIC. In order to ensure the consistency of estimating the long-run variance, \( \hat{\sigma}^2_{yi} \), Andrews (1991) lag selection procedure was applied to determine the maximum lag truncation order (bandwidth), \( \bar{K} \).

One problem with the LL (1993) tests was reported by Karlsson and Lothgren (2000) where they warn that, for large \( T \), panel unit root tests have high power and there is the potential risk of concluding that the whole panel is stationary even when there are only a small number of stationary series in the panel.

In single time series an alternative to unit root tests is to reverse the hypotheses and test for the null of stationarity. This alternative also exists in panel tests on time series properties. As a result of the potential power problems indicated by Karlsson and Lothgren (2000), it was decided to use this alternative test in conjunction with the LL (1993) tests.

### 4.7.2.2 Hadri Panel Stationarity Test

Hadri (2000) proposes a test of the null that the time series for each \( i \) are stationary around a level or a deterministic trend, against the alternative hypothesis of a unit root in the panel data. The framework is the one dealt with in KPSS (1992), but now for a multiple series rather than for a single series. The following two processes are considered:

\[
y_{it} = r_i + \varepsilon_{it}, \tag{4.7.20}
\]
and

\[ y_{it} = r_{it} + \xi_t + \epsilon_{it}, \quad (4.7.21) \]

where \( y_{it} \) for \( t = 1, 2, ..., T \) and \( i = 1, 2, ..., N \) are the observed series for which stationarity is tested for all \( i \), \( r_{it} = r_{i,t-1} + u_{it} \), and \( \epsilon_{it} \) and \( u_{it} \) are mutually independent normal variates which are \( i.i.d \) across \( i \) and over \( t \). Thus \( r_{it} \) is a simple random walk and \( \epsilon_{it} \) is a stationary process. Equation (4.7.21) is equivalent to equation (4.7.9) of KPSS, but now with augmentation for panel. The stationarity hypothesis is simply \( \sigma_{\epsilon}^2 = 0 \). The initial values \( r_{i0} \) are treated as fixed unknowns and play the role of heterogeneous intercepts.

Using back substitution, equation (4.7.21) can be written as:

\[ y_{it} = r_{i0} + \xi_t + \sum_{t=1}^{i} u_{it} + \epsilon_{it}, \quad (4.7.22) \]

\[ = r_{i0} + \xi_t + \epsilon_{it}, \quad (4.7.23) \]

where \( \epsilon_{it} = \sum_{t=1}^{i} u_{it} + \epsilon_{it} \). The same procedure can be applied to (4.7.20) and it can be written as:

\[ y_{it} = r_{i0} + \sum_{t=1}^{i} u_{it} + \epsilon_{it}, \quad (4.7.24) \]

\[ = r_{i0} + \epsilon_{it}. \quad (4.7.25) \]
If $\sigma_u^2 = 0$, then $e_t$ is reduced to be identical to $\epsilon_t$ and is stationary ($r_t$ reduces to a constant), whereas if $\sigma_u^2 \neq 0$, then $e_t$ is stationary ($r_t$ is a random walk). More specifically, the null and alternative hypotheses to be tested are:

$$H_0 : \lambda = 0,$$
$$H_1 : \lambda > 0,$$

where $\lambda = \frac{\sigma_u^2}{\sigma_\epsilon^2}$. The one-sided LM test statistic is used to test the null hypothesis. The computation of the LM statistic is straightforward. Let $\hat{\epsilon}_t$ be the residuals from the regression $y$ on an intercept in (4.7.20), and an intercept plus a time trend in (4.7.21), then the LM statistic is:

$$LM = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{T^2} \sum_{t=1}^{T} S_t^2 \hat{\epsilon}_t^2,$$  

(4.7.26)

where $S_t$ is defined as the partial sum of the residuals,

$$S_t = \sum_{j=1}^{t} \hat{\epsilon}_j,$$

and $\hat{\sigma}_\epsilon^2$ is a consistent estimator of $\sigma_\epsilon^2$ under the null hypothesis where\(^59\):

\(^59\) The simulation conducted by Hadri (2000) showed that as $T$ and $N$ get larger, the test becomes more accurate but not in a monotonic fashion. To correct for the degrees of freedom in finite samples, equation (4.7.27) should be $\hat{\sigma}_\epsilon^2 = \frac{1}{N(T-1)} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{\epsilon}_t^2$, as an estimator of $\sigma_\epsilon^2$ with an intercept and $\hat{\sigma}_\epsilon^2 = \frac{1}{N(T-2)} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{\epsilon}_t^2$ with a trend.
\[ \hat{\epsilon}^2 = \frac{1}{NT} \sum_{t=1}^{N} \sum_{i=1}^{T} \hat{\epsilon}_i^2. \] (4.7.27)

The LM statistic for testing the null hypothesis can be written as

\[ \overline{LM} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{1}{T^2} \sum_{t=1}^{T} S_{\mu}^2 \right). \] (4.7.28)

Then it can be shown that for testing the null of level stationary:

\[ \overline{LM}_{\mu} \overset{p}{\rightarrow} E \int_0^1 V(r)^2 \, dr = \eta_{\mu}, \]

and that for testing the null of trend stationary:

\[ \overline{LM}_{\tau} \overset{p}{\rightarrow} E \int_0^1 V_{2}(r)^2 \, dr = \eta_{\tau}, \]

where \( V(r) \) is a standard Brownian bridge \( V(r) = W(r) - rW(1) \), where \( W(r) \) is a standard Wiener process and \( \overset{p}{\rightarrow} \) denotes the weak convergence in probability.

As \( T \to \infty \) followed by \( N \to \infty \), the test statistic for the null of level stationary has the following limiting distribution:

\[ Z_{\mu} = \frac{\sqrt{N} (\overline{LM}_{\mu} - \eta_{\mu})}{\bar{\xi}_\mu} \Rightarrow \text{N}(0,1), \] (4.7.29)
where $\zeta_\tau^2 = \text{var}(\int V^2) = 1/45$, $\eta_\mu = 1/6$ and $\Rightarrow$ indicates the weak convergence in distribution.

Also, as $T \to \infty$ followed by $N \to \infty$, the test statistic for the null of trend stationary has the following limiting distribution:

$$ Z_\tau = \frac{\sqrt{N}(LM - \eta_\tau)}{\zeta_\tau} \Rightarrow \text{N}(0,1), \quad (4.7.30) $$

where $\zeta_\tau^2 = \text{var}(\int V^2) = 11/6300$, $\eta_\tau = 1/15$ and $\Rightarrow$ indicates the weak convergence in distribution.

Further, Hadri (2000) allowed the disturbance term to be heteroskedastic across $i$.\(^{60}\)

By doing so, $\sigma_i^2$ for each individual time series $i$, say $\sigma_{\varepsilon,j}^2$, will be computed and the LM statistic will be:

$$ \hat{LM} = 1 \sum_{i=1}^{N} \left( \frac{1}{T^2} \sum_{i=1}^{T} \sigma_{\varepsilon,j}^2 \right). \quad (4.7.31) $$

Hadri (2000) also relaxed the assumption on the errors $\varepsilon_\mu$ being i.i.d $\text{N}(0,\sigma_\varepsilon^2)$ over $t$ to accommodate serial dependence cases. Under these conditions, $\sigma_\varepsilon^2$ will be replaced with the long-run variance $\sigma^2$, which is defined as:

\(^{60}\)Relaxing the homoskedasticity and the serial dependence of the error term was conducted earlier in a previous working paper (see Hadri (1999)).
\[
\sigma^2 = \frac{1}{N} \lim_{T \to \infty} T^{-1} \left( S^2_{TT} \right).
\]

A consistent estimator of the long-run variance, \( \sigma^2 \), can be obtained using an automatic truncation data dependent method.

In this thesis, the Hadri (2000) panel stationary tests were applied using EViews 5.0 (Quantitative Micro Software (2004)) with the pre-condition that the series in the panel may be stationary around a deterministic level specific to each series or around a unit-specific deterministic trend. These results were then validated using STATA 8.0 StataCorp (2003). The Hadri (2000) LM test statistics and their related \( Z \) distribution were obtained under each of the following assumptions:

- The error process may be assumed homoskedastic across \( i \) and serially uncorrelated over \( t \),
- The error process may be assumed homoskedastic across \( i \) and serially correlated over \( t \), and
- The error process may be assumed heteroskedastic across \( i \) and serially correlated over \( t \).

In determining the maximum lag truncation order (bandwidth), the Newey and West (1987) automatic lag selection method was applied.
4.8 Summary

In conclusion, this chapter has provided a discussion of the methods and procedures which will be employed. The chapter started with a very general panel model nesting different pooled-panel volatility structures. A testing process was then outlined following the general to specific approach pioneered by Hendry (1995) to choose between competing pooled-panel volatility models with a GARCH (1,1) structure. Specifically, five nested models, including the general model, were proposed for modelling the volatility structure of the ESM based on five different hypotheses. The procedure for estimating the proposed five models is the principle of ML. In practice, this requires the use of a numerical optimisation method. One frequently used in volatility modelling, and the one applied in this thesis, is that of BHHH (1974). Lastly, testing down the five proposed models to determine which model best describes the DGP for each data panel, the LRT proposed by Neyman and Scott (1948) was used.

Since modelling in levels or differences may lead to very different predictions, a preliminary step that should be conducted before estimating the proposed volatility models in a panel data context is to ensure the stationarity of each panel and in particular, to test if logarithmic prices are stationary in levels or first differences. In doing so, panel unit root tests and panel stationarity tests that examine if all the series in a panel are unit root or stationary as the null hypothesis versus the alternative hypothesis that all series in a panel are stationary or unit root were identified as preliminary tests to the analysis in this thesis. This includes the Levin and Lin (1993) panel unit root tests and Hadri (2000) stationarity tests. However, these two tests are based on the ADF and KPSS single time series unit root or stationarity tests.
Therefore, it was necessary to first discuss these single time series unit root and stationarity tests.

Prior to giving the results of the pre-analysis tests and the general to specific specification tests, it is important to describe the data used and their sources. This is the subject of the next chapter.
CHAPTER FIVE

5. CHAPTER 5: DATA DESCRIPTION AND SAMPLE SELECTION

5.1 Introduction

The previous four chapters have provided the foundations for the analysis of this thesis. To recapitulate briefly, Chapter 1 established the objective and the significance of this research and the intention to examine the nature of volatility in the ESM, by using novel GARCH structures.

Chapter 2 described the theoretical and practical research on stock market volatility, establishing the significance of this body of research to the recent experience of stock market performance around the world. The existing empirical research on developed and emerging markets has shown that there is evidence of volatility clustering, and such clustering means that the EMH is not valid in financial markets (especially in emerging markets). Hence, it may be possible to predict some aspects of stock price movements. The evidence of stock market volatility in emerging markets such as Egypt has been relatively scant, when compared to the evidence on developed markets.

Chapter 3 described the key characteristics of the ESM, in particular, the factors that have important implications for stock market volatility. The chapter provided evidence of the increasing significance of the ESM, being one of the major markets in the MENA region and its rapid development since the introduction of economic reforms in the early 1990s (Abdel (2002)). In fact, it has been shown that the Egyptian Stock Exchange is one of the biggest and most active markets in the MENA region,
making it a dominant Arab stock market and, therefore, an important market to study (Bolbol and Omran (2004)).

Moreover, it has been widely recognised and demonstrated in the literature that equities from emerging capital markets have different characteristics to the equities of developed capital markets. One of the key differences is that equities from emerging markets exhibit higher levels of volatility than equities from developed markets (Bekaert and Harvey (1997)). As stated in Chapter 2, in recent years emerging markets have been receiving more attention as their importance in world financial markets has increased\(^6\). Therefore, studying an emerging market such as Egypt is important.

Chapter 4 developed the research models explaining the hypothesis testing procedure and model development using the general to specific methodology. Prior to reporting the results of the analytical methods described in Chapter 4, it is important to clarify the nature of the data used and their sources. This is the purpose of this chapter. Section 5.2 deals with the sample period selection and, particularly, the issue of temporal data crossing different policy regimes is addressed. This is followed by Section 5.3 which deals with the nature of the dependent variable and how it is estimated. Sections 5.4 and 5.5 give an indication of the data used and their sources. The former deals with the stock market sector index data and the latter deals with the individual stock data. This is followed by Section 5.6 which gives the descriptive statistics for the data used in analysis. Finally, Section 5.7 gives a summary of the chapter.

5.2 Sample Period Selection

One of the first considerations in the data selection process is to determine the period of time in which to model the ESM volatility. Since this thesis aims to model the volatility of the ESM, this analysis should cover a period where high volatility is clearly evident. High periods of volatility on the ESM are identified by graphically depicting the behaviour of the key ESM indices over time.

Recalling from Chapter 3, Figure 3-3 (Panel A) displayed the daily closing values for three major ESM indices: CMAI, HFI, and PIPO from 1\textsuperscript{st} of January, 1995 to December, 2004\textsuperscript{62}. It was clear that the market was generally performing well in 1997 and from 2000 to 2004. Moreover, Figure 3-3 (Panels B, C, and D) showed the returns of the three indices where it appeared that the volatility of returns on the ESM changed substantially around 1997 and again from 2000 till mid 2002. The graph indicates that the volatility of the ESM has increased significantly over the period 1997 to 2002.

As discussed in Chapter 3, there are three main factors which have contributed to the increasing volatility on the ESM in this period. The first was the market liberalisation program which began in the early 1990s and consisted largely of privatisation. The second was the fact that Egyptian firms began to issue GDRs on foreign stock exchanges such as the London Stock Exchange. This issuance of GDRs was one of the important factors that brought about the increasing attention of international investors to the ECM (see Karolyi (1999)). Thirdly, there was an accelerating demand for mutual funds in the ECM in this same period (Central Bank of Egypt (2003, 1\textsuperscript{st} of January, 1995 is taken as the base year.

\textsuperscript{62}
Each of these factors resulted in improved activity on the ESM and saw the rise in its prominence. It is for these reasons that the period 1997 to 2002 is an interesting period to study and, as such, this thesis attempts to model volatility within the period from 1997 to 2002.

In addition, a further consideration in the sample period selection is to ensure that the data is free from any external non-market related changes which may affect the stock market volatility. For example, in the case of the ESM, changes were made to the market regulations, one of which was to restrict the degree of price change. This important change in regulation may have implications for the volatility on the ESM and must be considered when choosing the sample for this analysis. It could be argued that the issue of policy switching could be accommodated by the use of suitable binary variables indicating the switches. However, this would increase the number of parameters to be estimated in what is already a model with a significant number of parameters. Further, it could detract from the focus of the thesis which is to identify the similarities and differences in volatility structures between units in the same panel.

Chapter 2 examined the debate in the literature regarding the effect of price limits on stock market volatility, and Chapter 3 detailed the changes in price limits which were implemented on the ESM. To recapitulate, one of the most significant changes affecting ESM activity and its associated volatility in recent years was the imposition and removal of price limits. The CMA introduced a trading price limit (+/-5% daily and +/-20% weekly) on all stocks listed and traded on the stock exchange from the 2nd of February, 1997. On the 21st of July, 2002 the CMA partially removed the price limit for the most active stocks on the stock exchange, which initially consisted of
twelve stocks. The effect of these price limits on stock markets is debateable (see Brennan (1986), and Phylaktis, Kavussanos and Manalis (1999)).

It must be made clear here that using data which spans the regulation changes may produce artificial (non-market) changes in the data, which may affect the analysis. The important issue here is not only whether regulations increase or decrease volatility, but also the study of volatility must be conducted under constant regulatory conditions. For this reason, the study period was limited to the period where the price limit mechanism was imposed, that is, from the 2\textsuperscript{nd} of February, 1997 until the 18\textsuperscript{th} of July, 2002.

### 5.3 Return Calculation

Financial data, in general, are not stationary in levels and as a common practice returns are calculated since they are usually stationary. As mentioned in Chapter 4, unit root tests will be used to determine if stocks and indices returns are stationary, that is integrated order zero, I(0) or, in other words, that stock and index prices are integrated order one, I(1).

Following Fama (1965), and other subsequent studies, the continuously compounded rate of return on a stock at time $t$ is defined as the first difference of the natural logarithm of the stock prices, this is calculated as:

$$ R_t = \ln \left( \frac{P^*_t}{P^*_{t-1}} \right) = \ln(P^*_t) - \ln(P^*_{t-1}), \quad (5.3.1) $$
where $P$ is the actual closing price and $P^*$ is the price of a stock adjusted for capital changes in the following way:

\[
P_t^* = \frac{S_t}{S_{t-1}} \left[ P_t \left( 1 - \frac{RI_t SP_t}{S_{t-1} PR_t + RI_t SP_t} \right) + D_t \right], \tag{5.3.2}
\]

where:

\begin{align*}
S_t &= S_{t-1} + RI_t + SS_t + SD_t; \\
S &= \text{shares outstanding;} \\
RI &= \text{shares issued through rights;} \\
SS &= \text{shares issued through stock splits;} \\
SD &= \text{shares issued through stock dividends;} \\
SP &= \text{subscription price for rights;} \\
PR &= \text{stock price at the time of rights (ex-date);} \\
D &= \text{cash dividends;} \text{ and} \\
t &= \text{time period.}
\end{align*}

In the absence of rights issues, cash dividends, stock dividends and stock splits, the adjusted price equals the actual closing price; that is, $P_t^* = P_t$. As for the sector indices, the return of an index is calculated in the same manner as in (5.3.1); that is, as the differences in log index prices. However, no adjustment for capital changes is performed since the indices obtained were already adjusted for dividends, where dividends were reinvested in the index on the day the security was quoted ex-dividend.
5.4 Data Description: Market Indices

5.4.1 Morgan Stanley Capital International Inc. (MSCI)

There are numerous organisations which produce global equity indices that track the performance of global equity markets. Morgan Stanley Capital International Inc. (MSCI) is perhaps the single most important provider of international equity indices. MSCI develops and maintains equity, fixed income, multi-asset class, and hedge fund indices that serve as a benchmark for an estimated USD 3 trillion on a worldwide basis (Morgan Stanley Capital International (2006)).

MSCI provides global equity indices which, over the last 30 years, have become the most widely used equity benchmarks by international investors. Almost 2,000 organisations worldwide currently use MSCI global equity benchmarks. Sector, industry groups and industry indices are calculated based on the Global Industry Classification Standard (GICS) developed by MSCI and S&P. MSCI consistently applies its equity index construction and maintenance methodology across regions, developed and emerging markets and, therefore, their indices are a reliable source of data on which to base this analysis.

As equity markets have evolved, MSCI’s methodology has also evolved to ensure that its equity indices accurately represent the investment opportunities of global investors (Morgan Stanley Capital International (2006)). Thus, MSCI global equity indices have become an important equity benchmark for international investors in recent years and, for this reason, the MSCI global equity indices are employed in this study.
The purpose of the MSCI standard index series is to serve as a gauge for measuring the performance of an equity market. The aim is to provide “benchmark indices” of equity performance, where it is possible, for example, to get an historical perspective on the volatility of returns. Therefore, MSCI base their construction methodology on seven guiding principles. These include: broad and fair market representation; investability and replicability; consistency; index turnover; disciplined approach; transparency; and objectivity (Morgan Stanley Capital International (2006)).

In addition, the MSCI standard index series adjusts the market capitalisation of index constituents for free float and aims for an index inclusion of 85 percent of the free float-adjusted market capitalisation in each industry group, for each country. There is no target regarding the specific number of stocks that should be included in its indices. All securities in a market are then classified into industries following GICS based on their principal business activity. As of January 2006, GICS classified stocks into 10 different economic sectors, 24 Industry groups, 64 Industries and 139 sub-Industries and this is revised on an annual basis (Morgan Stanley Capital International (2006)).

The MSCI sector indices for Egypt were obtained and six different sector indices were identified covering the period from February 2\textsuperscript{nd}, 1997 to July 18\textsuperscript{th}, 2002 (with February 2\textsuperscript{nd}, 1997 as the base year). These six sectors are: (1) Construction Materials; (2) Chemicals; (3) Commercial Banks; (4) Food, Beverage & Tobacco; (5) Pharmaceuticals; and (6) Real Estate. Each sector comprises a panel of stocks, each of

\footnote{For more information about the GICS sector definitions, and index calculations, coverage and products visit http://www.msci.com/equity/index2.htm/.

\footnote{The MSCI sector indices for Egypt were obtained from the Perfect Analysis database (Perfect Information (2005)).}
which can be analysed using the general to specific methodology outlined in Chapter 4. Further, the six indices themselves then form a panel of aggregate data which can also be analysed using the same methodology to test whether temporal volatility structures are common or different within and between different sectors or industries. The next section will provide some preliminary statistics for these six panel indices.

5.4.2 Summary Statistics

The return of each of the MSCI sector indices was calculated as the differences in log prices and they are presented in Figure 5-1. The returns for all indices appear to support the volatility clustering hypothesis where a large increase in price is followed by another large increase in price and vice versa.

Whilst these graphs give a visual indication of volatility clustering, it is important to note that definitive conclusions can only be drawn from a deeper statistical analysis. Further, the objective of the thesis is to test for similarities and differences in volatility patterns for different stocks. This is not possible using a simple graphical analysis. However, as discussed in Chapter 2, these initial graphical findings are consistent with the evidence in existing studies in both developed and emerging markets.

Table 5-1 provides some insights into the size of each sector in the study. Size is measured using market capitalisation, that is, market price times the number of shares.

---


66 The monthly bulletins for 1997 did not include detailed information about all companies listed on CASE (only the most active 100 stocks) and there was no published fact book for that year either. However, it is believed that it has minimum effect on the analysis since the average market capitalisation will be used as a proxy of the size for each sector.
Figure 5.1 MSCI Sector/Industry Indices Returns (January 1997-December 2002)

Source: Perfect Information (2005)
### Table 5-1 Total Market Capitalisation for each Sector and for the ESM

<table>
<thead>
<tr>
<th>Sector</th>
<th>Market Capitalisation per Sector (L.E.)</th>
<th>Average Market Capitalisation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1998</td>
<td>1999</td>
</tr>
<tr>
<td>Chemicals</td>
<td>4,548,736,923</td>
<td>2,674,777,750</td>
</tr>
<tr>
<td>Commercial Banks</td>
<td>13,890,880,151</td>
<td>13,970,166,558</td>
</tr>
<tr>
<td>Food, Beverage and Tobacco</td>
<td>9,008,219,307</td>
<td>10,033,519,107</td>
</tr>
<tr>
<td>Real Estate</td>
<td>5,772,299,110</td>
<td>5,243,725,041</td>
</tr>
<tr>
<td>Total Market Capitalisation for all Sectors</td>
<td>44,818,974,220</td>
<td>45,828,120,882</td>
</tr>
<tr>
<td>Total ESM Market Capitalisation (Common stocks)</td>
<td>82,232,363,196</td>
<td>111,913,335,894</td>
</tr>
<tr>
<td>Percentage of total ESM Market Capitalisation</td>
<td>54,502,841,070</td>
<td>40,949,651,347</td>
</tr>
</tbody>
</table>

Note: The sector classification used by CASE is slightly different for the sector classification used by MSCI. Therefore, companies were reclassified according to the current sector classification used by MSCI Inc.

outstanding. The size of a sector is the summation of the market capitalisation of all the stocks included in that sector.

The average sector size is calculated for the period under investigation and will be used as a proxy for the sector’s size. It can be noticed that the Banking sector is the largest sector followed by Food, Beverage and Tobacco, and Construction Materials sectors. Also, there was a big increase in the total ESM market capitalisation from 1998 to 1999. This was mainly due to the increase in the number of listed companies during 1999, increasing from 870 listed companies in 1998 to 1,033 listed companies in 1999. All six sectors under study represent at least 30 percent or more of the total ESM market capitalisation for each year. Moreover, the average market capitalisation for all sectors over the entire period of study represents 40 percent of the total ESM market capitalisation over the same period, which can be considered a fair representation of the ESM.

5.5 Data Description: Individual Stocks

5.5.1 ESM Individual Stocks

All firms listed on the CASE over the period of February 2\textsuperscript{nd}, 1997 to July 18\textsuperscript{th}, 2002 were identified from various issues of the CASE Fact books. The average number of firms listed on the stock exchange for this period was 979. However, after an examination of the CASE statistics, it is clear that the ESM still lacks depth as the majority of the listed firms on CASE were inactive (see Azab (2002)).

As of December, 2002, 1,151 firms were listed on the CASE of which 671 companies were traded. The total market capitalisation was L.E. 122.04 billion (approximately
USD 20 billion) and an annual turnover of 21.1 percent. Of the 671 securities traded
(with a total of 833,704 trading operations and a total trade average value of L.E.
34.176 billion), the 100 most heavily traded securities accounted for 96 percent of
trading by value, 85 percent of trading by volume, and 34 percent of total market
capitalisation (Cairo and Alexandria Stock Exchanges (2002)).

Since the major concern is modelling volatility, it is necessary to exclude inactive
stocks. As a result, a number of criteria were imposed to limit the sample of firms to
those firms that were the most active in the period from February 2\textsuperscript{nd}, 1997 to July
18\textsuperscript{th}, 2002 and to ensure that these stocks are a representative sample of the ESM.
These criteria are:

1. The stocks that did not have available data from the period of February 2\textsuperscript{nd},
   1997 to July 18\textsuperscript{th}, 2002 were removed.
2. Stocks that did not trade at least 70 percent or more of the total available
   number of trading days were also removed.
3. The remaining stocks should have at least an average of six trades per year.
4. If firms were subject to any delisting, mergers or acquisitions in the period of
   February 2\textsuperscript{nd}, 1997 to July 18\textsuperscript{th}, 2002, they were removed.
5. Finally, stocks that could not be classified under any of the available MSCI
   sector indices were excluded.
The final sample comprises the daily closing prices of the 42 most active stocks listed on CASE covering the period from February 2nd, 1997 to July 18th, 2002. The temporal sample is 1,425 observations for each of the included 42 stocks.67

To analyse the similarities and differences in the volatility patterns of the selected sample of stocks, the sample of 42 stocks will be classified into sectors, each of which will represent a certain industry or submarket in Egypt. Following from Section 5.4.1, the GICS sector classification used by MSCI will be used in classifying the sample of stocks. Following the GICS sector classification, the sample of 42 stocks was classified into sectors, resulting in a total of six sectors. A balanced panel data structure for each sector (for simplicity it will be referred to in this thesis as “Panel Sector”) was created.

Table 5-2 summarises the details of the stocks included in each panel sector including the day the stock was listed in the ESM and the Reuters code of each of the listed stocks on CASE. It can be seen from Table 5-2 that most of the stocks were listed on CASE in the mid 1990s, with the exception of Suez Canal Bank, which was first listed in 1982. Also, from the six sectors created, the Food, Beverage and Tobacco sector has the highest number of stocks with ten stocks included. The remaining sectors, in general, have six stocks included in them. Fortunately, this current sample of stocks classification satisfies the restriction imposed on the maximum number of stocks to be included in each panel or sector which was stated in Chapter 4 Section 4.1.

67 The data source is the CD-ROM issued by CASE for the 100 most heavily traded stocks, December 2002.
<table>
<thead>
<tr>
<th>Company Name</th>
<th>Reuters Code</th>
<th>Listing Date</th>
<th>Company Name</th>
<th>Reuters Code</th>
<th>Listing Date</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Construction Material:</strong></td>
<td></td>
<td></td>
<td><strong>Food, Beverage and Tobacco:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alexandria Cement</td>
<td>ALEX.CA</td>
<td>27/09/1995</td>
<td>Al Ahram Beverages (ABC)</td>
<td>PYBR.CA</td>
<td>16/08/1995</td>
</tr>
<tr>
<td>Ameriyah Cement</td>
<td>AMRI.CA</td>
<td>2/02/1995</td>
<td>East Delta Flour Mills</td>
<td>EDFM.CA</td>
<td>19/06/1996</td>
</tr>
<tr>
<td>National Cement</td>
<td>NCEM.CA</td>
<td>30/11/1995</td>
<td>Egyptian Starch &amp; Glucose</td>
<td>ESGL.CA</td>
<td>29/05/1996</td>
</tr>
<tr>
<td>Suez Cement</td>
<td>SUCE.CA</td>
<td>8/02/1995</td>
<td>Extracted Oils</td>
<td>ZEOT.CA</td>
<td>17/09/1995</td>
</tr>
<tr>
<td>Torah Cement</td>
<td>TORA.CA</td>
<td>30/03/1995</td>
<td>Middle &amp; West Delta Flour Mills</td>
<td>WCDF.CA</td>
<td>11/05/1996</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Middle Egypt Flour Mills</td>
<td>CEFM.CA</td>
<td>27/03/1996</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>North Cairo Mills</td>
<td>MILS.CA</td>
<td>17/09/1995</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>South Cairo &amp; Giza Mills &amp; Bakeries</td>
<td>SCFM.CA</td>
<td>11/05/1996</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Upper Egypt Flour Mills</td>
<td>UEFM.CA</td>
<td>1/08/1996</td>
</tr>
<tr>
<td><strong>Chemicals:</strong></td>
<td></td>
<td></td>
<td><strong>Pharmaceuticals:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Abou Kir Fertilizers</td>
<td>ABUK.CA</td>
<td>12/09/1994</td>
<td>Alexandria Pharmaceuticals</td>
<td>AXPH.CA</td>
<td>27/02/1995</td>
</tr>
<tr>
<td>Egyptian Financial &amp; Industrial</td>
<td>EFIC.CA</td>
<td>10/03/1996</td>
<td>Cairo Pharmaceuticals</td>
<td>CPCI.CA</td>
<td>9/04/1996</td>
</tr>
<tr>
<td>Misr Chemical Industries</td>
<td>MICH.CA</td>
<td>3/08/1994</td>
<td>Medical Union Pharmaceuticals</td>
<td>MEDU.CA</td>
<td>18/04/1995</td>
</tr>
<tr>
<td>Paint &amp; Chemicals Industries (PACHIN)</td>
<td>PACH.CA</td>
<td>3/08/1994</td>
<td>Pfizer</td>
<td>PFIZ.CA</td>
<td>16/08/1995</td>
</tr>
<tr>
<td><strong>Commercial Banks:</strong></td>
<td></td>
<td></td>
<td><strong>Real Estate:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commercial International Bank (Egypt)</td>
<td>COMI.CA</td>
<td>2/02/1995</td>
<td>El Kahera Housing</td>
<td>ELKA.CA</td>
<td>30/03/1995</td>
</tr>
<tr>
<td>Egyptian American Bank (EAB)</td>
<td>EABK.CA</td>
<td>26/12/1996</td>
<td>El Shams Housing &amp; Urbanization</td>
<td>ELSH.CA</td>
<td>12/09/1995</td>
</tr>
<tr>
<td>El Watany Bank of Egypt</td>
<td>WATA.CA</td>
<td>12/09/1994</td>
<td>Heliopolis Housing</td>
<td>HELI.CA</td>
<td>7/05/1995</td>
</tr>
<tr>
<td>Export Development Bank of Egypt (EDBE)</td>
<td>EXPA.CA</td>
<td>14/12/1995</td>
<td>Medinet Nasr Housing</td>
<td>MNHD.CA</td>
<td>7/05/1995</td>
</tr>
<tr>
<td>Misr International Bank (MiBank)</td>
<td>MIBA.CA</td>
<td>3/07/1996</td>
<td>United Housing &amp; Development</td>
<td>UNIT.CA</td>
<td>14/12/1994</td>
</tr>
<tr>
<td>National Development Bank</td>
<td>DEVE.CA</td>
<td>19/06/1996</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Suez Canal Bank</td>
<td>CANA.CA</td>
<td>15/09/1982</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.6 Descriptive Statistics

This section deals with the descriptive statistics of the data used for the analysis. These statistics are important in that they orientate the reader in terms of relative magnitudes with respect to the data set. At the outset, it must be made clear that these descriptive statistics are devoid of any analysis of the stationary versus non-stationary characteristics of the time series included. In modern applied time series econometrics, it has become standard to include descriptive statistics outlining the order of integration of time series. However, in this thesis, the reporting of unit root test statistics will be discussed in the results chapter. This is because of the sheer number of statistics to report and the close relationship between panel unit root tests and panel stationary tests on the one hand, and the general to specific tests surrounding the GARCH models in the pool/panel context on the other hand.

Table 5-3 reports the sample descriptive statistics for the return of the six panel sectors as well as the panel indices. The latter is given in the first row of statistics. The final row gives the sample statistics for the entire 42 stocks. The intermediate rows give the descriptive statistics calculated for each panel sector. That is, the sample for each panel is \( N \times T \), where the \( N \) is the number of stocks and \( T \) is the length of the time series. The third column of the table reports the mean of returns for each of the six panel sectors, the panel indices, as well as, for the entire sample of stocks. It is clear from these values that the mean returns are not substantially different across the six panel sectors and the panel indices. Moreover, it should be mentioned that during the period of study the panel indices exhibit a negative mean return. Similarly all sectors, with the exception of the Health and Pharmaceutical sector, exhibited
Table 5-3 Descriptive Statistics for Panel Indices, Panel Sectors and the Complete Stocks Sample

<table>
<thead>
<tr>
<th>Sector</th>
<th>No. of Indices or Stocks</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel Indices</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>-0.00085</td>
<td>0.0194713</td>
<td>-0.0251100</td>
<td>8.689787</td>
<td>8,544</td>
<td></td>
</tr>
<tr>
<td><strong>Panel Sectors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construction Materials</td>
<td>6</td>
<td>-0.00049</td>
<td>0.0214680</td>
<td>0.0718714</td>
<td>3.611761</td>
<td>8,544</td>
</tr>
<tr>
<td>Chemicals</td>
<td>6</td>
<td>-0.00064</td>
<td>0.0227265</td>
<td>0.0713581</td>
<td>3.288057</td>
<td>8,544</td>
</tr>
<tr>
<td>Commercial Banks</td>
<td>8</td>
<td>-0.00031</td>
<td>0.0212229</td>
<td>0.0053991</td>
<td>3.624378</td>
<td>11,392</td>
</tr>
<tr>
<td>Food, Beverage and Tobacco</td>
<td>10</td>
<td>-0.00058</td>
<td>0.0207179</td>
<td>0.0656157</td>
<td>3.791638</td>
<td>14,240</td>
</tr>
<tr>
<td>Pharmaceuticals</td>
<td>6</td>
<td>0.00031</td>
<td>0.0194925</td>
<td>0.0537510</td>
<td>5.452290</td>
<td>8,544</td>
</tr>
<tr>
<td>Real Estate</td>
<td>6</td>
<td>-0.00078</td>
<td>0.0256161</td>
<td>0.0720782</td>
<td>2.716555</td>
<td>8,544</td>
</tr>
<tr>
<td><strong>Complete Stocks Sample</strong></td>
<td>42</td>
<td>-0.00042</td>
<td>0.0218107</td>
<td>0.0522766</td>
<td>3.626617</td>
<td>59,808</td>
</tr>
</tbody>
</table>
negative mean returns, which reflect the general trend of the market during this period. This can also be seen in the negative mean returns reported for the entire sample of stocks.

The variability, as reflected by the reported standard deviations, is highest in the Real Estate sector; however, in general, all sectors exhibit similar volatilities. A point worth noting is that it can be concluded from the descriptive statistics for the panel indices and sectors are that the Pharmaceutical sector has the lowest volatility and yet the highest mean return of the entire panel sectors as well as panel indices. This indicates that this sector should have been an attractive sector for investors since it provided the lowest risk and highest return. Negative skewness is an indication of the clustering of higher values to the right of the mean, and having a longer tail in the direction of the lower values to the left of the mean.

The market, represented by the panel indices, showed a small negative skewness. As shown in existing studies, developed markets generally exhibit negative skewness, while emerging markets exhibit positive skewness (see Aggarwal, Inclan and Leal (1999)). However, this is not conclusive. As shown by Aggarwal, Inclan and Leal (1999), the emerging markets of Brazil, Mexico, Taiwan and Thailand all showed negative skewness, while for the markets of Argentina, Chile and India, the skewness was found to be positive. Therefore, the negative skewness found for the panel indices of the first row of Table 5-3 is consistent with the results of some emerging markets. On the other hand, the sub-samples based on sectors, as well as the entire sample of stocks, all showed a positive skewness. This is consistent with previous studies on
emerging markets and with studies of the ESM (see, for example, Ebeid and Bedeir (2004), Mecagni and Sourial (1999), and Tooma and Sourial (2004)).

The fact that the market level skewness is negative represented by the panel indices, while the panel sectors reported a positive skewness can be explained by the problems associated with using index level data as discussed previously in Chapter 1, Section 1.2, where it was argued that using index data may lead to false perceptions of price changes (see Laurence (1986)). This is often the case as the index may include stocks which are not traded frequently on the market, namely, inactive stocks. This argument was confirmed further when the skewness for the entire sample of stocks, which as mentioned before constitutes more than 40 percent of the market size and considered a fair representation of the market, was calculated and found to be positive.

For the MSCI indices employed in this study, there are no restrictions regarding the level of trade that should occur for individual stocks which constitute the market index. Therefore, some of the stocks in the index may not be active stocks, while the individual stocks used in this analysis are the most actively traded stocks. This could explain the difference in the results between the two samples. That is, this result is in support of the arguments of Laurence (1986) and Xu and Malkiel (2003), among others, that market indices may not be the most appropriate method of analysis and it is for this reason that this thesis extends the volatility analysis to individual stocks.

Panel indices, most panel sectors and the complete sample of stocks have positive kurtosis values greater than three, with the panel indices having the highest kurtosis of 8.69. The Real Estate sector had a kurtosis of 2.72 which is close to normality. These
findings suggest that all panel sectors distributions (except for the Real Estate sector), and the market in general, can be described as being leptokurtic distributions. The results for the kurtosis support the argument that the behaviour of individual stocks may not be effectively represented by the market index. There is a large difference between the kurtosis score for the panel indices and the scores for each of the panel sectors. The results for the kurtosis show some panel sectors may be normally distributed whilst the panel indices may not be normally distributed. By examining the panel indices, this type of information regarding individual stocks is overlooked.

The scores for the skewness and kurtosis generally reflect the findings of previous studies on emerging and regional markets previously cited in Chapter 2 (see Bekaert and Harvey (1997), Aggarwal, Inclan and Leal (1999), Ebeid and Bedeir (2004), Mecagni and Sourial (1999)). That is, the skewness scores are generally positive and the sample distribution is leptokurtic.

5.7 Summary

This chapter has provided a detailed description of the data employed in this thesis, and the criteria used to select the data. First, the sample period was selected based on two criteria. A graphical analysis was used to identify a period of relatively high volatility. This was from 1997 to 2004. Then, due to the fact that changes have been made to the regulations controlling market activity and, therefore, affecting stock market volatility, the sample was limited to the dates at which these price restrictions remained on the ESM; that is, from February 2\textsuperscript{nd}, 1997 to July 18\textsuperscript{th}, 2002. After selecting the sample period, the key characteristics of the sector indices employed in this study were described.
It was mentioned in Chapter 1, however, that in recent years the approach of using market indices has been criticised. Various weaknesses identified include: market indices may lead to false perceptions of price changes due to the inclusion of inactive stocks (Laurence (1986)); stocks performance may not be reflective of the markets performance (Xu and Malkiel (2003)); and the problem of volatility changes cancelling out due to the aggregation of individual stocks. This highlighted the need to analyse individual stock level data. Thus, the second part of the chapter described the selection criteria for the individual stocks included in the analysis, in addition to describing the key characteristics of the 42 individual stocks and their associated six sectoral panels.

The next chapter will present the results of the preliminary test of time series and panel unit root and stationarity tests used to determine if the returns are stationary, that is, I(0). Further, the chapter will discuss the results of implementing the proposed models, discussed in Chapter 4, utilising the general to specific method to choose between competing hypotheses. Finally, some applications concerning volatility, specifically the persistence and the HL of volatility will be analysed in light of the proposed results.
CHAPTER SIX

6. CHAPTER 6: ANALYSIS AND DISCUSSION OF RESULTS

6.1 Introduction

The behaviour of stock prices has been an enduring topic of interest in the finance literature. Understanding the behaviour of stock prices and the ability to identify behavioural patterns offers the potential to predict stock prices, and the ability to earn abnormal profits. Indeed, an original objective of the newly founded Cowles Commission in 1931, following the 1929 Wall Street market crash, was the ability to predict change\textsuperscript{68}. It is now accepted that this ability to predict stock prices counters the proposition of the EMH, which states that stock prices are random and, therefore, unpredictable. One component of stock prices which has received considerable attention in the literature is that of volatility clustering. This is a form of stock market volatility that offers the potential to predict aspects of future stock price changes.

Stock market volatility has popularly been modelled through various ARCH/GARCH models. In fact, GARCH modelling has proven to be one of the most useful time series tools of the last 15 years in the area of financial econometrics. These models have allowed for greatly improved testing of hypotheses about risk and uncertainty (Cermeno and Grier (2001)). Chapter 2 has provided an overview of the stock market volatility literature and has established that there is a large body of theoretical and empirical research attempting to model volatility. However, this mostly covers the developed stock markets.

\textsuperscript{68} For more details about the Cowles Commission see http://www.coloradocollege.edu/dept/ma/history/Topics/Cowles.html.
It has been shown that, although the OLS estimator is still the best linear unbiased estimator in the presence of conditional heteroskedasticity, non-linear GARCH models can provide efficiency gains over OLS estimators. Whilst it is argued that applying GARCH modelling to panel data is important in those areas where there are not sufficiently long individual time series to identify temporal volatility structures, it is not the case here. The individual time series for each stock on the ESM are of a length and frequency suitable for GARCH modelling for each stock individually. Further, it can be argued (see Cermeno and Grier (2001)) that, in panel data, the least squares estimator is less reliable than the GARCH estimator and thus a panel GARCH approach will be more efficient. However, in this thesis, it is only through a pooled-panel approach to GARCH modelling that it is possible to identify the similarities and differences in the structure of conditional heteroskedasticity between stocks.

Chapter 3 discussed the key characteristics of the ESM. It was established that the ESM has become an important market in the MENA region having rapidly progressed through extensive market reforms. The ESM is a large and active emerging market and, for this reason, it was shown that the examination of volatility in this market is an important consideration. In Chapter 4, a general to specific framework (see Hendry (1995)) was established within which to test hypotheses around the similarities and differences in volatility structures between different stocks in the same sector and between different sectors in the same market. Following from this, Chapter 5 provided a description of the data used in this analysis and how this sample was selected. This chapter gives the results of the model estimation and tests from general to specific models employed in this analysis.
Table 6-1 summarises the actual testing process and the related hypotheses. This table should be used in conjunction with Figure 4.1 in Chapter 4. The path, Model A, B, C to D is a nested path, and it is significant that none of the panels tested reached the completely homogeneous equation characterised by Model D. Model E is nested within Model B.

<table>
<thead>
<tr>
<th>Model</th>
<th>Description of Model</th>
<th>Hypothesis</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>The General Model (Varying Parameters Model)</td>
<td>All parameters are free to vary</td>
</tr>
</tbody>
</table>
| B     | Pooled Mean with Varying Parameters in GARCH Model | $H_0: \mu_1 = \mu_2 = \ldots = \mu_N = \mu$  
$H_1: \mu_1 \neq \mu_2 \neq \ldots \neq \mu_N \neq \mu$ |
| C     | Pooled Mean with Panel Fixed Effects in GARCH Model | $H_0: \begin{cases} \alpha_{i1} = \alpha_{i2} = \ldots = \alpha_{iN} = \alpha_1, \\ \delta_{i1} = \delta_{i2} = \ldots = \delta_{iN} = \delta_1. \end{cases}$  
$H_1: \begin{cases} \alpha_{i1} \neq \alpha_{i2} \neq \ldots \neq \alpha_{iN} \neq \alpha_1, \\ \delta_{i1} \neq \delta_{i2} \neq \ldots \neq \delta_{iN} \neq \delta_1. \end{cases}$ |
| D     | Pooled Model | $H_0: \alpha_{01} = \alpha_{02} = \ldots = \alpha_{0N} = \alpha_0$  
$H_1: \alpha_{01} \neq \alpha_{02} \neq \ldots \neq \alpha_{0N} \neq \alpha_0$ |
| E     | Pooled Mean and Variance with Varying GARCH Parameters Model | $H_0: \alpha_{01} = \alpha_{02} = \ldots = \alpha_{0N} = \alpha_0$  
$H_1: \alpha_{01} \neq \alpha_{02} \neq \ldots \neq \alpha_{0N} \neq \alpha_0$ |
For most panel sectors which followed the path A, B, C to D, the testing procedure was halted at Model C in Table 6-1. Stocks within the same panel had the same parameter in the mean model, and a GARCH equation characterised by a panel fixed effects model. That is, the coefficients on the lagged terms were identical for all stocks, but the constant in the variance equation was different for each stock. The one exception to this is the Food, Beverage and Tobacco panel sector, which is characterised by more than one industry. More details on this will be given further into this chapter.

The panel indices were halted at Model E, the restrictions of Model B and alternatively C being separately tested and rejected. Thus, the panel indices show homogeneity in the constant in both the mean and variance equations and heterogeneity in the lagged terms for each of the indices. This finding seriously questions the practice of testing volatility structures in stock markets using aggregate indices.

Prior to discussing these results, it is necessary to give the results of the tests for unit root and stationary processes. These are an important precursor to effective model estimation. It transpires that for all variables to be modelled, the differences in the logarithmic value of the phenomena to be modelled (index price or stock price) are tested to ensure stationarity. Therefore, all variables were tractable in terms of GARCH models. Detailed results of the unit root and tests for stationarity are given in the next section, Section 6.2. This will be followed by a section giving detailed results of the nested tests in the estimated GARCH models. Finally, Section 6.4 provides a summary of the chapter and the results obtained from the analysis.
6.2 Unit Root and Stationarity Tests

As stated in Chapter 4, before estimating any models using time series data it is necessary to perform diagnostic tests to ensure that the data is clear from problems which could bias the results of the estimation. In terms of modelling in this thesis, it is important to test for unit roots. Unit roots may result in biased estimation.

In the vast majority of previous volatility studies, it is the volatility of returns, measured by the first difference in logarithmic prices, which has been analysed. Logarithmic prices themselves were usually found to be unit root process and, therefore, difference stationary. Similarly, here it is necessary to identify whether logarithmic prices are first difference stationary or are stationary themselves, in order to determine whether to model in logarithmic prices or logged first differences.

The results of all tests indicate that in all models it is appropriate to model in first differences. That is, as in previous research, the volatility of the instantaneous returns given by logged first differences is analysed in the various estimated GARCH models.

This section of tests on unit root and tests for stationarity is split into two parts. The first deals with the panel unit root tests attributable to Levin and Lin. For panel indices and all panel sectors, with the exception of the Food, Beverage and Tobacco panel sector, the null hypothesis of panel unit roots could not be rejected. However, for tests on logged first differences, for all panels the null of a panel unit root could be rejected against the alternative hypothesis that all panels are stationary.
The second part of this section gives detailed results of the Hadri tests, where the hypotheses are reversed; that is, the null hypothesis of panel stationarity versus the alternative hypothesis of panel unit root. In this case, the tests on the logarithmic prices resulted in a rejection of the null of panel stationary. The same panel tests in differences resulted in the non-rejection of the null hypothesis of panel stationary. Detailed results follow in the next two subsections.

6.2.1.1 Panel Unit Root Tests: Levin and Lin Tests

The first tests to be considered when testing for a unit root in a panel context are the Levin and Lin (1993) tests. As specified in Chapter 4, only LL_9 and LL_10 tests will be estimated for the panel indices and each of the panel sectors. Since modelling volatility in panel is the aim of this study, then the hypothesis testing of the LL_9 and LL_10 tests appears desirable because the null hypothesis is rejected only when all the series in the panel are stationary. Recalling from Table 4.2, these tests have the null hypothesis that all units in the panel have a unit root against the alternative that all of them are level or trend stationary.

The LL_9 and LL_10 tests were estimated for the panel indices and each of the panel sectors, firstly, in levels using the logarithmic indices and stock prices, and then in first differences using the logged first differences of indices and stock prices (continuous compounded return). Again, the aim of conducting the LL_9 and LL_10 tests is to determine if the logarithmic prices are first difference stationary or stationary in levels.
Table 6-2, Section I, reports the $t_\rho^*$ statistics and their associated Probability (P) values for the LL_9 and LL_10 tests in levels. The results suggest that in the case of a constant only, that is the LL_9 test, the null hypothesis that all panel indices are unit root could not be dismissed.

The panel sectors, however, showed mixed results with the Chemicals, Food, Beverage and Tobacco, and Real Estate panel sectors having significant P values suggesting that these panel sectors are stationary in levels around a deterministic level. When a trend was added to the regression, that is the LL_10 test, only the Food, Beverage and Tobacco panel sector had a significant P value. Therefore, it was classified as a trend stationary process.

<table>
<thead>
<tr>
<th></th>
<th>LL_9: Constant</th>
<th>LL_10: Constant and Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$t_\rho^*$</td>
<td>P value**</td>
</tr>
<tr>
<td>1-Panel Indices</td>
<td>0.30238</td>
<td>0.6188</td>
</tr>
<tr>
<td>2-Panel Sectors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construction Materials</td>
<td>-0.95483</td>
<td>0.1698</td>
</tr>
<tr>
<td>Chemicals</td>
<td>-2.52481</td>
<td>0.0058</td>
</tr>
<tr>
<td>Commercial Banks</td>
<td>-0.91642</td>
<td>0.1979</td>
</tr>
<tr>
<td>Food, Beverage &amp; Tobacco</td>
<td>-6.13596</td>
<td>0.0000</td>
</tr>
<tr>
<td>Pharmaceuticals</td>
<td>0.35030</td>
<td>0.6369</td>
</tr>
<tr>
<td>Real Estate</td>
<td>-2.09508</td>
<td>0.0181</td>
</tr>
</tbody>
</table>

**Probabilities are calculated assuming asymptotic normality.

Table 6-2: Levin and Lin (1993) Panel Unit Root Tests

---

Section II: Levin and Lin (1993) Tests in First Differences

<table>
<thead>
<tr>
<th></th>
<th>LL_9: Constant</th>
<th>LL_10: Constant and Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$t_\rho^*$</td>
<td>P value**</td>
</tr>
<tr>
<td>1- Panel Indices</td>
<td>-99.3350</td>
<td>0.0000</td>
</tr>
<tr>
<td>2-Panel Sectors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construction Materials</td>
<td>-80.6810</td>
<td>0.0000</td>
</tr>
<tr>
<td>Chemicals</td>
<td>-78.7016</td>
<td>0.0000</td>
</tr>
<tr>
<td>Commercial Banks</td>
<td>-78.8232</td>
<td>0.0000</td>
</tr>
<tr>
<td>Food, Beverage &amp; Tobacco</td>
<td>-107.630</td>
<td>0.0000</td>
</tr>
<tr>
<td>Pharmaceuticals</td>
<td>-84.8243</td>
<td>0.0000</td>
</tr>
<tr>
<td>Real Estate</td>
<td>-85.1020</td>
<td>0.0000</td>
</tr>
</tbody>
</table>
Table 6-2, Section II, reports the $t^\rho$ statistics and their associated P values for the LL_9 and LL_10 tests in first differences. All panels classified as a unit root process in levels were found to be stationary in first differences with significant P values for each test.

Recall from Chapter 4, however, that Karlsson and Lothgren (2000) found that when $T$ is large, there is the potential risk of concluding that the whole panel is stationary even when there are only a small number of stationary series in the panel. This may explain the LL unit root test result for the Chemicals, Food, Beverage & Tobacco and Real Estate panel sectors and suggests the use of a different test where the null hypothesis is the stationarity of the entire panel. Such a test was developed by Hadri (2000).

6.2.1.2 Panel Stationarity Tests: Hadri Tests

Although the hypothesis testing for the Hadri (2000) panel stationary tests is different from the LL tests, both assume that there is a common unit root process so that $\rho_j$ is identical across individual cross-sections. The Hadri (2000) panel stationary tests were applied to each of the panel sectors with the pre-condition that the series may be stationary around a deterministic level, specific to the stock (that is, a fixed effect) or around a unit-specific deterministic trend. Recalling from Chapter 4, the Hadri (2000) LM test statistics were obtained under each of the following hypotheses:

- The error process may be assumed homoskedastic across $i$ and serially uncorrelated over $t$, 

• The error process may be assumed homoskedastic across $i$ and serially correlated over $t$, and

• The error process may be assumed heteroskedastic across $i$ and serially correlated over $t$.

Table 6-3 reports the Hadri (2000) panel stationary test results in levels under each of the test hypotheses. The second and third columns give the $Z$ statistics and their related P values when a constant term is included in the regression. The fourth and fifth columns give the $Z$ statistics and their related P values when a constant and trend terms are included in the regression.

The null of level or trend stationary was rejected for the panel indices and for all panel sectors under each of the test hypotheses. That is, panel indices and panel sectors appeared to be generated by unit root processes. To determine the degree of integration, these tests were then repeated on the first differences of all series. The results are reported in Table 6-4. The panel indices and Chemicals, Commercial Banks and Pharmaceuticals panel sectors appear to be stationary in first differences for both test regressions and this result is robust to serially correlated and heteroskedastic errors. This robustness does not carry over to the Construction Materials and Real Estate panel sectors. However, for both test regressions, these two panel sectors appear to be panel stationary in first differences with serially correlated errors. The null hypothesis of trend stationary cannot be rejected for the Food, Beverage and Tobacco panel sector, but the null hypothesis of level stationary is rejected.
Table 6-3: Hadri Stationarity Tests in Levels

### 1- Panel Indices

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>( Z_{\mu} )</th>
<th>P value*</th>
<th>( Z_{\tau} )</th>
<th>P value*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Homoskedastic and Serially Independent errors</td>
<td>2214.85</td>
<td>0.0000</td>
<td>631.660</td>
<td>0.0000</td>
</tr>
<tr>
<td>Homoskedastic and Serially Dependent errors</td>
<td>70.5957</td>
<td>0.0000</td>
<td>20.0475</td>
<td>0.0000</td>
</tr>
<tr>
<td>Heteroskedastic and Serially Dependent errors</td>
<td>68.7896</td>
<td>0.0000</td>
<td>13.3510</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

### 2- Panel Sectors

#### Construction Materials

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>( Z_{\mu} )</th>
<th>P value*</th>
<th>( Z_{\tau} )</th>
<th>P value*</th>
</tr>
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<tbody>
<tr>
<td>Homoskedastic and Serially Independent errors</td>
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#### Chemicals:

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#### Commercial Banks

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<th>( Z_{\tau} )</th>
<th>P value*</th>
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#### Food, Beverage & Tobacco

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#### Pharmaceuticals

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<th>( Z_{\tau} )</th>
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#### Real Estate

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<th>( Z_{\tau} )</th>
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* Probabilities are computed assuming asymptotic normality.
Table 6-4: Hadri Stationarity Tests in First Differences

1- Panel Indices

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2-Panel Sectors

Construction Materials

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<th>P value*</th>
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Chemicals

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Commercial Banks

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Food, Beverage and Tobacco

<table>
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<th>$Z_{\tau}$</th>
<th>P value*</th>
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<tr>
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Pharmaceuticals

<table>
<thead>
<tr>
<th>Hypotheses</th>
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<th>P value*</th>
<th>$Z_{\tau}$</th>
<th>P value*</th>
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<tbody>
<tr>
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<td>0.22183</td>
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Real Estate

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>$Z_{\mu}$</th>
<th>P value*</th>
<th>$Z_{\tau}$</th>
<th>P value*</th>
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<tbody>
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<td>0.20571</td>
<td>0.4185</td>
<td>0.56916</td>
<td>0.2846</td>
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</table>

* Probabilities are calculated assuming asymptotic normality.
The final conclusion that can be drawn from the panel unit root and stationarity test results is that in levels, logarithmic prices seem to be a unit root process when considered in a panel context. To determine the level of integration for the panel indices and each of the panel sectors, the first log differences of prices were taken and the results suggest that sector indices and panel sectors are stationary in first differences. Therefore, the volatility of the ESM, using panel indices and panel sectors, will be modelled in first differences. That is, the primary focus of the volatility analysis, like most other volatility studies, will be the instantaneous returns of indices and stocks.

6.3 GARCH Modelling

The results of the data analysis are divided into two key components. First, the outcomes of the estimated parameters for the different models, especially in terms of the existence and the nature of volatility clustering are reported. Secondly, and of great importance to this thesis, are the Likelihood Ratio Test Statistics (LLR) associated with the different sets of restrictions used to test down from the general model to the various pooled-panel models nested within it.

The results of five particular models estimated within the general to specific methodology are given in the next subsection. This is followed by a subsection dealing with the likelihood ratio tests of restrictions given the various different nested models. It is these results which will give indications of the similarities and differences in volatility structures between panels of sectors or industries operating in the same market and panels of stocks operating in the same sector or industry. The Food, Beverage & Tobacco panel sector is examined further due to the fact that this
sector may contain stocks operating in different industries and this may have led to the inconsistency of the results obtained for this panel sector compared to other panel sectors. This section ends with an examination of the persistence of volatility for the panel indices and each of the panel sectors based on the appropriate models selected by the analysis.

6.3.1 GARCH Modelling Results

This section provides the results of the GARCH modelling for the five proposed models, using the general to specific methodology, applied to the panel indices and each of the panel sectors. The key features of the estimated models are the significance of the estimated parameters and the level of persistence implied by the models. Thus, this analysis will focus on these two characteristics for the five models.

6.3.1.1 Model A: The General Model (Varying Parameters Model)

Recalling Chapter 4, Model A is the general unrestricted model. It allows all of the estimated parameters in the mean and the variance equation to vary between units in the same panel. This general model, in standard linear form with constant conditional variance, is given in Hsiao (2003, p.15), equation (2.2.1). There, Hsiao states that such a model could be estimated by individual regressions for each cross-sectional unit included in a panel. Moreover, Hsiao goes on to give models nested within this general model, where the nested models are distinguished by differences and commonality in the intercept and/or slope parameters.

The general model here, but with a GARCH structure, performs a similar function and, just as the model in Hsiao could be estimated by $N$ separate OLS regressions, this
model was estimated by $N$ separate ML, one for each cross-sectional unit in the panel. However, even though the parameters were estimated by individual ML for each cross-sectional unit, the parameters for all units must be treated as one model. Further, the ML value for this model is the sum of the individual maximised likelihoods.

This general model was estimated for the panel indices and the six panel sectors as given in Chapter 5. That is, seven general models were estimated in total. Each of these models comprises a large number of parameters, $4N$ parameters, where $N$ is the number of units in each panel. Because of the large number of estimated parameters, the results are given in Appendix A, Tables 1-A to 7-A. Each table reports the constant term of the mean equation, $\mu$, in row one; the constant in the variance equation, $a_0$, in row three; the ARCH (1) term, $\alpha_1$, in row five; and the GARCH (1), $\delta_1$, term in row seven. Each of these rows is followed by the probability score (P value) of the estimated t ratio, with the null of zero, for each parameter.

Table 1-A for the panel indices and Tables 2-A to 7-A for the panel sectors, indicate that at the 5 percent level of significance, only one panel (pharmaceuticals) reported that all $\mu$ are not significantly different from zero. All other panels showed mixed results. That is, some estimated $\mu$ were significant, whilst others were not. Moreover, all panels showed a negative average return over the period of analysis. However, this simply reflects the time period of the data used for the analysis.

Importantly, the significance of the estimated parameters in the variance equation (the ARCH (1) and GARCH (1) coefficients) determines whether or not GARCH effects exist for each unit. Evidence of GARCH effects means that there is volatility
clustering and the scale of returns (not its sign) can be predicted. If there is evidence of GARCH effects, the next step is to examine the persistence of such volatility shocks. The persistence, as measured by the sum of the GARCH (1,1) parameters, has significant implications for the pricing of stocks. As suggested by Chou (1988), shocks to volatility have to persist for a long period of time in order for volatility to have a significant impact on stock prices. It was argued that if shocks to volatility are only transitory, the future discount rate will not be adjusted by the market and, therefore, prices are not affected by the volatility movement. On the other hand, if it can be shown that there is strong persistence of volatility shocks, then prices are likely to be affected by the volatility movement. Thus, the significance of the estimated coefficients and the persistence parameters are an important consideration of this thesis.

In the variance equation, the constant (time independent component) and the ARCH (1) and GARCH (1) coefficients (time varying components) are all positive and significant at the 5 percent level for all panel indices and panel sectors. The ARCH (1) coefficient, measuring the ‘news effect’, determines the effect of past shocks or innovations on the return process. The GARCH (1) coefficient measures the influence of past volatility on the current returns process. Therefore, there is strong evidence of conditional heteroskedasticity in the sample, at the aggregate level and the individual level. This is consistent with the findings of other studies on the ESM (see, for example, Mecagni and Sourial (1999), Moursi (2000), and Sourial (2002)). The persistence parameter is generally close to one for all estimations, suggesting that there is strong persistence of volatility shocks. Thus, it appears that the varying parameter in GARCH model does reflect the DGP on the ESM. The next section
examines the results for the more parsimonious model specification, Model B. Given the mixed results of the significance tests on the mean model, an initial restriction to test is the restriction that each panel has a common value for $\mu$.

6.3.1.2 Model B: Pooled Mean with Varying Parameters in GARCH Model

Model B has the restriction imposed that the constant in the mean equation is the same for all panel indices and panel sectors. Recalling Chapter 4, this restriction is appropriate and supported by the industrial economics literature which states that stocks from the same industry are affected by common factors and, therefore, have a similar returns process (see, for example, Porter (1979), and Cubbin and Geroski (1987)). It is expected that stocks from the same industry will have a similar mean return. The effect of imposing this restriction is that there is a predictable component of the returns process on the ESM and that this predictable component is the same across different indices and individual stocks in the same panel. By restricting this coefficient, the model becomes more parsimonious and, hence, may result in a model that better represents the underlying DGP on the ESM. Again, because there are a large number of estimated parameters for each estimated model, the results for Model B are presented in Appendix B, Tables 1-B to 7-B.

All panels experienced a negative average return in the mean equation. Recalling Section 4.3.2.2, because this parameter was fixed as the mean of means, no significance tests are reported. The specification of the variance equation in Model B is the same as Model A. Consequently, similar results were found for the panel indices and panel sectors. At the 5 percent level, the constant in the variance equation, the ARCH (1) and the GARCH (1) coefficients are all significantly different from
zero, confirming the results of Model A that there is positive evidence that the returns on the ESM exhibit volatility clustering. Similarly, the persistence parameters for the estimated models are generally close to one, indicating strong persistence of volatility shocks (see Lamoureux and Lastrapes (1990b)).

Model B may be the more appropriate model to represent the underlying DGP on the ESM, as it is more parsimonious. However, this is subject to test, the results of which are detailed later in this chapter.

Model B imposed the restriction that the constant term in the mean equation is the same for all panel indices and panel sectors. Further restrictions may be imposed on the model to increase parsimony. Recalling Figure 4-1, restrictions on the mean model are now exhausted and further restrictions can now only be placed on the conditional variance equation.

6.3.1.3 Model C: Pooled Mean with Panel Fixed Effects in GARCH Model

Model C maintains the restriction on the mean constant from Model B and further imposes that the GARCH (1,1) parameters, $\alpha_1$ and $\delta_1$ are restricted to be constant across units in each panel. Recalling Chapter 4, this restriction can be justified for the panel sectors since a shock or news related to a certain industry will equally affect all stocks included in that industry. However, this restriction may not be true in the panel indices case since market shocks or news may have a different effect on certain sectors or industries than others. Therefore, it is expected that panels that include stocks from the same industry will have a similar volatility structure.
Table 6-5 reports the results for Model C. The constant in the mean equation, \( \mu \), remains negative for the panel indices and all panel sectors, confirming that negative average returns was the theme during the period of study. However, in this model, the constant in the mean equation is significant for the panel indices and each of the panel sectors, except for the pharmaceuticals panel sector. As stated before, this simply reflects the length of the sample and the market conditions including the strong market reforms and liberalisations that were occurring during the sample period.

The constants in the variance equation for each of the panel sectors are all positive and significant at the 5 percent level of significance. This is similar to that found for Models A and B. With the restriction that the ARCH (1) and GARCH (1) terms are constant and the same across units in each panel, all parameters remain positive and significantly different from zero at the 5 percent level of significance. The persistence of volatility shocks is relatively high and is strongest in the panel indices, the Construction, Commercial Banks and Real Estate panel sectors. Because it is more parsimonious, Model C might well be an improvement on Model B. However, again this is subject to test and is reported later in this chapter.

The next section examines the results for the pooled GARCH model. Following the path of restrictions, and recalling the extreme left hand path of Figure 4.1, the next set of constraints is to restrict the constant term in the variance equation to be common for all panel units. This, combined with all the other restrictions already imposed, leads to Model D, the pooled model.
Table 6-5: Pooled Mean with Panel Fixed Effects in GARCH Model Results

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6.3.1.4 Model D: Pooled Model

Model D maintains the previous restrictions with the additional assumption that the constant in the variance equation is the same across all panel indices and sectors. This assumption is more restrictive and not necessarily valid, as it implies that all units in the panel indices and panel sectors have the same mean volatility. However, there is no reason why all stocks or sectors in a panel should have the same individual firm or sector specific risk.

However, this pooled GARCH model is estimated and tested for the purpose of determining whether it is comparable to Model C. The reason for this is because other studies (see Grier and Grier (2001)) have found that the pooled model outperforms their version of Model C for some economic data. Therefore, by imposing this restriction, it is possible to determine which model most accurately reflects the DGP on the ESM.

Table 6-6 reports the results for Model D. At the 5 percent level of significance, the mean equation for Model D maintains the same specification as Model C. Consequently, the constant in the mean equation is found to be negative and significant for the panel indices and all panel sectors (except for the pharmaceuticals sector). Thus, in this regard, Models C and D show similar and consistent results.

The results for the variance equation are also consistent with the estimates for Model C. The constant in the variance equation is positive and significant for the panel indices and all panel sectors. Similarly, the ARCH (1) and GARCH (1) terms are positive and significant for all the models estimated. The persistence parameters for
the panel indices and panel sectors are similar in size to that of the estimates for all previous three models. Thus, the pooled model results appear to represent the DGP on the ESM consistently. Although Model D is a more parsimonious model, it is still subject to test which is reported later in this chapter.

### Table 6-6: Pooled Model Results

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#### 6.3.1.5 Model E: Pooled Mean and Variance with Varying GARCH Parameters Model

Recalling Figure 4.1, if the restrictions associated with Model C can be rejected then testing in this direction is halted. The restrictions are abandoned and alternative restrictions would then be imposed on Model B. From this model a more parsimonious specification can be identified by imposing the restriction that the constant in the conditional variance equation, $\alpha_0$, is the same for all cross-sectional units included in each panel.
Model E was estimated for the panel indices and all panel sectors. However, as in Model A and Model B, because there are a large number of estimated parameters for each model, the results for Model E are presented in Appendix C, Tables 1-C to 7-C.

The mean and variance equations for Model E maintain the same specification as Model B. The ARCH (1) and GARCH (1) terms are positive and significant for all of the models estimated. Recalling Section 4.3.2.5, the intercept parameters in the mean and the conditional variance equations were fixed and, consequently, significance statistics are not reported. The persistence parameters for the panel indices and panel sectors are similar in size to those of the estimates for Models A, B, C and D.

The focus of the thesis is the identification of the similarities and differences in the volatility structure of indices and stocks in the same panel rather than the estimation of general models. This is done through a series of specification tests following Figure 4.1. The results of these specification tests are given in the following subsection.

6.3.2 Model Specification: The Likelihood Ratio Test (LRT)

The LRT is used to determine which model is the most appropriate for the DGP on the ESM. Following the extreme left hand route outlined in Figure 4.1 in Chapter 4, first Model A is compared against Model B, then Model B against Model C and Model C against Model D, to determine the most applicable model for the panel indices and each of the panel sectors. If Model C can be rejected then testing down in this direction is halted. The restrictions are abandoned and alternative restrictions would then be imposed on Model B.
Table 6-7 presents the results of the likelihood ratio tests for the panel indices and each of the panel sectors. Table 6-7, Section I, reports the results for the test between Model A and Model B. Section II gives the results for the test between Model B and Model C and Section III reports the results for the test between Model C and Model D. Finally, Section IV gives the results for the test between Model B and Model E. The first two columns of the table report the log of the likelihood value for each of the models. The third column reports the LLR. The last three columns report the chi squared critical values, for the associated degrees of freedom\textsuperscript{69}, at the 10, 5 and 1 percent significance levels, respectively.

Firstly, examining Section I of Table 6-7 and comparing the LLR with the critical values for the panel indices and each panel sector, it can be seen that the LLR is less than the critical values at all significance levels for all models estimated. Therefore, the null hypothesis of the restricted model cannot be rejected in all cases. That is, Model B cannot be rejected and further restrictions are imposed to come to a more parsimonious specification for modelling the volatility on the ESM.

Section II of Table 6-7 gives the results for the Likelihood ratio tests between Models B and C for the panel indices and each of the panel sectors. For all panel sectors, except for the Food, Beverage & Tobacco panel sector, the LLR is less than the critical values at all levels of significance. Therefore, Model C, the restricted model, cannot be rejected for these panel sectors, and further restrictions are imposed. However, for the panel indices and the Food, Beverage & Tobacco panel sector, the LLR is greater than the critical values at all levels of significance. Thus, in this case,

\textsuperscript{69} The degrees of freedom of the chi squared statistics for the LRT is equal to the reduction in the number of parameters as a result of imposing restrictions. Further details of the LRT can be found in any basic econometrics book (see, for example, Verbeek (2000), and Greene (2003)).
### Table 6-7: Likelihood Ratio Tests

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<td>Model A versus Model B</td>
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<tr>
<td>II</td>
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<td>1- Panel Indices</td>
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<tr>
<td>III</td>
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<td>IV</td>
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<tr>
<td>2- Panel Sectors</td>
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</table>
Model C is rejected. Further testing in this direction is stopped and further restrictions must be placed on Model B.

This is an interesting counter intuitive result for the Food, Beverage & Tobacco panel sector. However, it turns out that the GICS classification is rather broad and that the Food, Beverage & Tobacco sector contains a series of stocks operating in different industries. This may be the reason causing the inconsistency in the aggregated Food, Beverage & Tobacco panel sector’s results, compared to the results for the other sectors in this study and this will be investigated further in Section 6.3.3.

Alternatively, the result for the panel indices is not unexpected and is indicative of differences in the temporal volatility structure between sectors or industries included in that panel. As was mentioned in Chapter 4, restricting the GARCH (1,1) parameters to be common for all sectors included in the panel indices may not be appropriate because market shocks or innovations may have different effects on each sector and, therefore, the lagged volatility will also be different.

For the remaining sectors further testing of the restrictions is continued until the imposed restrictions are rejected. Section III of Table 6-7 reports the results of the likelihood ratio tests between Models C and D for these panel sectors. For all panels, the LRT statistic is greater than the critical value at all levels of significance. That is, in all cases, Model D is rejected and, therefore, the most appropriate model for these sectors is Model C, the pooled mean with panel fixed effects in GARCH model, and not the pooled model.
The results of the likelihood ratio tests show that for the panel indices and the Food, Beverage and Tobacco panel sector, the most appropriate model for the DGP is not Model C. For all the remaining panel sectors Model C is the most appropriate model to represent the volatility dynamics on the ESM.

Testing down for the panel indices and the Food, Beverage and Tobacco panel sector cannot yet stop at Model B. Restrictions can still be placed on the constant in the conditional variance equation whilst the GARCH (1,1) parameters remain free to vary. These are the restrictions associated with Model E.

Section IV of Table 6-7 gives the results of the LRT between Model B and Model E, for the panel indices and the Food, Beverage & Tobacco panel sector. For the panel indices, the LLR is less than the critical values at all levels of significance. Therefore, Model E, the restricted model, cannot be rejected. This indicates that there are no significant differences between the individual sectors’ mean variances while there are significant differences between the temporal volatility of each sector included in the panel indices. One explanation for this is related to the problem of aggregation when indices are used in modelling volatility. Since a sector index is a weighted average of the stocks included in that sector, the constant in the conditional variance is, in fact, the mean of the mean variances of the sectors represented by the panel indices. This may be the reason for the results found for the panel indices, that is, that there are no significant differences between the individual sectors’ mean variances.

On the other hand, the LLR for the Food, Beverage & Tobacco panel sector exceeds the critical values at all levels of significance. Thus, the null hypothesis of the
restricted model can be rejected, and, Model B seems to be the appropriate specification for this panel sector.

The result for the panel indices was expected, and is consistent with the hypothesis that different sectors would experience different temporal volatility pattern and will have the same mean variance. However, this result is unexpected for the Food, Beverage & Tobacco panel sector. The next section deals with this panel sector in more depth.

6.3.3 The Food, Beverage & Tobacco Panel Sector: Further Analysis

One explanation for the Food, Beverage & Tobacco panel sector result is related to the classification methods used to group individual stocks into appropriate industries. As reported in Chapter 5, the stocks were classified into sectors according to the GICS classification system (see Morgan Stanley Capital International (2006)). According to the GICS classification, all food, beverage and tobacco related firms form one industrial group or sector. Accordingly, ten stocks were included in that sector of which six stocks are mills stocks. According to the CASE sector classification, mills stocks are classified as one sector, known as the Mills sector, rather than combining it with all food, beverage and tobacco related firms, as required by GICS. CASE classifies Mills into its own sector due to its size and significance for the Egyptian economy. Associating this with the industrial economics literature which suggests firms from the same sector will have similar returns processes (see Porter (1979)), it can then be deduced that stocks of the Mills sector may not have the same returns and volatility structure as stocks of the Food, Beverage & Tobacco sector, because they are a separate industry and, therefore, affected by different industry specific effects.
To test for this, stocks included in the Food, Beverage & Tobacco panel sector are divided into two sub-panel sectors. The first panel sector, which includes six mills stocks, is called the Mills panel sector and the second panel sector, which includes the remaining four stocks, represents the Food, Beverage & Tobacco panel sector.

Prior to the re-estimation of the relevant variance models, the panel unit root and stationarity tests were re-estimated for these two sub-panel sectors and the results are reported in Appendix D Tables 1-D and 2-D. The results were consistent with that of the other panel sectors, previously reported in Section 6.2, in that each of the two sub-panel sectors were identified as stationary in first differences. Therefore, modelling the volatility dynamics of these two sub-panel sectors will be done using stock returns.

### 6.3.3.1 Mills Panel Sector

As indicated earlier in the chapter, according to the GICS classification, the mills stocks are classified in the Food, Beverage and Tobacco Industry. However, according to CASE, due to the size and importance of the mills industry for the Egyptian economy, mills stocks are classified into their own sector. Recall Porter (1979), Chapter 4-Section 4.2.2, that stocks from the same industry are affected by similar factors. If mills stocks are classified into their own sector, then one would expect stocks in the Mills panel sector to have the same volatility process. At the same time, one would expect that newly classified Mills panel sector to have a different volatility process in comparison to the remaining stocks in the Food, Beverage and Tobacco panel sector. This justifies separate analysis of the mills stocks in
comparison to the other stocks included in the Food, Beverage and Tobacco panel sector.

This subsection provides an examination of the results for the five estimated models for the Mills panel sector which comprises six of the ten stocks included in the Food, Beverage and Tobacco panel sector. Following the extreme left hand route outlined in Figure 4.1 in Chapter 4, Table 6-8 presents the results for the estimation of Models A and B. It can be seen that the constant in the mean equation for both models is mainly negative and, for Model A, not significantly different from zero at the 5 percent level of significance.

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<tr>
<td>P value</td>
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<td>$\delta_{1i}$</td>
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**Model B: Pooled Mean with Varying Parameters in GARCH Model**

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Models A and B show that the returns process is determined by a random variable and is, therefore, unpredictable. Likewise, the constant in the variance equation and the GARCH (1,1) parameters are positive and significant for both models indicating the existence of volatility clustering. The persistence of volatility shocks is relatively strong with the sum of the ARCH (1) and GARCH (1) coefficients close to one.

Table 6-9 presents the results for Models C and D. The constant in the mean equations for both models is significant at the 5 percent level of significance. The estimates for the variance equation for both models show that there are significant positive ARCH (1) and GARCH (1) effects indicating the existence of volatility clustering. The persistence of volatility shocks is quite strong and similar for both models, with a persistence parameter of 0.89 and 0.90 for Models C and D, respectively.

To determine which specification is most appropriate for modelling the volatility for the Mills panel sector, Table 6-10 presents the results for the likelihood ratio tests and has the same structure as Table 6-7. The first two columns report the log of the likelihood function. The third column reports the LLR, and the last three columns report the chi-squared critical values at the 10, 5 and 1 percent levels of significance.

Section I gives the results for the likelihood ratio tests between Model A and Model B. The LLR is less than the critical values at all levels of significance and, therefore, the null hypothesis cannot be rejected. That is, Model B could not be rejected and further restrictions are imposed.
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<td>10%</td>
<td>5%</td>
</tr>
<tr>
<td>Model A versus Model B</td>
<td>21,818.5543</td>
<td>21,816.8762</td>
<td>3.3562</td>
<td>9.2360</td>
<td>11.0700</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Section II</th>
<th>Model B</th>
<th>Model C</th>
<th>LLR</th>
<th>Chi Square Critical Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model B versus Model C</td>
<td>21,816.8762</td>
<td>21,813.5956</td>
<td>6.5612</td>
<td>15.9870</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Section III</th>
<th>Model C</th>
<th>Model D</th>
<th>LLR</th>
<th>Chi Square Critical Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model C versus Model D</td>
<td>21,813.5956</td>
<td>21,795.1133</td>
<td>36.9646</td>
<td>9.2360</td>
</tr>
</tbody>
</table>

Section II gives the results for the likelihood ratio tests between Model B and Model C. The LLR is less than the critical values at all levels of significance, thus the null hypothesis cannot be rejected. That is, Model C could not be rejected and further restrictions are imposed. Section III gives the results for the likelihood ratio tests between Model C and Model D. The LLR is greater than the critical value at all levels of significance. Therefore, Model D is rejected. It is concluded that the most appropriate model for the Mills Panel sector is Model C, the pooled mean with panel fixed effects in GARCH model.

This result is consistent with the results for the other panel sectors, where it was found that panels of stocks operating in the same sector or industry have the same volatility structure where the conditional variance or total risk of a sector or industry consists of the individual firm specific risk of each stock included in the panel, the common previous shocks or innovations that affected all stocks equally, and the previous volatility or risk of that sector or industry.
6.3.3.2 Food, Beverage & Tobacco Panel Sector: Reconstruction and Analysis

As stated previously, stocks included in the Food, Beverage & Tobacco panel sector are divided into two panels, notably the Mills panel sector, which includes six mills stocks and the second panel which includes the remaining four stocks representing the Food, Beverage & Tobacco panel sector. These four stocks, although classified by GICS as being in one sector, are for firms operating in three different industries. These four stocks and their related industries are presented in Table 6-11 where it can be seen that the four stocks are following three different industries with two stocks in the food industry, one in the beverage and one in the tobacco industry.

| Table 6-11: Modified Food, Beverage & Tobacco Panel Sector Stocks' Details |
|-----------------------------|-------------------------------|----------------------|
| Company Name                | Reuters code                  | Related Industry     |
| Extracted Oils              | ZEOT.CA                       | Food                 |
| Ahram Beverages(ABC)        | PYBR.CA                       | Beverage             |
| Eastern Tobacco             | EAST.CA                       | Tobacco              |
| Egyptian Starch and Glucose | ESGL.CA                       | Food                 |

Because the remaining four sectors in this panel are now quite diverse, one would expect heterogeneity in the temporal structure. This subsection provides an examination of the results for the five estimated models for the modified Food, Beverage and Tobacco panel sector which comprises four stocks operating in three different industries.

Following the extreme left hand route outlined in Figure 4.1 in Chapter 4, Table 6-12 presents the results for the estimation of Models A and Model B. Like the other panel sectors, the modified Food, Beverage and Tobacco panel sector exhibited a negative mean return with mixed significance P values at the 5 percent level of significance for Model A.
Moreover, the constant in the variance equation and the GARCH (1,1) parameters are positive and significant for both Models A and B indicating the existence of volatility clustering. Again, as in other panel sectors, the persistence of volatility shocks is relatively strong with the sum of the GARCH (1,1) parameters close to one.

Table 6-12: Modified Food, Beverage & Tobacco Panel Sector-Model A and Model B

<table>
<thead>
<tr>
<th></th>
<th>ZEOT.CA</th>
<th>PYBR.CA</th>
<th>EAST.CA</th>
<th>ESGL.CA</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu_i )</td>
<td>-0.00130</td>
<td>-0.00017</td>
<td>-0.00061</td>
<td>-0.00064</td>
</tr>
<tr>
<td>P value</td>
<td>0.00609</td>
<td>0.74963</td>
<td>0.14638</td>
<td>0.18410</td>
</tr>
<tr>
<td>( \alpha_{0i} )</td>
<td>0.00002</td>
<td>0.00009</td>
<td>0.00005</td>
<td>0.00003</td>
</tr>
<tr>
<td>P value</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>( \alpha_{1i} )</td>
<td>0.09162</td>
<td>0.17097</td>
<td>0.25856</td>
<td>0.12081</td>
</tr>
<tr>
<td>P value</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>( \delta_{1i} )</td>
<td>0.86968</td>
<td>0.62607</td>
<td>0.59139</td>
<td>0.79786</td>
</tr>
<tr>
<td>P value</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>LLF</td>
<td>14,530.3221</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Model B: Pooled Mean with Varying Parameters in GARCH Model

<table>
<thead>
<tr>
<th></th>
<th>ZEOT.CA</th>
<th>PYBR.CA</th>
<th>EAST.CA</th>
<th>ESGL.CA</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu )</td>
<td>-0.0006782</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \mu_{0i} )</td>
<td>0.00002</td>
<td>0.00010</td>
<td>0.00005</td>
<td>0.00003</td>
</tr>
<tr>
<td>P value</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>( \alpha_{1i} )</td>
<td>0.09127</td>
<td>0.17471</td>
<td>0.26042</td>
<td>0.12115</td>
</tr>
<tr>
<td>P value</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>( \delta_{1i} )</td>
<td>0.86908</td>
<td>0.61948</td>
<td>0.59036</td>
<td>0.79755</td>
</tr>
<tr>
<td>P value</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>LLF</td>
<td>14,528.8498</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6-13 presents the results for Models C and D. The constant in the mean equations for both models is significant at the 5 percent level of significance. The estimates for the variance equation for both models show that there are significant positive ARCH (1) and GARCH (1) effects indicating the existence of volatility clustering. The persistence of volatility shocks is quite strong and similar for both
models, with a persistence parameter of 0.90 and 0.91 for Models C and D, respectively.

<table>
<thead>
<tr>
<th>Table 6-13: Modified Food, Beverage &amp; Tobacco Panel Sector-Panel/Pooled GARCH (1,1) Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model C: Pooled Mean with Panel Fixed Effects in GARCH Model</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Coefficients</td>
</tr>
<tr>
<td>P value</td>
</tr>
<tr>
<td>Model D: Pooled Model</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Coefficients</td>
</tr>
<tr>
<td>P value</td>
</tr>
</tbody>
</table>

Apparently, panel sectors with stocks operating in different industries have mean, volatility and persistence characteristics similar to those with stocks operating in the same industry. The question is, regardless of these similarities, do they have the same or different volatility structures? Answering this question lies in determining which model is most appropriate for modelling the volatility for the modified Food, Beverage and Tobacco panel sector.

Table 6-14 presents the results for the likelihood ratio tests. The first two columns report the log of the likelihood value. The third column reports the LLR, and the last three columns report the chi-squared critical values at the 10, 5 and 1 percent levels of significance. Section I gives the results for the likelihood ratio tests between Model A and Model B. The LLR is less than the critical values at all levels of significance; therefore, the null hypothesis cannot be rejected. That is, Model B could not be rejected and further restrictions are imposed. Section II gives the results for the likelihood ratio tests between Model B and Model C. The LLR is greater than the
critical values at all levels of significance; therefore, Model C is rejected and testing in that direction is stopped and further restrictions must be placed on Model B. That is, Model E, the restricted model, should be estimated and compared to the unrestricted Model B.

Model E was estimated for the modified Food, Beverage & Tobacco panel sector and the results are presented in Table 6-15 where the mean return is negative. The mean variance tends to be small but significant. The GARCH (1,1) parameters tend to be significant implying the existence of volatility clustering. Finally, there is still clear persistence in volatility for this model.

Table 6-16 gives the results of the LRT between Model B and Model E for the modified Food, Beverage & Tobacco panel sector. The first two columns report the
log of the likelihood value. The third column reports the LLR, and the last three columns report the chi-squared critical values at the 10, 5 and 1 percent levels of significance.

Table 6-16: LRT Results between Model B and Model E for the Modified Food, Beverage & Tobacco Panel Sector

<table>
<thead>
<tr>
<th></th>
<th>Model B</th>
<th>Model E</th>
<th>LLR</th>
<th>10%</th>
<th>5%</th>
<th>1%</th>
</tr>
</thead>
<tbody>
<tr>
<td>LRT</td>
<td>14,528.8498</td>
<td>14,513.0479</td>
<td>31.6038</td>
<td>6.251</td>
<td>7.815</td>
<td>11.345</td>
</tr>
</tbody>
</table>

The LLR is greater than the critical values at all levels of significance. Therefore, Model E, the restricted model, is rejected leading to the conclusion that Model B is the appropriate model for describing the DGP for this sector.

This result is expected since stocks included in the modified Food, Beverage & Tobacco panel sector are operating in different industries. That is, the volatility structure of panel sectors with stocks from different industries is different from other panel sectors with stocks from the same industry in that the conditional volatility is made up of a time independent component which reflects the firm specific risk of each stock, \( \alpha_0i \), and the time varying component which reflects each stock’s own-innovation spillovers, \( \alpha_1i \); and lagged volatility spillovers, \( \delta_{1i} \).

6.3.4 Volatility Persistence

A consistent finding for each of the estimated models for the panel indices and panel sectors is that there are significant GARCH (1,1) effects. That is, there is evidence of volatility clustering on the ESM. Moreover, the persistence of this volatility is quite strong for all the estimated models (and is similar to results found in other studies, such as Mecagni and Sourial (1999)). The high persistence in volatility on the ESM
suggests that stock prices are likely to be affected by the volatility movement (Chou (1988)).

To provide some perspective on the implied persistence of volatility shocks, the HL measure of volatility persistence is calculated for the final models for the panel indices and each of the panel sectors and is shown in Table 6-17. The HL measures the period of time (number of days) over which a shock to volatility diminishes to half its original size (Lamoureux and Lastrapes (1990b)).

<table>
<thead>
<tr>
<th>Sector</th>
<th>Final Model</th>
<th>$\lambda$</th>
<th>HL (in days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-Panel Indices*</td>
<td>Model E</td>
<td>0.95423</td>
<td>15.7949</td>
</tr>
<tr>
<td>2-Panel Sectors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construction Materials</td>
<td>Model C</td>
<td>0.92072</td>
<td>9.3917</td>
</tr>
<tr>
<td>Chemicals</td>
<td>Model C</td>
<td>0.92853</td>
<td>10.3476</td>
</tr>
<tr>
<td>Commercial Banks</td>
<td>Model C</td>
<td>0.89525</td>
<td>7.2642</td>
</tr>
<tr>
<td>Pharmaceuticals</td>
<td>Model C</td>
<td>0.84845</td>
<td>5.2177</td>
</tr>
<tr>
<td>Real Estate</td>
<td>Model C</td>
<td>0.94454</td>
<td>13.1483</td>
</tr>
<tr>
<td>Mills</td>
<td>Model C</td>
<td>0.88988</td>
<td>6.9412</td>
</tr>
<tr>
<td>Modified Food, Beverages &amp; Tobacco*</td>
<td>Model B</td>
<td>0.88100</td>
<td>6.4709</td>
</tr>
</tbody>
</table>

*The HL calculated for these panels is the mean HL which was obtained by applying the HL formula to the mean $\lambda$.

The sum of the GARCH (1,1) parameters, $\lambda$, for the panel indices and panel sectors is generally very close to one, suggesting substantial persistence in variance. The HL for each of the panel sectors varies from as low as 5.2177 days for the Pharmaceuticals sector to as high as 13.1483 days for the Real Estate sector. The average HL for the panel sectors is 8.3973 days. For the panel indices the HL is the highest with a volatility shock reducing to half its size after 15.7949 days.

See Lamoureux and Lastrapes (1990b) for a discussion of the HL measure.
One reason for the high volatility persistence evident in the ESM may be related to Lamoureux and Lastrapes’ (1990b) hypothesis that persistence in variance may be overestimated if structural or deterministic shifts in variance are not accounted for. They also added that conclusions regarding the persistence in variance may be misleading if the shifts in variance in the sample are ignored. Therefore, further analysis regarding the volatility persistence in the ESM may be required.

6.4 Summary

In summary, this chapter has examined the applicability of various GARCH models to represent the volatility dynamics on the ESM. The approach taken was innovative in that the modelling was conducted using GARCH structures but applying them in the context of a panel data set. Four main models, nested within the general model, were proposed. The general to specific modelling technique, using the LRT as a method of testing the validity of the imposed constraints, was employed to identify the most appropriate model specification.

As a preliminary analysis, it was important to conduct unit root and stationarity tests for each panel to determine whether to model volatility in levels or first differences. That is, should modelling volatility be conducted using indices and stock prices or indices and stock returns. As expected, it was identified that all panels are stationary in first differences and, therefore, modelling volatility was conducted in first differences, that is, using returns on indices and stocks.

The next step was to estimate the five volatility models proposed in this thesis, namely Models A through to Model E. In general, for each of the estimated models,
the evidence suggested that the ESM experienced negative returns during the period of study. Very importantly, there was evidence of volatility clustering, where, in all models, the estimated coefficients for the ARCH (1) and GARCH (1) terms were significantly different from zero at the 5 percent level of significance. In addition, volatility persistence, as measured by the persistence parameters, was found to be strong.

The next section of the chapter dealt with the results of the model specification tests where the LRT was used to test the imposed restrictions to determine the most appropriate model for the DGP of the ESM. Each restriction was tested to deduce the nested models within the general model. If a restriction could not be rejected then further restrictions were imposed until a constraint was rejected. In general, all results for panel indices and all panel sectors suggested that there was no significant difference between the individual return of each unit included in each panel. That is, all panels rejected Model A in favour of a common mean return.

The results show that the panel indices followed Model E, Table 1-C Appendix C. That is, there was a difference between the time varying components of volatility, but the mean conditional variance was common for all panel entities. Whilst this latter phenomenon was initially counter intuitive, because in terms of individual stocks this time independent component reflected firm specific risk, it was explained by the fact that this term in the panel indices was aggregated over many individual stocks. Thus, individual differences were smoothed out. However, the differences in the time varying components of volatility did not contradict the hypothesis that this part of the conditional variance reflected sector or industry specific risk. Indeed, if this was the
case, then one would expect differences in the time volatility structure in a panel of indices representing different sectors. Moreover, this was reinforced by the results for the disaggregated Food, Beverage and Tobacco panel sector, where the modified panel of four disparate stocks followed Model B, Table 6-12. That is, the results reflected different mean volatility and different temporal patterns of volatility, reflecting the fact that the stocks are from disparate sectors or industries.

Further, all panel sectors which include stocks from the same sector or industry followed Model C, Table 6-5. Again this did not contradict the hypothesis that the elements in the conditional variance equation are twofold. On the one hand, the mean volatility structure reflects firm specific risk and the time varying structure of volatility reflects industry or sector specific risk. In Model C, the mean variance was different for each entity in the panel; that is, there were panel fixed effects, but the slope parameters of the lagged terms in the variance equation were common to all units in the panel. Stocks in the same sector exhibited firm specific risk, but innovation in volatility over time would be common to stocks in the same sector.

The final section went on to examine the volatility persistence that was suggested by the results. Calculating the HL for the panel indices and each of the panel sectors, it was found that a shock persists within the range of 5 to 15 days till it reaches half its original size. This level of persistence for all panels is quite strong. However, it has been suggested that the persistence evident on the ESM may be related to the Lamoureux and Lastrapes’ (1990b) hypothesis that persistence in variance may be overestimated if structural or deterministic shifts in variance are not accounted for.
Following the discussion above, the principle conclusion for this thesis is that there are similarities in the temporal volatility structures of stocks from the same sector or industry, but there are significant differences in the temporal volatility structures of stocks from different sectors or industries. This suggests that using indices alone for modelling the volatility of an equity market, which is the method used in the majority of studies in the literature, may not be appropriate.
CHAPTER SEVEN

7. CHAPTER 7: SUMMARY AND CONCLUDING REMARKS

7.1 Introduction

The objective of this study was the derivation of a method, within the general to specific framework of nested tests, to test for the similarities and differences in panels of returns on indices and stocks. The raison d’être for this was the contention that analysing temporal volatility patterns in an equity market using a single representative index leads to a high level of aggregation which would hide considerable variation in volatility structures. Particularly, it was argued that volatility on stocks would reflect firm specific and sector or industry risks. The latter would lead to differences in temporal volatility patterns, exemplified by the GARCH specification, between sectors or industries in the same market. Further, this testing procedure required estimation of general and nested specific models with pooled-panel specification in the variance equation of models of volatility. Particularly important here was the estimation of a model with panel fixed effects in the variance equation. Whilst there was limited evidence of panel estimations in variance equations, there was no evidence that this had been done within the GARCH specification and this is claimed as an innovation by this thesis.

Whilst it can be argued that the framework of nested tests within pooled-panel specifications is an addition to the general literature on volatility modelling, the application of this methodology to an analysis of the ESM has increased the understanding of an important emerging equity market. The literature survey for this thesis revealed a small but increasing volume of work on emerging stock markets in
terms of volatility analysis. A general finding in this literature was that emerging markets are more volatile than their developed counterparts. Therefore, it was appropriate to test this methodology in an emerging market. In particular, the ESM has recently been subject to considerable change and deregulation and despite the existence of price ceilings and floors, the market has exhibited significant volatility in measures such as the continuous compounded return on stocks. Whilst some important previous analysis had been undertaken on volatility in the ESM, it concentrated on single representative indices and was developed along the lines of more complex temporal volatility structures on the same index. This work has given a new direction to the analysis of volatility in the ESM by exploring the richness of different volatility structures in that market.

The remainder of this chapter is structured as follows. Section 7.2 presents an overview of the chapters included in this thesis. This is followed by a section providing a discussion of the results and some possible implications. Finally, there are two related sections dealing with the limitations of this study and some recommendations for further research.

7.2 Overview of the Thesis

Chapter 1 provided a general overview of stock market volatility. It highlighted the importance of stock market volatility and described the motivation for this research. It was established that this research was motivated by the examination of stock market volatility through individual stocks rather than market indices and this necessitated the application of GARCH models to pooled-panel data, rather than single time series data. It was also shown that there is a gap in the literature regarding stock market
volatility of emerging markets and, in particular, the relatively small amount of literature focusing on Egypt. The chapter also described the main objectives of the thesis and the significance of the research.

Chapter 2 provided an overview and analysis of the research in the area of stock market volatility. The importance of stock market volatility in the finance literature was established and the stylised facts regarding financial market volatility and its definition and measurement were described.

In particular, the importance of stock market volatility and its relationship to the EMH, one of the most important theories in, and a cornerstone of, finance were shown. The EMH, first proposed by Fama (1970), suggests that in an efficient market, all relevant information is already reflected in stock prices, such that it is not possible to earn abnormal profits based on this information. Three forms of market efficiency were described by Fama (1970), which depend on the level of information and which are reflected in stock prices.

Since this proposition, the literature has expanded rapidly with various empirical tests to examine the validity of this hypothesis. Numerous approaches have been taken to test the EMH. In this chapter, it was established that one particular method was to test for patterns in stock prices or returns; that is, analysis of volatility clustering. If there are identifiable patterns in stock prices or returns, then it is possible to use this information to predict stock prices, which contradicts the EMH.
Also, it was established that the two main forms of empirical models designed to capture one particular aspect of stock market volatility, namely, volatility clustering, were the ARCH class and SV models. These two models are examples of the attempt to identify patterns in stock returns as a means of testing the EMH. The ARCH model, first proposed by Engle (1982) and later generalised by Bollerslev (1986), have become the most popular volatility models. These models have the ability to capture the volatility clustering phenomenon through the persistence parameters. If volatility clustering exists, then it may be possible to predict the change in stock prices, violating the EMH.

The empirical evidence of the application of the various ARCH class models was given and classified according to the type of market; that is, the developed, emerging, African and MENA, and the Egyptian markets. These studies were conducted on time series data for these markets and have strongly supported the existence of volatility clustering.

Chapter 2 also referred to the limited development in the literature regarding the application of the ARCH class models to panel data. Further, this chapter showed that the current study expanded on this literature by extending the panel fixed effects model to the GARCH specification. This procedure was seen to be beneficial, having many advantages over standard time series and cross-sectional analysis, and was shown to provide a greater depth of understanding for the underlying data generating process.
Finally, Chapter 2 described theories and explanations of the causes of market volatility, with a particular focus on circuit breakers and their implications for stock market volatility. The chapter made it clear that there are many unresolved issues regarding stock market volatility and this research attempts to contribute to the literature by thoroughly investigating the case of Egypt using a panel of sector indices and panels of individual stocks. In particular, it was established that the pooled-panel GARCH specifications could be used to identify similarities and differences in the temporal volatility structures of panels of sector indices and individual stocks.

Chapter 3 outlined the key characteristics of the ECM with a major focus on the ESM. The main purpose of this chapter was to identify and explain common factors which the literature has shown to affect market volatility, and directly relating this to the key features of the ECM. The chapter began with a description of the Egyptian economy, especially since the economy is regarded as a mirror of the activity of the stock market. The focus was on the factors which may potentially affect stock market volatility.

This chapter showed that, since the 1990s, the Egyptian government has embraced market liberalisation policies by implementing financial and economic deregulatory changes in addition to the major privatisation program which involved the selling off of more than 314 publicly owned firms. This change in policy approach by the Egyptian government was significant for ESM volatility in two regards. In the first instance, the actual privatisation program contributed to the volatility evidenced on the exchange since its introduction in the early 1990s, as it successfully induced activity and interest in a market which was essentially dormant prior to this. In the
second instance, the reforms stimulated activity in the private sector and essentially the ESM, thus contributing to market volatility. This provided a suitable environment within which to apply an analysis that focuses on the identification of similarities and differences in volatility structures.

The second part of the chapter examined the structure and features of the CASE. This included a discussion of the listing requirements, trading system and clearing, settlement and central depository. The market microstructure literature showing how the regulatory and structural features of the market filter through and influence market volatility was also examined. The main proposition here was that the market microstructure affects the transaction costs of trading in a market, as transaction costs influence stock returns and, hence, it has implications for stock prices and the volatility of stock returns.

Following this, the chapter introduced the main market indices for the Egyptian market which are commonly used as a benchmark. The performance of the ECM was then described using four main indicators, namely, market activity, size, liquidity and concentration. Using these four indicators, Chapter 3 highlighted the big improvements in the ECM over a relatively short period of time. This was linked to the market volatility literature that makes it clear that there is some form of relationship between market activity, size, liquidity and concentration and the market volatility evidenced on the exchange.

Other main features that were discussed included the profile of the securities traded on the market. It was shown that, of the total capital market, the stock market accounts
for 86 percent. Bonds and mutual funds together only accounted for 14 percent of the market. Again it was shown that, market volatility may rise or fall depending on the type of securities that are traded on the market and the movement of funds between securities. Similarly, the type of market participant was shown to also have a differing impact on market volatility. For example, some have argued that institutional traders have a more stabilising effect on the market because they have better access to information when compared with individual market participants who lack such resources. On the other hand, institutional investors may exert herding behaviour and thus may have a potentially destabilising effect on prices and volatility. This is also the case when examining foreign versus local market participants.

The chapter concluded by comparing the performance of Egypt with other emerging markets and MENA countries. It was shown that Egypt exhibited a strong contemporary performance and compared well with the other markets. In terms of market volatility, market theories have extensively illustrated the fact that markets in different regions are inter-linked, such that the volatility in one market may be transferred to another market. Considering this fact, the basic performance of each market was compared and it was generally shown that there was a link between performances in each of these markets.

Chapter 4 was pivotal to this thesis. It described the research methods and models that were employed in this thesis. Using panel data techniques, this chapter developed five nested GARCH (1,1) models that are based on theoretical and empirical findings in the literature. Research hypotheses were developed to be used as testable restrictions on the general model to identify and determine the most appropriate model through
the examination of the validity of the mooted restrictions. That is, the chapter examined the general to specific modelling methodology employed in the process of identifying the most appropriate volatility model describing the DGP underlying the ESM.

The estimation procedure involved the method of ML with the use of the BHHH (1974) algorithm for numerical optimisation. It was shown that BHHH (1974) is one of the most popular procedures for achieving a solution to the maximisation problem since the algorithm facilitates convergence in the GARCH likelihood function. To test down from the general model to a more parsimonious model, the imposed restrictions were tested using the LRT. If the hypothesis could not be rejected, then further restrictions were imposed until a restriction was rejected and the most appropriate model identified.

Additionally, as the thesis aimed to measure the existence of volatility clustering, one of the important measures to consider was the level of persistence of a volatility shock. The thesis used the HL as a measure of volatility persistence in the estimated models, and the last section of the chapter described this.

Finally, it was shown that one of the most common problems to plague financial data analysis is the presence of unit root. A unit root means that the data is not stationary and this may lead to model misspecification. As a preliminary analysis, it was important to conduct unit root and stationarity tests. Further, since volatility modelling is done in a panel context, testing for time series properties was conducted using panel
unit root and panel stationary tests including the Levin and Lin panel unit root tests and the Hadri stationarity tests.

Chapter 5 provided a detailed description of the sample period and data selection criteria used in this study. The period of analysis was selected based on two main criteria. The first was to ensure that the period of analysis contained evidence of strong volatility. The second criterion was to ensure that the period of analysis was not affected by any external factors that are not controlled for in the model itself. The data sample consisted of the sector indices produced by MSCI covering six main economic sectors in Egypt and the most active individual stocks listed on CASE representing each of these economic sectors. The chapter also described the method used to calculate the daily stock returns, with an emphasis on the price adjustment process followed to adjust prices for stock dividends, splits and rights issues. The chapter concluded with an analysis of the descriptive statistics of the sample selected for the study.

Chapter 6 presented and discussed the results of the preliminary panel unit root and panel stationary tests. The results of the estimates of the proposed volatility models for the panel indices and each of the panel sectors were also given in this chapter.

The results of the panel unit root and panel stationary tests suggested that the panels were stationary in first differences. That is, modelling volatility on the ESM was conducted using the daily log differences of indices and stock prices. In other words, the analysis was of the daily continuous compounded returns.
The main focus of the results chapter was the likelihood ratio tests results. These were the vehicle for discriminating between the general model and the various different specifications nested within that general model. Further, given the nature of the different kinds of panels tested, it was possible to use this process of model selection to test hypotheses around the similarities and differences of volatility structures.

Generally, the results did not contradict the hypothesis that stocks from the same sector or industry would have volatility patterns which reflected individual or firm specific risks and sector or industry risks. Thus, for panel sectors with stocks from the same sector or industry, the testing down procedure stopped at Model C. For this model, the mean return was the same for all panel entities, as were the GARCH parameters. However, the conditional variance equation exhibited panel fixed effects, representing stock or firm specific volatility.

Moreover, the results did not contradict the hypothesis that stocks in different sectors would have different volatility patterns. Panel sectors with stocks from different sectors or industries stopped at Model B and the panel indices stopped at Model E. The main difference between these two models and Model C is that the GARCH parameters are different for each entity in the panel. That is, entities in the panel had different volatility structures.

Both of these results indicate that, for the ESM at least, the true structure of volatility is best captured by a panel data approach. Moreover, even though there are significant differences in volatility structures between panels, all exhibited volatility persistence albeit to different degrees. Finally, these results may well carry over to different
equity markets, whether emerging or developed. However, this is a proposition yet to be tested.

7.3 Implications of the Results

The findings of this research have great implications for volatility modelling in general and for modelling volatility in the ESM in particular. These implications can be summarised as follow:

1. Modelling the volatility of return on the aggregate level using indices is different from that using individual stocks in that each has a different volatility structure in general and different temporal volatility in particular. This may have implications for forecasting the volatility of an equity market using indices alone or stocks alone.

2. Modelling volatility using panel sectors of stocks operating in the same sector or industry is different from using panel sectors of stocks operating in different industries in that each of these panel sectors have a different volatility structure in general and different temporal volatility in particular.

3. Although there are differences in the volatility structure of panel sectors, depending on whether the stocks included in the panel sector are from the same industry or not, there is similarity in the volatility structure within each of the panel sectors suggesting that stocks from the same industry have the same volatility structure and vice versa.
4. In general, the return process on the ESM, has a predictable component inconsistent with the findings of Fama (1965) and consistent with the findings of studies conducted on other emerging markets (see, for example, Laurence (1986), and Butler and Malaikah (1992)).

5. The volatility on the ESM seems to exhibit volatility clustering. These findings confirm other results found for the ESM (see, for example, Mohieldin and Sourial (2000), Moursi (2000), and Sourial (2002)) and those for other emerging markets (see, for example, De Santis and Imrohoroglu (1997), Su and Fleisher (1998), Aggarwal, Inclan and Leal (1999), and Siourounis (2002)) as well as those for other regional markets (see, for example, Omet, Khasawneh and Khasawneh (2002), and Hassan (2003)). The existence of volatility clustering in the ESM contradicts the EMH and any conclusion regarding the efficiency of the market must be interpreted with caution.

6. The volatility on the ESM was found to be highly persistent for all panels with the GARCH (1,1) parameters close to one, implying that shocks to volatility continue for a long period. This is consistent with other studies conducted on the ESM using single time series (see, for example, Mohieldin and Sourial (2000), and Moursi (2000)). Although volatility persistence is high for all panels, the HL of the volatility persistence is different between panels ranging from as low as 5 days and as high as 15 days. This difference in the length of time that volatility persists may have implications, not only for forecasting price changes but also for trading in other financial instruments such as index and stock option contracts.
7.4 Limitations of the Study

This study, like most other studies, has its limitations. These limitations are determined by time constraints and current inadequacies in the analytical techniques used.

An example of the former limitation is the fact that the current study sample was limited to a period where the price limit mechanism (+/-5% daily and +/-20% weekly) was imposed on all stocks listed and traded on CASE. The period of study was convenient for this research because a study of volatility must be conducted under constant regulatory conditions. However, in order to draw further generalisations from the results, volatility on the ESM must be modelled for a period before or after the sample period used in this research where a price limit was imposed on all listed stocks. However, this would require the augmentation of estimated models with autonomous variables reflecting different policy regimes and which would potentially detract from the focus of this thesis, the panel estimation in a general to specific framework.

In terms of the latter limitation, the current analysis is limited to panel methods using fixed effects in the GARCH equation. Currently, the fixed effects parameter has to be estimated explicitly, so that large panels lead to a large number of parameters to be estimated. Associated convergence problems, therefore, limit this method to small panels and, presently, there appears to be no practical solution to this problem. However, within this limitation, fixed effects models appear to be a valid way of examining the variation of volatility structures between different series and it could be extended to other series beyond equity markets.
7.5 Areas for Future Research

The present study, using pooled-panel data, examined the similarities and differences in the volatility structure of stocks from emerging markets using Egypt as a case study. The analysis has produced some interesting results and one avenue for future research is to extend the investigation to other emerging markets. The incentives for further research on other emerging markets come from the results and the limitations of those studies that currently exist. By doing so, a generalisation can be drawn about the volatility structure of stocks when studied in a panel context.

The originality of this thesis, as mentioned before, is the modelling of volatility with GARCH (1,1) structures in a panel data context. The direction and possibilities for future research in that area are manifold. For example, the proposed models can be extended to include the conditional variance in the conditional mean equation; that is, GARCH-M class of models pioneered by Engle, Lilien and Robins (1987). The importance of such models is related to asset pricing models such as the CAPM where risk and return are related. With such a model, a conclusion can be drawn regarding the effect of the volatility structure of a certain panel sector on the return process of that sector.

A further area of research could be to extend the proposed GARCH (1,1) models to include exogenous variables in the conditional variance equation. For example, Lamoureux and Lastrapes' (1990b) hypothesis that persistence in variance declines if deterministic structural shifts in variance are accounted for can be tested by incorporating dummy variables in the conditional variance equation.
Also, research needs to be done on the relationship between the volatility on the ESM and the characteristics of stocks listed on that market. That is, whether the conditional volatility of panel sector returns is affected by the size of the firms (market capitalisation) included in that panel sector.\textsuperscript{71} Recalling from Chapter 3, the ESM has witnessed a significant increase in the total market capitalisation for the period 1991 to 2004. Although all stocks used in this research are active stocks, they represent firms with different market sizes. Moreover, firms in certain sectors may have increased significantly in size and, thereby, may have affected the volatility of returns for that sector.

The current study is a first attempt to model the volatility of daily stock returns in a full panel context. It has employed a well-defended testing methodology and produced a set of results which are interesting. Although there are still some limitations to this research, it has, however, provided a number of insights which could form the basis for both further research in Egypt, and comparative research in other equity markets. The literature on modelling volatility is large, and it remains a core issue of modern financial econometrics. In examining this issue, therefore, the thesis has helped to reveal much about the nature and the structure of market and sectoral volatility on the ESM, and potentially opened up wider issues around the effect of such volatility structures in emerging capital markets like Egypt.

\textsuperscript{71} Cheung and Ng (1992) examined the relation between stock price dynamics and firm size and found evidence that conditional volatility of stock returns is negatively related to the level of stock price and that this effect is stronger for small firms with high financial leverage.
8. REFERENCES


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9. APPENDICES

Appendix A: Model A: The General Model (Varying Parameters Model)

Table 1-A: Panel Indices

<table>
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<th>FOOD, BEVERAGE &amp; TOBACCO</th>
<th>COMMERCIAL BANKS</th>
<th>PHARMACEUTICALS</th>
<th>REAL ESTATE</th>
<th>CONSTRUCTION MATERIALS</th>
<th>CHEMICALS</th>
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## Appendix B: Model B: Pooled Mean with Varying Parameters in GARCH

### Table 1-B: Panel Indices

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LLF: 21,821.1339

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LLF: 21,073.1830
Table 4-B: Commercial Banks Panel

**Mean Equation**

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**Variance Equation**

| \( \mu \) | -0.0005229 |

Table 5-B: Food, Beverage and Tobacco Panel

**Mean Equation**

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**Variance Equation**

| \( \mu \) | -0.0005423 |

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### Table 6-B: Pharmaceuticals Panel

#### Mean Equation

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#### Variance Equation

### Table 7-B: Real Estate Panel

#### Mean Equation

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Appendix C: Model E: Pooled Mean and Variance with Varying GARCH Parameters Model

Table 1-C: Panel Indices

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Table 2-C: Construction Materials Panel

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<td>μ</td>
<td>α₀</td>
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<td></td>
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<th>SUCE.CA</th>
<th>HELW.CA</th>
<th>ALEX.CA</th>
<th>TORA.CA</th>
<th>NCEM.CA</th>
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<td>α₁ᵢ</td>
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<td>0.259745</td>
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<td>0.175342</td>
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</tr>
<tr>
<td>δ₁ᵢ</td>
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<td>0.657986</td>
<td>0.704508</td>
<td>0.762762</td>
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Table 3-C: Chemical Panel

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<th>KZPC.CA</th>
<th>NMPIL.CA</th>
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<tr>
<td>α₁ᵢ</td>
<td>0.260106</td>
<td>0.155207</td>
<td>0.201445</td>
<td>0.274337</td>
<td>0.201823</td>
<td>0.303797</td>
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<td>δ₁ᵢ</td>
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<td>0.684756</td>
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<td>0.534075</td>
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325
### Table 4-C: Commercial Banks Panel

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</tr>
<tr>
<td>( \alpha_0 )</td>
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<table>
<thead>
<tr>
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<th>EABK.CA</th>
<th>COMI.CA</th>
<th>CANA.CA</th>
<th>MIBA.CA</th>
<th>DEVE.CA</th>
<th>EXPA.CA</th>
<th>NSGB.CA</th>
</tr>
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<tbody>
<tr>
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<td></td>
<td></td>
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<tr>
<td>P value</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>( \delta_{1i} )</td>
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### Table 5-C: Food, Beverage and Tobacco Panel

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<th>EAST.CA</th>
<th>ESGL.CA</th>
<th>SCFM.CA</th>
<th>EDFM.CA</th>
<th>WCDF.CA</th>
<th>CEFM.CA</th>
<th>MILS.CA</th>
<th>UEFM.CA</th>
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</thead>
<tbody>
<tr>
<td>( \alpha_{1i} )</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \delta_{1i} )</td>
<td></td>
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<td>P value</td>
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<td>36,328.0632</td>
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326
Table 6-C: Pharmaceuticals Panel

**Mean Equation**

\[ \mu = -0.0002365 \]

**Variance Equation**

\[ \alpha_0 = 0.0000597 \]

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<thead>
<tr>
<th>Reuters Code</th>
<th>PFIZ.CA</th>
<th>MPCL.CA</th>
<th>AXPH.CA</th>
<th>CPCL.CA</th>
<th>MEDU.CA</th>
<th>PHAR.CA</th>
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<tbody>
<tr>
<td>( \alpha_{1i} )</td>
<td>0.164371</td>
<td>0.157378</td>
<td>0.185930</td>
<td>0.218950</td>
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<td>0.227140</td>
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<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
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<tr>
<td>( \delta_{1i} )</td>
<td>0.764006</td>
<td>0.647671</td>
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LLF: 22,638.5529

Table 7-C: Real Estate Panel

**Mean Equation**

\[ \mu = -0.000949 \]

**Variance Equation**

\[ \alpha_0 = 0.0000402 \]

<table>
<thead>
<tr>
<th>Reuters Code</th>
<th>MNHD.CA</th>
<th>ELKA.CA</th>
<th>UNIT.CA</th>
<th>HELI.CA</th>
<th>ELSH.CA</th>
<th>DAPH.CA</th>
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<tr>
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<tr>
<td>( \delta_{1i} )</td>
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LLF: 19,928.9293
## Appendix D: Unit Root and Stationarity Tests for the Mills and Modified Food, Beverage & Tobacco Panel sectors

Table 1-D: Levin and Lin (1993) Panel Unit Root Tests for the Mills and Modified Food, Beverage & Tobacco Panel sectors

**Section I: Levin and Lin (1993) Tests in Levels**

<table>
<thead>
<tr>
<th>Sub-Panel Sector</th>
<th>(t^*_p)</th>
<th>(P\text{ value}^{**})</th>
<th>(t^*_p)</th>
<th>(P\text{ value}^{**})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mills</td>
<td>-3.0735</td>
<td>0.0011</td>
<td>-2.0836</td>
<td>0.0186</td>
</tr>
<tr>
<td>Modified Food, Beverage &amp; Tobacco</td>
<td>-0.5534</td>
<td>0.2900</td>
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<td>0.1845</td>
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</table>

**Section II: Levin and Lin (1993) Tests in First Differences**

<table>
<thead>
<tr>
<th>Sub-Panel Sector</th>
<th>(t^*_p)</th>
<th>(P\text{ value}^{**})</th>
<th>(t^*_p)</th>
<th>(P\text{ value}^{**})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mills</td>
<td>-86.2962</td>
<td>0.0000</td>
<td>-122.348</td>
<td>0.0000</td>
</tr>
<tr>
<td>Modified Food, Beverage &amp; Tobacco</td>
<td>-73.6825</td>
<td>0.0000</td>
<td>-104.268</td>
<td>0.0000</td>
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</table>

Probabilities are calculated assuming asymptotic normality.

Table 2-D: Hadri Stationarity Tests for the Mills and Modified Food, Beverage & Tobacco Panel Sectors

**Section I: In Levels**

<table>
<thead>
<tr>
<th>Sub-Panel Sector</th>
<th>Hypotheses</th>
<th>(Z_{\mu})</th>
<th>(P\text{ value}^{*})</th>
<th>(Z_{\tau})</th>
<th>(P\text{ value}^{*})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mills</td>
<td>Homoskedastic and Serially Independent errors</td>
<td>1606.96</td>
<td>0.0000</td>
<td>1456.62</td>
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<td></td>
<td>Homoskedastic and Serially Dependent errors</td>
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<td>Modified Food, Beverage &amp; Tobacco</td>
<td>Homoskedastic and Serially Independent errors</td>
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**Section II: In first differences**

<table>
<thead>
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<th>(P\text{ value}^{*})</th>
<th>(Z_{\tau})</th>
<th>(P\text{ value}^{*})</th>
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<tbody>
<tr>
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<td>0.5847</td>
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*Probabilities are computed assuming asymptotic normality.