The impact of the market risk of capital regulations on bank activities

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THE IMPACT OF
THE MARKET RISK
CAPITAL REGULATIONS
ON BANK ACTIVITIES

by
Emrah Eksi

A Doctoral Thesis
Submitted in partial fulfilment of the requirements
for the award of

Business School of Loughborough University

January 2006

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ABSTRACT

Banking has a unique role in the well-being of an economy. This role makes banks one of the most heavily regulated and supervised industries. In order to strengthen the soundness and stability of banking systems, regulators require banks to hold adequate capital. While credit risk was the only risk that was covered by the original Basle Accord, with the 1996 amendment, banks have also been required to assign capital for their market risk starting from 1998.

In this research, the impact of the market risk capital regulations on bank capital levels and derivative activities is investigated. In addition, this study also evaluates the impact of using different approaches that are allowed to be used while calculating the required market risk capital, as well as the accuracy of VaR models.

The implementation of the market risk capital regulations can influence banks either by increasing their capital or by decreasing their trading activities and in particular trading derivative activities. The literature review concerning capital regulations illustrates that in particular the impact of these regulations on bank capital levels and derivative activities is an issue that has not yet been explored. In order to fill this gap, the changes in capital and derivatives usage ratios are modelled by using a partial adjustment framework. The main results of this analysis suggest that the implementation of the market risk capital regulations has a significant and positive impact on the risk-based capital ratios of BHCs. However, the results do not indicate any impact of these regulations on derivative activities. The empirical findings also demonstrate that there is no significant relationship between capital and derivatives.

The market risk capital regulations allow the use of either a standardised approach or the VaR methodologies to determine the required capital amounts to cover market risk. In order to evaluate these approaches, firstly differences on bank VaR practices are investigated by employing a documentary analysis. The documentary analysis is conducted to demonstrate the differences in bank VaR practices by comparing the VaR models of 25 international banks. The survey results demonstrate that there is no industry consensus on the methodology for calculating VaR. This analysis also indicates that the assumptions in estimating VaR models vary considerably among financial institutions. Therefore, it is very difficult for financial market participants to make comparisons across institutions by considering single VaR values.

Secondly, the required capital amounts are calculated for two hypothetical foreign exchange portfolios by using both the standardised and three different VaR methodologies, and then these capital amounts are compared. These simulations are conducted to understand to what extent the market risk capital regulations approaches produce different outcomes on the capital levels. The results indicate that the VaR estimates are dependent upon the VaR methodology.

Thirdly, three backtesting methodologies are applied to the VaR models. The results indicate that a VaR model that provides accurate estimates for a specific portfolio could fail when the portfolio composition changes.

The results of the simulations indicate that the market risk capital regulations do not provide a ‘level playing field’ for banks that are subject to these regulations. In addition, giving an option to banks to determine the VaR methodology could create a moral hazard problem as banks may choose an inaccurate model that provides less required capital amounts.

Keywords: Banking, Capital, Risk-Based Capital Regulations, Derivatives, Market Risk, Value at Risk, Backtesting
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This thesis is dedicated to my wife ‘İpek’ and my daughter ‘Buse’, for being so caring and supportive.
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CHAPTER ONE

INTRODUCTION

1.1 Introduction

Banks have a unique role in the well-being of an economy by providing a link between lenders and borrowers, influencing the functioning of securities markets, affecting the quantity of money, and influencing levels of investment and economic growth. These roles make banking one of the most heavily regulated and supervised industries around the globe. The main underlying rationale of bank regulations is to counter the potential effects of bank failures on the economy and to avoid systemic risk by creating a sound and stable financial system.

Capital adequacy regulations are one of the most important components of bank regulations and are relied upon by policy-makers to ensure the stability of the banking system. While the original Basle Accord only covers the credit risk of banks, a need emerged to cover market risk of banks during the 1990s. Accordingly, the Basle Committee published the 'Amendment to the Capital Accord to Incorporate Market Risks' in 1996. In addition to the assignment of capital for credit risks, banks - with the implementation of the market risk capital regulations - have also been required to assign capital for their market risks since 1998.

From the beginning of the 1990s, the increased prominence of trading activities, in particular derivative activities, together with publicly disclosed trading activity losses, have drawn the attention of bank regulators to market risk. Accordingly, regulators integrated market risk into the risk-based capital regulations framework. There are a few more factors that also urged bank regulators to implement the market
risk capital regulations. First of all, as a result of the increased trading activities, large banking institutions developed internal control systems to measure and manage their market risk exposures. Concurrently, criticisms on the 1988 Basle Accord for only considering credit risk and not covering other risks faced by banks have increased. As a result, the Basle Committee expanded the framework of the risk-based capital regulations by implementing the market risk capital regulations. Furthermore, following the developments in the risk measurement techniques of banks, these regulations allow banks to use the internal ‘Value at Risk’ (VaR) models to calculate the required capital against market risk.

The 1996 Basle Committee amendment is a revolution in financial regulation as it allows financial institutions to use their own VaR models to determine the required capital to cover market risk. While the original accord had imposed capital requirements to cover credit risk based on a uniform approach, the amendment requires additional minimum capital to cover market risk based on either a standardised approach or an internal VaR models approach. However, the use of the internal models approach is subject to approval of regulators.

On the other hand, even though the implementation of capital adequacy regulations has led to a considerable discussion, the effects of these regulations are still unclear (Dowd, 1998). The market risk capital regulations have been effective since the beginning of 1998 and the capital regulation theory supports the view that implementing capital regulations may have significant effects on different aspects of banking behaviour. Therefore, it is very important to understand the impact of these regulations on bank activities. Even though the impact of capital adequacy regulations has been analysed extensively in the literature, apart from the study of Danielsson et al. (2004), there is not much empirical evidence concerning the impact of the market risk capital regulations. In addition, although Hendricks and Hirtle (1997) raised the question of whether the market risk capital regulations have any impact on bank capital levels, they did not carry out an empirical investigation.

The main objective of this thesis is to empirically analyse the impact of the market risk capital regulations on bank capital levels and derivative activities. In addition,
this thesis also analyses the impact of using different approaches while calculating the required market risk capital, as well as the accuracy of VaR models that are allowed to be used within the framework of the market risk capital regulations. The contribution of the study and the research questions are presented in the following section.

1.2 Contribution of the Study and Research Questions

The essential contribution of this thesis lies in two areas. Firstly, this study investigates the impact of the market risk capital regulations on bank activities. The implementation of these regulations can influence banks either by increasing their capital or by decreasing their trading activities and in particular trading derivatives. Therefore, this analysis investigates the impact of the market risk capital regulations on bank capital levels and derivative activities.

The impact of the market risk capital regulations on bank capital levels and derivative activities is an issue that has not yet been investigated in the literature. On the other hand, the economic theory is unclear concerning the impact of the implementation of capital regulations on bank capital levels. Therefore, it is important to provide further empirical evidence on this issue.

Furthermore, the theory suggests that off-balance sheet (OBS) and derivative activities of banks increase due to the lack of capital regulations. Although previous studies investigated the growth of OBS activities and the impact of capital regulations on this growth, these studies generally concentrated on other activities rather than derivatives. In addition, although there are studies in the literature that investigated the characteristics of banks that are involved in derivative activities, there is not sufficient evidence concerning the relationship between bank capital regulations and derivative activities. Therefore, it is also important to investigate the relationship between the implementation of capital regulations and derivative activities.
In order to fill the gap in the literature concerning the impact of the market risk capital regulations on bank capital levels and derivative activities, this thesis carries out an econometric analysis by using a partial adjustment framework. More specifically, the research addresses the following questions:

1) What is the impact of the implementation of the market risk capital regulations on banks' capital levels?
2) What is the impact of the implementation of the market risk capital regulations on banks' derivative activities?
3) Do large banks have lower capital ratios?
4) Do large banks use more derivative instruments?
5) Is there a relationship between bank capital levels and bank risk-taking?
6) Is there a relationship between bank capital levels and bank derivative activities?
7) Is there a relationship between bank derivative activities and bank risk-taking?

In order to answer these questions, an econometric analysis is carried out and the changes in capital and derivative activities are modelled by using a partial adjustment framework. Then, the impact of the market risk capital regulations is tested by a panel data analysis employing quarterly US Bank Holding Company data from the fourth quarter of 1995 to the fourth quarter of 1999.

The second contribution of this thesis is to demonstrate the impact of using different approaches that are allowed to be used while calculating the required market risk capital and to evaluate the accuracy of VaR models.

Although bank regulators integrated the VaR models in the framework of capital adequacy regulations, these models have limitations and pitfalls. In addition, there is still no industry consensus on a methodology for calculating VaR. The aim of establishing a set of minimum capital levels is not only necessary to strengthen the safety and soundness of the banking system but also necessary to ensure a 'level playing field' for financial institutions in order to eliminate competitive inequalities.
On the other hand, the reliance on the financial institutions’ self reported approaches to determine capital requirements could create a moral hazard problem as the institutions may have an incentive to choose inaccurate models that report less capital requirements. Therefore, it is very important to examine whether using different approaches and models that are allowed to be used by the market risk capital regulations have any potential to create a moral hazard problem.

In order to find an answer to this question, simulations are conducted to calculate the required capital amounts by using several approaches, and the different VaR models are evaluated by applying backtesting methodologies. The focus of this study is to demonstrate the outcomes of using different approaches. In particular, the research addresses the following questions

1) What kind of VaR models and parameters do banks use in their market risk measurement framework?
2) To what extent do the approaches of the market risk capital regulations produce different required capital amounts?
3) Do the market risk capital regulations provide a ‘level playing field’?
4) Do the internal VaR models provide accurate VaR estimates that reflect the market risk exposure of a bank?
5) Do the market risk capital regulations create a moral hazard problem?

In order to answer these questions, at first, differences on bank VaR practices are investigated by employing a documentary analysis. The documentary analysis is conducted to demonstrate the differences in bank VaR practices by comparing the VaR models of 25 international banks. Second, the required capital amounts are calculated for two hypothetical foreign exchange portfolios by using both the standardised and three different VaR methodologies. These simulations are carried out to make comparisons of required capital amounts. Finally, a number of backtesting methodologies are applied to the VaR models to evaluate the accuracy of these models. This analysis demonstrates a picture of the performances of the VaR models for a relatively long time period and for two foreign exchange portfolios. This analysis also demonstrates to what extent the accuracy of VaR models is affected by the portfolio compositions.
The framework of this research is shown in Figure 1.1.

Consequently, by analysing the impact of the market risk capital regulations on bank capital levels and derivatives activities and evaluating different approaches that are allowed to be used by these regulations, this research presents new evidence concerning the effectiveness of bank capital adequacy regulations. The main results of this research indicate that the implementation of these regulations has a significant and positive impact on bank capital levels. As these regulations require banks to increase their capital levels, they are effective from a regulatory perspective.
Considering derivative activities, no significant relationship was found between capital regulations and derivative usage. Therefore, the results do not support the argument that banks' derivative activities increase due to the lack of capital regulations.

Furthermore, the results of the documentary analysis demonstrate that there is no industry consensus on the methodology for calculating VaR and the assumptions in calculating VaR estimating vary considerably among financial institutions. The results of the analysis that is conducted to compare different approaches and to evaluate the accuracy of VaR models indicate that, the market risk capital regulations do not provide a 'level playing field'. In addition, the characteristics and risk nature of the portfolios could mislead bank regulators while allowing banks to use a VaR model. Furthermore, giving an option to banks to determine the VaR methodology could create a moral hazard problem as banks may choose an inaccurate model that provides less required capital amounts.

1.3 Structure of the Thesis

This chapter introduced the research objectives, contribution of the research and the research questions. Additionally, an outline of the following chapters is presented below.

Chapter 2 presents the rational for capital adequacy regulations and in particular the market risk capital regulations. Providing these concepts is crucial as they contribute to the theoretical framework of the study. The intermediary role of banks in economies and developments in banking activities, particularly the use of derivative activities, are discussed in this chapter. Next, the rationale for bank regulations is provided and the 'free banking theory' is discussed. The role of capital in a bank and capital adequacy regulations are also introduced in this chapter. Finally, the market risk capital regulations are introduced.

Chapter 3 presents the literature review concerning the impact of capital adequacy regulations. After discussing the interaction between deposit insurance and capital
regulations, the literature related to the impact of capital adequacy regulations on bank capital is reviewed. Then, the literature concerning the impact of capital adequacy regulations on bank risk-taking is reviewed. This is followed by reviewing the literature concerning the impact of capital adequacy regulations on bank off-balance sheet (OBS) activities, as well as reviewing the studies that examined the characteristics of banks that are involved in derivative activities. The literature review that is provided in this chapter is crucial as it provides the theoretical background of the empirical analysis that is provided in the fourth chapter.

Chapter 4 empirically investigates the impact of the market risk capital regulations on bank capital levels and derivative activities. In this study, the changes in capital and derivative usage ratios are modelled by using a partial adjustment framework. The study focuses on the large US BHCs as they are more involved in trading activities and therefore subject to the market risk capital regulations. Using quarterly data for the period 1995Q4 to 1999Q4, the estimates are obtained by the panel data analysis.

Chapter 5 introduces the concept of VaR. The chapter is organised in a way that shows how VaR was developed, uses, and limitations of VaR, and methodologies of VaR. The understanding of the VaR concept and in particular the understanding of different VaR methodologies is essential, as these methodologies are applied to the hypothetical foreign exchange portfolios to evaluate the market risk capital regulations in the eighth chapter. This chapter also introduces the literature review concerning the outcomes of choosing different VaR methodologies.

Chapter 6 reviews the backtesting methodologies that evaluate the accuracy of VaR measures. There are a variety of tests that are used to backtest VaR models and they focus on a particular transformation of the reported VaR and the realised profit and loss. In particular, the regulatory backtesting required by the Basle Committee amendment, the statistical tests and the ranking tests are explained in this chapter. The understanding of backtests is crucial, as these tests are applied to evaluate different VaR models in the eighth chapter.
Chapter 7 presents the disclosure practices of banks' VaR models. After introducing the regulatory efforts to increase disclosure concerning qualitative and quantitative market risk information, the annual reports of a bank are evaluated to demonstrate how the market risk disclosures have evolved. This is followed by conducting a documentary analysis to demonstrate the differences on bank VaR practices by comparing the VaR methodologies of 25 international banks.

Chapter 8 provides the empirical results of the simulation and backtesting analyses. In the simulation analysis, the required capital amounts are calculated for two hypothetical foreign exchange portfolios by using both the standardised and three different VaR methodologies and then these capital amounts are compared. These simulations are conducted to understand to what extent the approaches of the market risk capital regulations produce different outcomes on the capital levels. In addition, the models that provided the VaR estimates are validated by backtesting.

Finally, Chapter 9 summarises all the key findings of the research. The policy implications of the research are also presented in this chapter. In addition, suggestions for future research are provided.
CHAPTER TWO

THE RATIONALE FOR
CAPITAL ADEQUACY REGULATIONS AND
THE MARKET RISK CAPITAL REGULATIONS

2.1 Introduction

Banks have a unique role in economies. Therefore, it is crucial to have a sound and stable banking system. In order to ensure the soundness and stability of a banking system, policy-makers implement regulations. The main underlying rationale of these regulations is to counter the potential effects of bank failures on the economy and to avoid systemic risk.

Capital adequacy regulations are one of the most important components of banking regulations that policy-makers rely on to ensure the stability of a banking system. Even though bank regulators implement capital adequacy regulations, the impact of these regulations is not clear. Therefore, it is crucial to understand the effects of these regulations. As the main objective of this thesis is to evaluate the impact of the market risk capital regulations, this chapter introduces the rationale for bank capital regulations and in particular the market risk capital regulations.

The rest of this chapter is organised as follows. The second section presents the role of banks in economies. In particular, this section discusses the intermediary role of banks and the use of ‘derivatives’. The third section provides the rationale for bank regulations. The ‘free banking theory’ is also introduced in this section. The fourth section discusses the role of capital in the banking system and capital adequacy regulations. The fifth section examines the framework of market risk capital regulations. Finally, a chapter summary is provided.
2.2 The Role of Banks

Banks are traditionally defined as financial firms that accept deposits and lend money. They play a major role between borrowers and lenders, which ensures that the financial system and the economy run smoothly and efficiently.

In traditional banking, banks serve two principal intermediary functions. Firstly, banks use the funds of those who have financial surpluses and lend these funds to those who need funds for their activities. Therefore, the liability side of a bank balance sheet mainly consists of deposits and the asset side mainly consists of commercial loans and investments. Secondly, banks provide payment systems to liability holders and a positive return for their savings.

There are two factors that enable banks to perform these intermediary roles. These are 'information costs' and 'liquidity preferences.' As a consequence of 'information costs', it will be more costly for lenders to offer their funds to borrowers without the intermediary function of banks. Fama (1985) states that "a bank has a low-cost ongoing history of financial information that gives it a comparative cost advantage in making and monitoring repeated short-term inside loans." Heffernan (1996) points out four factors that cause 'information costs'. These factors are: searching, verification, monitoring, and enforcement. In general, lenders lack the ability and skills needed when it comes to 'information costs'. Therefore, banks are needed to search and verify information about potential borrowers. In addition, banks monitor the management of borrowing firms by enforcing loan agreements (Gorton and Rosen, 1995). Without the intermediation of a bank, many lenders would only be able to fund a few projects. Thus, they would not be able to diversify their risks and would be forced to lend large amounts of funds to a very few projects (Bhattacharya et al., 1998). Correspondingly, Koppenhaver (1989) argues that in a world of transaction costs, financial intermediaries achieve economies of scale through specialisation in documentation, information collection, and monitoring. Koppenhaver also argues that informational asymmetries between borrowers and lenders provide an opportunity for financial intermediaries to access the quality of specific information on the borrower better than the lender, thus allowing the
financing of a particular project to be at a lower cost for individual borrowers. Accordingly, intermediaries are useful for resolving ex post informational asymmetries between borrowers and lenders, as intermediary diversification lowers the cost of information production because of the economies of scale (Diamond, 1984).

'Liquidity preference' is the second factor that enables banks to perform their intermediary role. Without the intermediary function of banks, it will be very costly for lenders and borrowers to find suitable counterparties with the same liquidity preferences. By pooling a large number of borrowers and lenders, banks match parties with the same liquidity preferences. In addition, banks could provide liquidity to lenders on their demand, as they could transform illiquid assets into liquid funds (Diamond and Dybvig, 1983)\(^1\). In summary, borrowing and lending have been an important part of the traditional intermediation function of banks and historically banks have been very successful as an intermediary (Gjerde and Semmen, 1995). In traditional banking, banks identify potential borrowers, perform credit evaluations, fund loans with bank deposits, and service these loans.

However since the 1970s, banking has changed substantially and traditional banking has declined. Traditionally, banks act as intermediaries by transferring funds from lenders to borrowers. Non-traditional activities range from custodial services and underwriting activities to off-balance sheet (OBS) activities. Since the 1970s, an important shift has occurred in the traditional intermediary function of banks and banks have started to offer more non-traditional OBS activities to their customers.

OBS items (acceptances, guarantees, other commitments, and derivative activities) are contingent commitments that are not captured on the balance sheet as assets or liabilities. These contingent commitments are possible future commitments and they are not accounted for by an adjustment on the financial statements, but are added to the notes section of the balance sheet.

\(^1\) If banks face any liquidity problems, they could also access the sources of central bank, which is the 'lender of last resort' in an economy.
In particular, derivative activities have increased dramatically since the 1980s. And until the early 1970s, there was relatively little volatility in both exchange rates and interest rates in the financial markets. Matten (1996) argues that there was no need to worry regarding the efficient allocation of resources until the 1970s. That was an age of 3-6-3 banking (borrow at 3 percent, lend at 6 percent and be at a golf course by 3 pm). However, starting from the early 1970s, banking has become more competitive. With the breakdown of the Bretton Woods Agreement\(^2\) and with the major increase in the level of interest rates during the 1970s, foreign exchange and interest rates have become increasingly volatile. The volatile rates and prices have had a damaging impact not only on borrowers but also on lenders as well (Howcroft, 1985). Increased volatility in the financial markets, increased competition, global deregulation, advances in finance theory and technology, and regulatory changes have created a demand for instruments that could assist borrowers, lenders, banks and other institutions to reduce their financial risks.

Accordingly, in order to actively manage the interest rate and exchange rate risks, financial institutions start to use derivative activities, which are formal agreements to transfer risk without transferring the underlying basic instrument.

‘Derivatives’ is a general term that covers four major types of instruments, namely forwards, futures, options and swaps. These instruments are briefly explained in Appendix 2.1. These instruments are called ‘derivatives’ as they are derived from a reference rate (such as interest rate, exchange rate or stock index) or from an underlying asset, which can be either a commodity, or a financial asset.

Although risk-taking is in the nature of banking, the explosive growth of derivative activities in the last three decades has increased the concerns of policy-makers. In particular, bank regulators concerned about the rapid increase in derivative activities of banks after some financial institutions reported large trading losses that occurred from derivative activities during the 1990s. It is generally accepted that huge losses incurred from derivative activities could not only pose a risk to the stability of

\(^2\) The Bretton Woods Agreement, which was established during the Second World War, had maintained monetary order by fixing currency exchange rates (providing exchange rate and consequently interest rate stability).
individual institutions but to the financial system as a whole. After pointing out the increase in the total amount of interest rate, currency, commodity and equity derivative contracts at the US commercial and saving banks, Simons (1996) expresses the concerns of regulators with the following words:

"A major concern facing policymakers and bank regulators today is the possibility that the rising use of derivatives has increased the riskiness of individual banks and of the banking system as a whole."

Graph 2.1 demonstrates the upward trend of the trading losses that have occurred from derivative activities very clearly. While publicly disclosed derivative transaction losses were less than USD 5 billion at the end of 1993, these losses increased to USD 30 billion as of December 1998.

Although financial derivative instruments have been innovated to manage market risk, they can also be used for speculative purposes. Banks use 'derivatives' either to reduce the risks arising from their banking activities, i.e. hedging, or to obtain profits through higher exposure, i.e. speculating. Therefore, it is generally accepted that there are two main reasons to use derivative instruments, namely hedging and speculation.

Hedging is a tool for transferring risk from those wishing to avoid it to those willing to assume it. This activity involves taking a position to cover or reduce risk on an open or anticipated position. By hedging a risk, losses from adverse movements are
compensated by offsetting gains from the hedge. However, hedging not only reduces the risk of loss from adverse price or rate fluctuations, but also limits the gain from favourable changes. In order to hedge a certain risk position, it is crucial to understand the nature and the extent of risks.

Although derivative instruments offer certain advantages to hedge financial risks, they also provide speculative opportunities. Speculation involves taking an open risk position with a view of profiting from perceived future market movements or earning from bid/offer spreads. Speculators are necessary for the efficient working of any financial market because they provide the necessary liquidity that makes it possible for hedgers to cover their risk.

Financial institutions participate in ‘derivatives’ markets as either ‘end-users’ or ‘dealers’. As ‘end-users’, institutions can either use derivatives to hedge their own exposure or speculate on the movements of the underlying economic variables. On the other hand, ‘dealers’, which are generally banks and securities firms, act as counterparties and provide over-the-counter (OTC) derivative instruments to other banks or clients. When a dealer takes a position, it immediately matches this position by entering into an opposite position. While almost every bank participates to a certain extent as ‘end-users’, only a few of the largest institutions are dealers of OTC derivative instruments.

Financial derivative instruments have been innovated to manage market risk arising from volatile interest rates and floating exchange rates. However, if market risk is not managed properly, as the ‘derivative disaster’ cases of Metallgesellschaft, Barings, Orange County, Daiwa, and Procter and Gamble have demonstrated, the institutions could either fail or realise enormous losses. These derivative disasters highlighted the need for a better understanding of risk management in financial institutions. After the collapse of Barings in 1995, Alan Greenspan (1997) explained his concern about risk management with these words:

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3 The general point of all these cases is that all of these companies suffered from derivative trading. For example, Barings Bank of the UK went bankrupt when a rogue trader, Nick Leeson, lost USD 1.3 billion from derivative trading. Metallgesellschaft, a German firm, also lost USD 1.3 billion and Daiwa Bank lost USD 1.1 billion from derivative trading.
"The Barings episode suggests that further improvements to internal risk management systems are needed."

Similar to other businesses, banks face risks in their activities. However, because of their crucial role in economies, it is more important for banks to manage their financial risks. The most important financial risks that banks face are; credit, market, liquidity, country, operational, legal and reputation risks. These risks and types of market risks are described in Appendix 2.2 and Appendix 2.3, respectively.

For banks, the role of risk management is crucial as it ensures that the bank’s activities do not expose it to losses that could result in a failure. However, risk management in banks is also important from a regulatory point of view, due to the crucial role of banks in economies. Therefore, banks are among the most highly regulated industries in an economy as it is generally accepted that the overall health of the financial system depends on the adoption of sound risk management practices at the individual bank level.

Especially, in recent years bank regulators place significant emphasis on the adequacy of an institution’s management of risk, including the establishment of a management structure that adequately identifies, measures, monitors and controls financial risks. In 1997, the Basle Committee issued ‘Core Principles for Effective Banking Supervision’, which is a comprehensive set of 25 core principles for effective banking supervision. Among these principles, 10 of them are related to risk management in banks. Furthermore, the market risk capital regulations require banks to establish both qualitative and quantitative risk management criteria.

Traditionally, the main concern of bank regulators has been credit risk. The Basle Accord of 1988 was implemented as a principal measure to control bank credit risk-taking. However, in recent years market risk has gained importance with the increase in trading activities and derivative usage. Consequently, since 1998 banks have been required to hold capital against their market risks as well. As the aim of this thesis is to investigate the impact of the market risk capital regulations, it is important to understand the characteristics of these regulations. The next sections present the rationale for bank regulations and capital regulations.
2.3 The Rationale for Bank Regulations

The previous section has provided the unique role of banks in economies. This role not only distinguishes banks from other companies, but also makes them one of the most regulated industries in almost any economy. According to the Financial Services Authority (FSA), the financial regulator of the UK, “Banks are different from other companies because of their responsibilities to depositors and potential depositors and because of the potential impact on the wider financial system if they run into difficulties.” (www.fsa.gov.uk)

In general, it is believed that banks should be regulated as these regulations could prevent them from failures. Otherwise, the failures of banks could cause a large scale cost not only to the national economy but also to the global economy due to the contagion effect. Concerning the cost of banking crises, Llewellyn (2000) states that in approximately 25 percent of the cases (Spain, Venezuela, Bulgaria, Mexico, Argentina and Hungary are the examples of countries that experienced high losses) the cost of bank failures exceeded 10 percent of gross national product (GNP). The cost of banking crises were more dramatic for Indonesia and Thailand as the costs exceeded 45 and 40 percent of these countries’ gross domestic products (GDP), respectively⁴ (Evans, 2000).

The strength of the banking system is vital as problems in the banking sector affect other sectors rapidly. For example, the failure of a bank could reduce the amount of loans available to an economy, initiate withdrawals of deposits, and increase the demand for safe heaven instruments. In addition, the payments system could collapse and this would lead to turmoil in the financial markets (Kaufmann, 1999).

As bank failures not only affect the financial market members but also have consequences that affect the economy as a whole, regulators intervene in various ways in order to reduce the occurrence of financial crises and to lessen the damage

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⁴ These figures include the compensation that was paid to depositors under 100 percent coverage and the public sector payments to finance the recapitalisation of insolvent banks.
that these crises could cause. As a result, the banking industry is one of the most tightly regulated industries and banks operate under unusual regulatory restrictions; including liquidity requirements, loan diversification standards, activity and ownership restrictions, deposit rate ceilings, limitations on a bank's investment portfolio or lines of business, restrictions on the type of information that banks may release to the public and other restrictions intended to limit the type of risks which a bank may undertake (Flannery, 2001).

In addition to these regulations, regulators employ a large army of personnel engaged in supervision. These include resident examiners who are posted full-time in some of the larger banks and examiners who go on-site, usually once a year, to conduct bank examinations. Furthermore, in order to identify problem banks, bank regulators establish early warning systems and bank analysts perform off-site examinations on a regular basis. Pettway and Sinkey (1980) argue that the objective of an early warning system is to identify the risks of banks before those risks jeopardise the financial conditions of banks and notify bank management to take necessary measures to avoid bankruptcy.

Banks play a crucial role in the payment system of an economy and as they mainly collect deposits, they are highly leveraged. A failure of a bank could be very harmful as it could cause deposit runs and collapse of payment systems, which could lead to systemic risk. That is the main reason why regulators put special emphasis on controlling bank risk-taking. Aziz (2004) summarises the importance of prudential bank regulations by stating that:

"A well functioning and efficient banking sector is vital for the economic growth process. The banking institutions perform the important intermediation function of mobilizing funds to finance productive activities. This intermediation process needs to be performed in an environment of financial stability. Therein lies the importance of confidence and soundness of the financial system. Banking business inherently involves risks and these risks need to be rigorously managed. In an environment of heightened uncertainty and increased volatility, this needs to be reinforced with the development of a more robust and resilient banking system. Hence the importance of prudential regulations to ensure the soundness and stability of the financial system."
As a result, the central purpose of bank regulations is to reduce the probability of bank failures and consequently enhance a sound and stable financial system. However, while banks are subject to extensive regulations in nearly all facets of their operations, some argue that bank regulations are not necessary to the well-being of an economy. This argument is called the 'free banking theory' and it involves a financial system with no regulator and no government intervention. In 'free banking', financial institutions are allowed to operate freely and they are only subject to market forces and regular commercial law. The advocates of 'free banking' point out that especially in the 19th century there were several countries with unregulated banking systems and the experiences of these countries demonstrate that unregulated competition among banks does not destabilise the banking system.

According to the 'free banking theory', markets generally work better than governments and financial markets should be left to regulate themselves, as market forces could provide a more stable financial system (Dowd, 2001). One of the most important arguments of the 'free banking theory' is that, with no 'lender of last resort' or deposit insurance, market forces could exert market discipline. According to the theory of market discipline, bank depositors could exert market discipline either by withdrawing their funds or by requesting higher risk premium from riskier banks. In order to continue to do business, bank managers take some necessary measures, such as increasing the institution's capital level, publishing audited accounts, and pursuing conservative lending policies (Dowd, 1996).

In particular, bank capital level is crucial for a bank to maintain its activities as an adequately capitalised bank so that it could absorb unexpected losses. The advocates of 'free banking' consider that instead of government regulations, the precise amount of capital should be determined by market forces. However, capital is costly and without an efficient market discipline, bank managers may not prefer to increase the institution's capital level. Therefore, arguing that market forces, in particular depositors, might not be able to exert market discipline efficiently; financial system policy-makers implement financial safety nets, such as the 'lender of last resort' facility and deposit insurance to enhance the stability of the financial system.
When banks have urgent liquidity needs, central banks provide them necessary liquidity in order to prevent financial crises and this facility is known as the ‘lender of last resort’ facility. The main objectives of this policy are to protect the integrity of the payments system, avoid bank runs, and prevent illiquidity at an individual bank from unnecessarily leading to its insolvency (Folkerts-Landau and Lindgren, 1998). However, this facility could result in a moral hazard problem. If banks are aware of the fact that they could easily assess to the ‘lender of last resort’ facility, they might not carry out a prudent liquidity policy. This moral hazard problem is also a negative aspect of deposit insurance, which is another important component of the financial safety nets. Policy-makers generally consider that deposit insurance is necessary to protect small depositors and to prevent bank runs. Consequently, deposit insurance ensures the stability of the financial system. The advocates of deposit insurance argue that, in particular deposit insurance protects small depositors by covering the losses of those who are unable to foresee a bank failure. Otherwise, when depositors are suspicious concerning the financial condition of their banks, they would withdraw their deposits and deposit withdrawals could have a domino impact that could lead to bank runs. As a result, these bank runs could threaten the financial system as a whole. Therefore, deposit insurance is considered an important safety net that prevents panic and systemic risk.

On the other hand, while the existence of a deposit insurance scheme might prevent bank runs, it could also cause a moral hazard problem. When a deposit insurance scheme is implemented, depositors no longer have any incentives to monitor the financial conditions of their banks. Consequently, failing banks continue to engage in risky activities, as depositors do not punish these banks by withdrawing their deposits or by requiring higher interest rates.

As a result, deposit insurance could encourage risk-taking by banks, which is called the moral hazard problem. Dowd (1996) explains the effects of deposit insurance by stating:

“Once we introduce deposit insurance, depositors no longer have any incentives to monitor bank management and managers no longer need to worry about maintaining confidence. A bank’s rational response is to reduce its capital, since the main point of maintaining capital strength – to maintain
depositor confidence - no longer applies. Even if an individual bank wished to maintain its capital strength, it would be beaten by competitors who cut their capital ratios to reduce their costs and passed some of the benefits to depositors by offering them higher interest rates. The fight for market share would then force the good banks to imitate the bad. Deposit insurance consequently transforms a strong capital position into a competitive liability, reduces institutions' financial health and makes them more likely to fail. It also encourages more bank risk-taking at the margin: if a bank takes more risks and the risks pay off, then it keeps the additional profits; but if the risks do not pay off, part of the cost is passed on to the deposit insurer. The bank therefore takes more risks and becomes even weaker than its capital ratio alone would suggest."

These discussions lead to two main arguments concerning the effects of deposit insurance. According to 'stability theory', deposit insurance contributes to financial stability. On the other hand, according to 'risk-taking theory', as a result of moral hazard and reduced market discipline that arise from deposit insurance, banks increase their risk-taking.

The advocates of the 'free banking theory' argue that, as moral hazard creates a major risk, deposit insurance should not be implemented and the system should rely on market discipline. However, bank regulators consider that bank runs are a significant source of financial instability that could have disruptive and costly effects. In addition, they generally argue that it is difficult for depositors to exert market discipline by assessing the financial soundness of individual banks. According to Miles (1995), in practice it is not easy for depositors to assess a bank's capital strength due to the information asymmetry between bank and depositors. As a result, the advocates of 'stability theory' argue that depositors (in particular small depositors) should be protected by implementing a deposit insurance scheme.

On the other hand, Dowd (1999) argues that, in practice depositors can assess the capital strengths of banks especially by relying on shareholders to value bank capital. Dowd also states that "If the information exists for the regulator to formulate a feasible capital adequacy rule, that same information could also be used to convey credible signals to depositors about the capital strength of their banks."

Benston and Kaufman (1996) also argue that depositors and shareholders can
distinguish solvent banks from insolvent banks. However, they also state that deposit insurance exists 'in the world in which we live'. In addition, according to Benston and Kaufman, in order to counter the negative externalities that result from deposit insurance, banks should be regulated prudentially. They place a particular emphasis on capital adequacy regulations and conclude that if the moral hazard problems created by the existence of a deposit insurance scheme and a 'lender of last resort' facility encourage banks to take excessive risks, banks should be required to hold sufficient capital to absorb unexpected losses.

The role of capital in a bank and capital adequacy regulations are explained in the next section.

2.4 The Role of Capital and Capital Adequacy Regulations

Among several tools of prudential bank regulations, capital adequacy regulations attract the attention of regulators. Bank regulators require financial institutions to maintain adequate capital as a response to the negative externalities arising from bank failures and to the risk-shifting incentives created by deposit insurance. Furthermore, Kim and Santomero (1988) argue that capital regulations serve as a method of coinsurance as holding high capital results in absorbing higher losses in the event of a failure and therefore encourage additional prudence in management. In addition, Dowd (2000c) argues that bank capital is a device to give depositors rational confidence in a bank and if a bank has sufficient capital, there will be no bank stability problem.

While capital is considered as an important source from a regulatory perspective, it is not desirable for banks to hold much capital as they can fund themselves from other sources, such as deposits. In fact, the theory that was developed by Modigliani and Miller (1958) demonstrates that, in well-functioning capital markets the market value of a company does not depend on its capital structure, i.e. the value is not affected by changing the combination of debt and equity\(^5\). However, a firm's capital structure

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\(^5\) Referred as MM, this theory assumes a market with no taxation, information costs, or transaction costs.
does matter, as equity is a more expensive funding source than debt in a market
where returns to debt holders are tax deductible but returns to equity holders are
taxable (Pavel, 1988). Mingo (1975) and Pavel and Phillis (1987) also argue that
bankers find capital adequacy regulations stringent and hence, these regulations
create a funding disadvantage for banks. Therefore, while regulators consider capital
adequacy of banks as an important factor to maintain a safe and sound banking
system and prefer higher levels of capital, bank managers consider the
implementation of capital regulations as a regulatory cost.

As illustrated in Figure 2.1, capital is the difference between an institution’s assets
and liabilities in accounting terms. However, institutions and regulators have
different purposes for capital. From the perspective of an institution, capital is the
long-term source of funding, which is provided by investors or by the firm through
retained earnings to fund operations, and capital adequacy is an important issue of
controlling and running their portfolios. Howcroft (1985) states that, “Bankers view
of the function of capital is basically concerned with maintaining the lowest possible
capital base in an endeavour to maximise returns within an acceptable level of risk.”

Figure 2.1: A Basic Balance Sheet Example

BANK BALANCE SHEET

<table>
<thead>
<tr>
<th>ASSETS</th>
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<table>
<thead>
<tr>
<th>LIABILITY</th>
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<tbody>
<tr>
<td>CAPITAL</td>
</tr>
<tr>
<td>(Equity + Reserves)</td>
</tr>
</tbody>
</table>

On the other hand, the regulatory view considers capital as a cushion that absorbs
unexpected losses, which are caused by exposure to various risks that the firm faces
in its business activities. According to Greenspan (1998), capital is not only a topic
of never ending importance to bankers and their counterparties, but also to regulators
and central bankers whose job is to oversee the stability of the financial system.
Indeed, the primary role of bank regulators has always been to ensure that banks
have adequate capital to cover outstanding risk exposure and therefore safeguard the financial stability. From a supervisory perspective, capital has a crucial role in a financial firm, as it provides a buffer against losses. As an example, the FSA defines the role of bank capital as:

"Capital provides a buffer that enables a bank to absorb a level of losses without the interests of depositors being adversely affected, and thus protects the interests of depositors." (www.fsa.gov.uk)

Holding sufficient capital is believed to ensure a bank, and consequently the banking system, is safe and sound. However, it is important to mention that the sufficiency concerning the amount of capital is an issue that cannot be easily solved. On the contrary, regulators also raise their concerns while setting high capital standards. For example, Greenspan (1998) states that bank shareholders must earn a competitive rate of return and those returns are adversely affected by high capital requirements. He also points out that in times of difficulties, not only bank capital, but also sound policy actions are required to preserve financial stability. Indeed, although an essential one, capital requirements are only one of a larger set of tools used to protect the stability of the financial system. The tools of prudential bank regulations are demonstrated in Appendix 2.4.

As a matter of fact, it is generally accepted that policy-makers implement capital adequacy regulations to overcome the moral hazard problems created by deposit insurance and the existence of a ‘lender of last resort’ (Benston and Kaufman, 1996). However, there are two more arguments that justify the existence of capital adequacy regulations. While Miles (1995) argues that capital adequacy regulations should be implemented to counter market failure, Dewatripont and Tirole (1994) also argue that these regulations are needed to protect small depositors.

On the other hand, Dowd (1997) argues that the specific arguments that justify the existence of capital adequacy regulations are weak and unconvincing. According to Dowd, the market failure argument is based on a wrong basis and it is not so difficult for depositors to monitor the financial conditions of their banks by relying on shareholders to value bank capital. Concerning the Benston and Kaufman argument, Dowd argues that this argument does not offer any substantial challenge to the ‘free
banking theory’. Furthermore, he states that capital adequacy regulations can create a moral hazard problem by increasing banks’ risk-taking. Consequently, although the intention of regulators is to make banks safer by implementing capital adequacy, regulations may have the opposite effect and could result in banks increasing their risk-taking.

Nevertheless, because of the significance attached to capital in a financial institution, regulators affect bank capital by setting capital adequacy regulations to ensure that banks hold sufficient capital to absorb unexpected losses. Initially, the capital standards required banks to hold a flat minimum percentage of capital, which was set against all of the assets, irrespective of risk. However, capital adequacy regulations have changed dramatically since the 1980s. For example, prior to 1981, bank regulators did not enforce specific uniform guidelines for capital adequacy in the US. During that period, capital levels at individual banks were determined by considering the results of examinations and peer group capital levels. At the beginning of the 1980s, the bank regulators in the UK and US issued minimum capital standards for banks as a result of the significant decline in the capital position of many banking organisations throughout the 1970s (Jacques and Nigro, 1997). In the US, capital adequacy regulations implemented in 1981 required banks to hold a flat minimum percentage of capital, which was set against all of the assets, irrespective of risk (Avery and Berger, 1991). These minimum capital ratios for banks and BHCs were implemented in the US to bring more uniformity, objectivity, and consistency to the regulatory process (Baer and McElravey, 1993).

On the other hand, the first step towards risk-based capital regulations was taken by the implementation of the 1988 Basle Accord, which considers only the credit risk of banks. As the extension of credit is a primary activity of banks, regulators first concentrated on controlling the level of credit risk in order to ensure that banks are sufficiently capitalised to cover potential losses due to counter-party default.

Baer and McElravey (1993) explain the developments that have resulted in the implementation of the Basle Accord by stating that:

“In 1986, the Federal Reserve Board announced plans to impose risk-based
capital guidelines on U.S. banks, to better protect the deposit insurance fund, and to increase the safety of the banking system. However, the rapid growth of the international banking system and surging competition from foreign banks in the U.S. market made international coordination of capital requirements crucial in any attempts to increase the safety of the U.S. banking system. Regulators in many other countries also considered an international risk-based capital agreement to be desirable as a means of levelling the playing field, and allowing their banks to compete more effectively against foreign banks that seemed to be gaining worldwide market share. As a result, an international agreement on capital adequacy was produced under the auspices of the Bank for International Settlements.”

In July 1988, the Basle Committee on Banking Supervision (Basle Committee)⁶, whose members are representatives of the central banks and supervisory authorities of 12 industrialised countries⁷, published the ‘International Convergence of Capital Measurements and Capital Standards’, which is known as the Basle Accord. The main objectives of the Basle Accord are to strengthen the soundness and stability of the banking system and provide a ‘level playing field’ for banks, by requiring banks in member countries to hold a minimum level of capital in accordance with the perceived credit risk that banks face during their operations.

According to Baer and McElravey (1993), there are four main advantages of the risk-based capital regulations. These are:

1) The risk-based capital regulations incorporate off-balance sheet activities.
2) The risk-based capital regulations employ a more conservative and accurate definition of capital.
3) The risk-based capital regulations have increased the incentives for banks to raise additional capital in the form of preferred stock and subordinated debt that are included in tier-2 capital.
4) The risk-based capital regulations provide banks with additional flexibility for maintaining capital adequacy. The previous regulations

⁶ The Basle Committee on Banking Supervision is a committee of banking supervisory authorities, which was established in 1975. This committee usually meets at the Bank for International Settlements in Basle, Switzerland.
⁷ These countries are Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States.
allowed banks that fell below the regulatory minimum to have only two choices, i.e. to decrease assets or increase capital. However, the risk-based capital regulations allow banks to have an additional option by allowing them to classify bank assets according to their risk-weight categories to remain in compliance with the required capital.

The Basle Accord of 1988 requires banks to have a minimum eight percent risk-weighted capital ratio (the ratio of base capital to risk-weighted assets). Capital is defined in two tiers. Tier-1, or core capital, consists of equity and disclosed reserves. Tier-2, supplementary capital, which cannot exceed tier-1, contains undisclosed reserves, revaluation reserves, general provisions/general loan loss reserves, subordinated debt with maturity more than five years and hybrid debt capital instruments (e.g. perpetual debt instruments). The total of tier-1 and tier-2 is the base capital and in order to calculate the capital amount that is used in the risk-weighted capital ratio, goodwill and investments in financial subsidiaries should be subtracted from the base capital.

The rules are formula-based and apply risk weights to reflect different classifications of counter-party credit risk to assets and off-balance sheet items. The implementation of the risk-based capital regulations is a revolutionary development in bank regulations in terms of connecting capital to risk and requiring banks to hold capital against off-balance sheet items. Consequently, this accord has been adopted by several national bank regulators.

Following the publication of the Basle Accord, the European Community (EC) has subsequently issued two directives on the subject, the ‘Own Funds Directive’ and the ‘Solvency Ratio Directive’. While the ‘Own Funds Directive’ (89/299/EEC) defines what is regarded as a bank’s capital resources for supervisory purposes, the ‘Solvency Ratio Directive’ assigns weightings to the various classes of assets and establishes the minimum risk asset ratio. These directives mainly pick up the Basle Committee regulations and apply them to the EC member states.

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8 The Basle Accord rules have been adopted in more than 100 countries (Jackson et al., 1999).
Although the Basle Accord is a revolutionary development in the framework of capital adequacy regulations, it has been highly criticised not only by bankers (Price Waterhouse, 1991), but also by academics (Alfriend, 1988) and regulators themselves (Greenspan, 1998). One of the most important criticisms of the Basle Accord is that, these regulations only focus on credit risk and do not take into account other factors, such as interest rate risk, concentration of investments and loans, quality and level of earnings, problem and classified assets, and quality of management.

Other criticisms of these regulations are summarised below:

- These regulations do not consider the credit-worthiness of different private sector customers,
- These regulations do not recognise the effect of diversification on risk,
- These regulations do not take netting into consideration. Therefore, instead of the net exposure, banks raise capital for both of the transactions in which they match borrowers and lenders.

Since the publication of the Basle Accord in 1988, five amendments have been made. Four of them were specific changes to the language of the original Accord. However, the ‘fifth amendment’ was established to alter the capital requirements in order to include market risk of banks. According to Hall (1995), there are a number of developments that reflect the concerns of regulators which resulted in widening the risk-based capital regulations to capture market risk. These are:

1) The deregulation of interest rates,
2) The dismantling of capital controls,
3) The relaxation of constraints on banks’ permitted range of activities,
4) The erosion of the traditional distinction between ‘banks’ and ‘securities firms’,
5) The rapid growth of banks’ trading in derivatives, foreign exchange and securities, which increased the market risk faced by banks.
The amendment that covers banks' market risk, entitled 'Amendment to the Capital Accord to Incorporate Market Risks', was issued in January 1996. These new rules require banks with a significant amount of market risk to hold capital against their market risk. The next section examines the framework of the market risk capital regulations in detail.

2.5 The Market Risk Capital Regulations

While until the 1980s bank regulations have been affected on a national level, the gradual liberalisation of financial markets and increased cross-border transactions have raised the need for global capital adequacy rules (Kjeldsen, 1997). The Basle Accord was accepted as a result of such efforts in 1988. These regulations introduced uniform capital adequacy requirements for banks by forcing them to maintain at least eight percent capital for their traditional banking and off-balance sheet activities. However, these regulations are only related to credit risk and do not consider market risk of banks arising from interest rate and foreign exchange rate exposures. For example, although government bonds have an interest rate risk, the original accord does not require capital for these assets. Therefore, as the original accord only covers the credit risk of banks, a need emerged to cover banks' market risk with the increase of banks' trading activities in securities and derivatives.

In April 1993, the Basle Committee issued a consultative proposal to amend the Accord and required institutions to measure and hold capital to cover their exposure to market risk. However, this proposed amendment was offering a standardised approach. The standardised approach uses a 'building block' approach, which requires banks to apply certain uniform techniques to calculate a capital charge for each of the market risk categories. The total capital charge is the sum of the capital charges for each risk category. On the other hand, during the 1990's increased attention was paid to Value at Risk (VaR), which is a tool that financial institutions use to measure their market risk. Financial institutions that were invited to comment on this proposed amendment criticised the standardised approach and claimed that their internal VaR models provide more reliable forecasts of market risk.
The attempt made by financial institutions to use the VaR methodologies for measuring their market risk has led supervisors to introduce a new approach to calculate capital requirements for this special kind of risk. In 1996, the Basle Committee published the ‘Amendment to the Capital Accord to Incorporate Market Risks’. The Basle Committee’s objectives in introducing this amendment, which they call a ‘significant amendment’, are as follows:

1) To provide an explicit capital cushion for price risks, especially risks arising from trading activities, to which banks are exposed,
2) To strengthen the soundness and stability of the international banking system,
3) To achieve improvements in risk management techniques by implementing qualitative standards to the banks which base their capital requirements on the results of internal models.

This amendment establishes a capital adequacy framework to capture market risk, which is one of the primary risks that banks face in their operations. In particular, the amendment covers the following risks:

1) The risks pertaining to interest rate related instruments and equities in the trading book,
2) Foreign exchange risk and commodities risk throughout the bank’s balance sheet.

The framework of the market risk capital regulations is illustrated in Figure 2.2.
Market risk consists of 'general market risk' and 'specific risk'. The 'general market risk' refers to changes in the market value of on-balance sheet assets and liabilities and off-balance sheet items resulting from broad market movements, such as changes in the general level of interest rates, equity prices, foreign exchange rates and commodity prices. The 'specific risk' refers to changes in the market value of individual positions due to factors other than broad market movements and includes such risks as the credit risk of an instrument's issuer. On the other hand, the capital charges for foreign exchange and commodity risks apply to total currency and commodity positions of banks.

The 1996 amendment contains comprehensive capital adequacy rules to protect financial institutions against market risk on the trading book. According to the Basle Committee, a trading book consists of positions in financial instruments and commodities held either intent or in order to hedge other elements of the trading book. To be eligible for trading book capital treatment, financial instruments must either be free of any restrictive covenants on their tradability or able to be hedged completely. In addition, positions should be frequently and accurately valued, and the portfolio should be actively managed.

The trading book implies a bank's proprietary positions in financial instruments\(^9\),

\(^9\)To establish a relevant base for measuring market risk in the trading book, all items should be marked to market.
including positions in derivative instruments and off-balance sheet items, which are:

1) Intentionally held for short-term resale,
2) Taken on by the bank with the intention of benefiting in the short-term from actual and/or expected differences between their buying and selling prices, or from other price or interest rate variations,
3) Positions in financial instruments arising from matched principal brokering and market making,
4) Positions taken in order to hedge other elements of the trading book.

As a complement to the capital requirement calculation for credit risk that uses the traditional method, banks have also been required to hold capital for their market risks since the beginning of 1998. Under the Basle Committee’s market risk amendment, a bank with significant trading activity must calculate a capital charge for market risk using either a risk-weighting process (the standardised approach) or its own internal risk measurement model10 (the internal models approach). These approaches are explained below:

1) The Standardised Approach: The standardised methodology uses a building block approach in which a bank applies certain uniform techniques to calculate a capital charge for the general market risk positions in the four risk categories, as well as for the specific risk of debt and equity positions located in the trading book. The four risk groups addressed by this amendment are: interest rate, foreign exchange rate, equity position, and commodities risks. For example, according to the standardised approach, a bank’s net foreign exchange position is calculated as the higher of the total net short positions and the total net long positions in all currencies other than the bank’s reporting currency. The sum of the capital charges for each risk category comprises the total capital charge for market risk.

10 The US financial institutions are only subject to capital requirements based on the internal models approach, which allows banks to use risk measures derived from their own internal risk management models.
2) The Internal Models Approach: As an alternative methodology, banks are allowed to use the internal models approach to calculate risk measures by using their own VaR models. However, the use of VaR models is subject to qualitative and quantitative conditions. This approach requires a bank to employ an internal model to calculate the daily VaR measures that represent an estimate of the amount by which a bank's position in a risk category could decline due to the general market movements during a given holding period, measured with a specified confidence level for each of four risk categories, as well as related options in each risk category. For the regulatory capital purposes, the market risk amendment requires a bank to calculate the VaR estimates to a ten-day movement in the rates and prices and a 99 percent confidence level. In addition, a bank should base its VaR estimates upon the rates and prices observed over a period of at least one year. In deriving the overall VaR estimate, an institution could take into account historical correlations within a risk category (e.g., between interest rates), but not across risk categories (e.g., not between interest rates and equity prices). In other words, the overall VaR measure equals the sum of the VaR measures for each risk category. A bank's capital charge for the general market risk equals the greater of the previous day's overall VaR measure or the average of the preceding 60 days' overall VaR measures multiplied by a factor of three (the multiplication factor). Moreover, the market risk amendment requires institutions to hold additional capital for the specific risk associated with debt and equity positions in the trading book.

According to the Basle Committee, the simplicity of the VaR approach is the most important feature for allowing banks to use this method. The Committee argues that:

"VaR is an effective tool for describing and communicating risk because it assesses different risks in terms of a common loss relative to a standard unit of likelihood."

11 Financial institutions are allowed to derive their ten-day VaR measure by scaling up the daily VaR by the square root of ten.
Banks that prefer to use their own internal VaR models to calculate the required capital for market risk are subject to qualitative and quantitative criteria. These criteria are summarised in Table 2.1.

<table>
<thead>
<tr>
<th>QUALITATIVE CRITERIA</th>
<th>QUANTITATIVE CRITERIA</th>
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<tbody>
<tr>
<td>1. Independent risk control unit,</td>
<td>1. VaR must be computed on a daily basis,</td>
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<tr>
<td>2. Backtesting,</td>
<td>2. In calculating VaR, a 99th percentile and a one-tailed confidence interval should</td>
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<tr>
<td>3. Management actively involved in the risk</td>
<td>3. In calculating VaR, the minimum holding period should be ten trading days,</td>
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<td>control process,</td>
<td>4. Sample period should be minimum one year,</td>
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<td>4. The internal risk measurement model closely</td>
<td>5. Data sets should be updated no less frequently than once every three months,</td>
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<td>integrated into the day to day risk management</td>
<td>6. Freedom to use any model,</td>
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<td>process,</td>
<td>7. Banks will have discretion to recognise empirical correlations within broad risk</td>
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<tr>
<td>5. The risk measurement system should be used</td>
<td>8. Banks' models must accurately capture the unique risks associated with options,</td>
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<td>in conjunction with internal trading and exposure limits,</td>
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<tr>
<td>6. Stress testing,</td>
<td>9. Each bank must meet, on a daily basis, a capital requirement expressed as the</td>
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<tr>
<td>7. Well documented set of internal policies,</td>
<td>higher of (i) its previous day's VaR number, (ii) an average of the daily VaR</td>
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<tr>
<td>controls and procedures,</td>
<td>measures on each of the proceeding sixty business days, multiplied by a multiplication</td>
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<tr>
<td>8. An independent review of the risk measurement</td>
<td>10. Multiplication factor is minimum three. Banks could be required to add to this</td>
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<td>system should be carried out regularly in the</td>
<td>factor a 'plus', that ranges from 0 to 1, determined by backtesting,</td>
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<tr>
<td>bank's own internal auditing process.</td>
<td>11. Banks using models are subject to a separate capital charge to cover the specific</td>
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<tr>
<td></td>
<td>risk of interest rate related instruments and equity securities.</td>
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</table>

Source: Basle Committee, 1996
Hendricks and Hirtle (1997) point out two important advantages of using internal VaR models in the framework of capital adequacy regulations. Firstly, capital requirements based on the internal models produce minimum regulatory charges that closely match banks' true market risk exposures. Secondly, a capital charge based on the internal models might provide a common standard for the VaR estimates. As a result, it is easier and more reliable to make comparisons across institutions when the VaR estimates of these institutions are based on a uniform set of parameters.

On the other hand, the framework of the internal model approach has been criticised from four aspects. These are:

1) The choice of the multiplier has been found to be arbitrary and questioned as being too high\textsuperscript{12}. In particular, market participants argue that, the choice of the multiplier represents a discouragement for financial institutions to measure and report the risk of their trading portfolios accurately (Elderfield, 1995; Kjeldsen, 1997). According to Hendricks and Hirtle (1997), the most discussed issue of the 1996 amendment is the scaling factor. The scaling factor was criticised by practitioners as an ad hoc supervisory adjustment that limits the benefits of basing a capital charge on financial institutions' internal models. According to market participants, a scaling factor is not necessary to produce the desired level of coverage for the market risk capital charge as standards of a ten-day holding period and a 99\textsuperscript{th} percentile confidence level provide a reasonable base for a minimum capital standard ensuring that banks hold sufficient capital to cover market risk. However, Hendricks and Hirtle (1997) argue that even a ten-day and a 99\textsuperscript{th} percentile VaR estimate might not provide a sufficient degree of risk coverage to serve as a prudent capital standard, as the VaR estimates based on the recent historical market data may not

\textsuperscript{12} Brooks et al. (2000) explain an interesting discussion on how regulators achieve the multiplication factor of three by stating that: "This bizarre rule is a compromise. US regulators wanted institutions to be able to use the 'raw' minimum capital risk requirements value generated by the model, while the German delegation wanted this number to be multiplied by a factor of 5. The multiple of 3 represented a compromise – halfway between the multiples of 1 and 5."

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incorporate the possibility of severe market events. Therefore, a simple and easy to implement scaling factor could provide a capital cushion against unexpected incidents (such as regime shifts and market breaks).

2) As under normal market conditions many positions in a financial institution's trading portfolio could be liquidated in a shorter time period than 10 trading days, a ten-day holding period was criticised as being overly conservative. In addition, the 'square root of ten' rule, which is used to convert the daily VaR estimates to determine the required capital amount, may be inaccurate if the return distribution is not normal (Danielsson et al., 1998).

3) Arguing that longer observation periods do not result in more accurate VaR estimates, Hendricks and Hirtle (1997) criticise the year-long minimum historical observation period. However, as shorter observation periods tend to generate VaR estimates that are more volatile over time (Hendricks, 1996), by requiring a one-year of minimum historical observation period, banks with similar risk exposures face similar capital charges. According to Hendricks and Hirtle (1997), a one-year historical observation period is preferred for not producing the most accurate VaR estimate for capital but rather limiting inequality among institutions. They argue that for a set of banks with similar risk exposures, the dispersion of the VaR estimates across financial institutions would tend to be greater, when some of the financial institutions use short observation periods. As a result, the minimum one-year historical observation period is an attempt to limit this inequality.

4) Backtesting is likely to have limited power in detecting inaccurate risk estimates (Kupiec, 1995). In addition, the differences of holding period in calculating VaR (ten-day) and backtesting (one-day) may create an inconsistency. However, Hendricks and Hirtle (1997) argue that the reason for using a one-day holding period in backtesting is the practical limitations of testing the VaR estimates calibrated to a ten-day standard (backtesting of the VaR estimates based on a ten-day holding period could require a significant amount of historical data to generate a series of independent ten-day profit and loss figures).
Under the market risk amendment, bank supervisors evaluate a bank's internal modelling and risk management process in order to ensure that the calculation of VaR for capital purposes conforms to the specified quantitative criteria and that the risk management process meets certain qualitative criteria, such as requiring independent model validations. Backtesting and stress testing are two qualitative model validation techniques. While backtesting provides information concerning the accuracy of a VaR model by comparing a bank's daily VaR measures to its corresponding daily trading profits and losses, stress testing provides information concerning the impact of adverse market events on an institution's positions.

The use of accurate VaR models is very important while managing market risk of banks, as banks use internal VaR models to calculate the required capital for their market risk. Therefore, regulators require banks to do backtesting in order to determine the accuracy of VaR models. The concept of backtesting and backtesting methodologies are discussed in the sixth chapter of this thesis.

Although backtesting is a useful method to determine the accuracy of VaR models, it is only just one part of the risk management framework in financial institutions. Financial institutions are also recommended to regularly perform simulations to determine how their portfolios would perform under stress conditions (Group of Thirty, 1993). The calculation of VaR depends on the assumed probability distributions of the expected return and in some circumstances the probability distribution might not capture market risk. In order to overcome this problem, stress testing is recommended as a supplement to capture the risk of the unexpected.

Stress testing can be defined as a procedure used to identify possible losses that may accrue under extreme market movements of asset prices. When a portfolio is under stress, the assumptions underpinning the VaR methodology become invalid and historical correlation structures are also likely to breakdown. By performing stress testing, VaR could be complemented, as stress testing measures the behaviour of portfolios under various market conditions, such as the changes in key risk factors, correlations and large market moves, which is not captured by VaR.
The need for stress testing appears because of the unexpected market events. The Group of Thirty report on risk management and control over derivatives trading clearly states that stress testing should be done to calculate the impact of market shocks and disasters. The Basle Committee also requires banks that use the internal models approach to adopt a 'rigorous and comprehensive stress-testing program'.

History of market events such as the stock market crash of 1987 and the Russian default and the LTCM crises of 1998 have proven that in extreme events, a VaR model that assumes the normal distribution is ineffective. As a result, financial firms use stress tests to measure the potential impact of various large market movements on the value of an institution's portfolio. Such tests determine whether large changes in market conditions could lead to high losses. In addition, these tests are useful for identifying exposures that appear to be relatively small in the current environment but that grow more with changes in risk factors.

As well as the qualitative factors that are explained above, namely backtesting and stress testing, there are two quantitative factors of the internal models approach that should be considered carefully. These are the holding period and the confidence level. Although in general the industry practice is to limit the confidence level to 95 percent and the holding period to one day, the market risk capital regulations require banks to calculate the required capital amount by using a 99 percent confidence level and a ten-day holding period. However, many market participants believe that it is a conservative approach to use a 99 percent confidence level and a ten-day holding period in the calculation of the VaR estimates.

Although the market risk capital regulations are generally found to be conservative, the main objective of these regulations is to set aside adequate capital to protect a financial institution against failure due to adverse price movements. One of the main objectives of this thesis is to analyse whether the methodologies that are allowed by the market risk capital regulations produce adequate and accurate VaR estimates. In order to carry out this investigation, simulations are conducted and different VaR models are evaluated by applying backtesting methodologies in the eighth chapter of this thesis.
Concerning the impact of the market risk capital regulations, there is not much evidence in the literature. Although there are several studies related to the applications of VaR, to my best knowledge the study of Danielsson et al. (2004) is the only study that investigates the impact of these regulations. Danielsson et al. investigated the consequences of risk constrained trading by means of simulations of a general equilibrium model with a VaR constraint and compared the results to the case when there are no risk constraints. In particular, their study concentrates on the side effects of imposing VaR constraints in an economy where trades follow backward looking belief revision rules. Their findings indicate that while prices are lower on average in the presence of risk regulation, the volatility is higher. Therefore, instead of stabilising prices, the effect of such constraints is to induce behaviour that exacerbates the shocks further. They conclude that the market risk capital regulations might have the perverse effect as the widespread adoption of the internal VaR models may have the unintended and undesirable side effect of exacerbating short-term price fluctuations in financial markets. Apart from the study of Danielsson et al., there is not much empirical evidence concerning the impact of the market risk capital regulations. However, the impact of capital adequacy regulations has been analysed extensively in the literature. These studies are reviewed in the following chapter.

2.6 Chapter Summary

This chapter introduced the rationale for bank capital regulations and in particular the rationale for market risk capital regulations.

In order to provide systemic stability, policy-makers implement financial safety nets, such as prudential regulations, a 'lender of last resort' facility and deposit insurance. However, while the existence of a 'lender of last resort' facility and a deposit insurance scheme might prevent bank runs, they could also cause a moral hazard problem. Therefore, it is generally accepted that policy-makers implement capital adequacy regulations to overcome the moral hazard problems created by the existence of a 'lender of last resort' facility and deposit insurance.
On the other hand, the advocates of the 'free banking theory' argue that, as moral hazard creates a major risk, deposit insurance should not be implemented and the system should rely on market discipline. The moral hazard problems created by the existence of deposit insurance schemes and a 'lender of last resort' facility encourage banks to take excessive risks. Therefore, it is crucial for banks to hold sufficient capital to absorb unexpected losses.

As a result, bank regulators place emphasis on a banks capital adequacy and influence bank capital by setting capital adequacy regulations to ensure that banks hold sufficient capital to absorb unexpected losses. Initially, the main concern of bank regulators is credit risk. The Basle Accord of 1988 was implemented as a principal measure to control bank credit risk-taking. However, with the increase in trading activities and derivative usage, market risk has gained importance in recent years. With the implementation of the market risk capital regulations, as well as assigning capital for their credit risks, banks have also been required to assign capital to cover their market risks starting from 1998.

The 1996 Basle Committee amendment is a revolution in financial regulation as it allows financial institutions to use their own VaR models to determine the required capital to cover market risk. While the original accord has imposed capital requirements to cover credit risk based on a uniform approach, the amendment requires additional minimum capital to cover market risk based on either a standardised approach or any type of internal VaR models approach. However, the use of the internal models approach is subject to the approval of regulators. If financial institutions choose to determine required capital on the basis of their own internal VaR models, they are required to report daily their VaR at a 99 percent confidence level and over a ten-day horizon. On the other hand, even though the Basle Committee standardises the model parameters, banks could choose their individual particular models to estimate VaR.

Although the impact of capital adequacy regulations has been analysed extensively in the literature, apart from the study of Danielsson et al. (2004), there is not much
empirical evidence concerning the impact of market risk capital regulations. Danielsson et al. investigated the consequences of risk constrained trading by means of simulations with a VaR constraint and compared the results to the case where there are no risk constraints. They found that market risk capital regulations might have a perverse effect. This thesis is also projected to investigate the impact of market risk capital regulations. However, the focus of this study is another aspect of the impact of these regulations. The impact of these regulations on bank capital levels and derivative activities is an issue that has not yet been investigated in the literature. Therefore, one of the most important objectives of this thesis is to investigate the impact of the market risk capital regulations on bank capital levels and derivative activities. In order to analyse these issues, an econometric analysis was carried out in the fourth chapter of this thesis. However, before carrying out this analysis, the literature concerning the impact of capital adequacy regulations was reviewed in the next chapter.
CHAPTER THREE

THE LITERATURE REVIEW CONCERNING THE IMPACT OF CAPITAL ADEQUACY REGULATIONS

3.1 Introduction

The previous chapter demonstrated the importance of banks in an economy and discussed the role of capital regulations. Due to banks' intermediary role in economies, bank regulators put significant emphasis on bank soundness. Consequently, capital adequacy of banks has always been a primary concern of bank regulators as capital provides a buffer to absorb unexpected losses that result from the risks that the banks face in their operations. Kim and Santomero (1988) state that "The amount of capital influences the probability of bank solvency and thus the soundness of the entire banking system, the regulators, ceteris paribus, prefer more capital to less". Therefore, bank regulators shape bank capital by setting capital adequacy regulations, which could affect the activities of banks in more than one dimension.

Despite the fact that the implementation of capital adequacy regulations has led to a considerable discussion, the effects of these regulations are still unclear (Dowd, 1998). Another reason why this issue remains important is the evolving framework of capital regulations. The risk-based capital regulations were first imposed in 1988 and the 1996 amendment requires banks to cover their market risk exposure. In addition, new proposals were issued which will alter the Basle Accord in the near future. This evolving face of the capital regulations has interested researchers since the 1970s.

Therefore, whether the implementation of these regulations leads banks to hold
higher capital ratios or induces banks to substitute towards riskier assets, such as derivative activities, are important questions that should be investigated in order to understand the impact of these regulations. In this chapter, the literature concerning the impact of capital regulations is reviewed. This review is crucial as it provides the theoretical background for the empirical analysis that is provided in the fourth chapter.

The chapter is organised as follows. The second section presents the interaction between deposit insurance and capital regulations. In the third section, the literature related to the impact of capital adequacy regulations on bank capital levels is reviewed. The fourth section reviews the literature concerning the impact of capital adequacy regulations on bank risk-taking. This is followed by reviewing the literature on the impact of capital adequacy regulations on bank off-balance sheet (OBS) activities in the fifth section. In this section, the characteristics of banks that are involved in derivative activities are also examined. The chapter concludes with a summary of discussions.

3.2 The Interaction Between Deposit Insurance and Capital Regulations

Due to the important role of banks in a financial environment, academics and regulators have been questioning bank supervision and regulation. Among the financial safety nets that policy-makers rely on to ensure the stability of a banking system, deposit insurance and capital adequacy have always played a prominent role. Policy-makers generally consider that deposit insurance is necessary to protect small depositors and to prevent bank runs. However, the existence of a deposit insurance scheme could cause a moral hazard problem. According to Benston and Kaufman (1996), policy-makers implement capital adequacy regulations to overcome the moral hazard problems created by deposit insurance.

On the other hand, Dowd (2000c) argues that if financial institutions have adequate capital, depositors might not make a run on their investments and financial institutions would not fail. In his study, Dowd deals with the highly influential justification for deposit insurance provided by the work of Diamond and Dybvig
In the Diamond and Dybvig model, agents that face individual liquidity risk form an intermediary to pool their liquidity risks. Diamond and Dybvig argue that if individual investors believe that their financial institutions will fail, they may panic and bank runs might occur. Consequently, the institutions may fail. Therefore, Diamond and Dybvig suggest that as the banking system is fragile, in order to avoid a systemic risk that could be caused by bank runs, the government should provide deposit insurance to investors that guarantees them to be paid in full in case of a failure. In such an environment, investors would not withdraw their funds and the financial institution would not fail.

Dowd (2000c) criticises the Diamond and Dybvig model as their model considers that intermediaries have only one source of finance. In addition, Dowd also argues that when intermediaries have adequate capital to absorb shocks to their portfolios, they could maintain their ability to make payments to depositors.

In his study, Dowd provides a theoretical example. The Dowd model differs from the Diamond and Dybvig model by not considering every individual identical and by considering more 'realistic' financial institutions. In addition, different from the Diamond and Dybvig model, the Dowd model provides a natural role for bank capital, which gives a rational confidence to investors.

The results of the study of Dowd indicate that if banks have adequate capital, there is no need for deposit insurance. Dowd concludes that provided that a bank has adequate capital, "it can always meet its commitments and depositors can be fully confident of being repaid".

As a result, Dowd demonstrates that, although the underlying rationale of implementing capital adequacy regulations is to overcome the moral hazard problems created by deposit insurance, a deposit insurance scheme will not be needed if banks have adequate capital.
3.3 The Impact of Capital Adequacy Regulations on Bank Capital

The rules related to minimum capital adequacy requirements were implemented in developed countries at the beginning of the 1980s, which was followed by the implementation of the risk-based capital standards in the 1988 Basle Accord. Under the Basle Accord, banks are subject to minimum capital requirements that depend on the riskiness of their portfolio. The coverage of the risk-based capital regulations was enlarged in 1998 by the implementation of the market risk capital regulations.

Whether the implementation of capital adequacy regulations affects bank capital levels is an issue that has attracted a lot of attention. In this section, the literature concerning the impact of capital adequacy regulations on bank capital levels is reviewed.

The descriptive statistics of the US banks' capital levels provided in the study of Jacques and Nigro (1997) demonstrate that, after the implementation of the risk-based capital regulations in 1988, bank capital ratios were increased. For example, the equity-asset ratio for all commercial banks increased from 6.75 percent in 1988 to 8.01 percent in 1993. In addition, the risk-based capital ratio increased from 10.67 percent to 13.17 percent over the same period. The study of Jackson (1999) also presents supporting evidence that the introduction of the Basle Accord was followed by an increase in the risk-weighted capital ratios. She argues that the average ratio of capital to risk-weighted assets of major banks in the G-10 countries rose from 9.3 percent in 1988 to 11.2 percent in 1996. Graph 3.1 also demonstrates that the capital to risk weighted asset ratios of the US and UK banks started to increase in 1988.
Although the introduction of the Basle Accord was followed by an increase in the bank capital ratios, it is difficult to conclude that the implementation of the risk-based capital regulations was the only cause of this increase. Therefore, in order to explain the relationship between capital levels and capital regulations, an econometric analysis should be employed. Jackson (1999) also argues that econometric models are required to analyse such relationships, as it is possible for banks to be subjected to market pressure to increase their capital ratios or specific situations in their countries could lead to such a result.

The impact of capital regulations on the bank capital ratios has been empirically investigated since the beginning of the 1970s. However, the first two studies concerning the impact of capital regulations reached opposing conclusions. The first study that investigated this issue was carried out by Peltzman (1970). Peltzman analysed the impact of the ABC ratio, which is the ratio of actual bank capital to the capital desired by the regulator, on the US banks’ percentage capital growth. According to Peltzman, the crucial test for the effectiveness of regulation is to look at whether banks respond to regulatory pressure by increasing their capital. Peltzman investigated the magnitude of the effect of government regulation on capital investment in commercial banking. However, he could not find any evidence supporting that bank capital investment behaviour is affected by the regulatory standards.
Mingo (1975) also analysed the impact of the ABC ratio on the US banks' percentage capital growth. The results indicate that bankers treat deposit insurance as a substitute for bank capital. In addition, the evidence suggests that regulators have made no attempt to reduce this 'substitution effect'. On the other hand, Mingo's findings are inconsistent with Peltzman as the level and distribution of bank capital were found to be affected by regulation. Mingo found that the capital adequacy regulation had a substantial effect on the level of bank capital, indicating that the level of bank capital is now greater than it would be in the absence of bank capital regulation. These findings suggest that the lower is the ratio of actual capital to capital desired by the regulators, the more likely is the banker to add to capital over the next period.

The impact of the ABC ratios on the US banks' capital levels was also examined by Dietrich and James (1983). By using similar empirical tests to those employed by Peltzman and Mingo, Dietrich and James investigated whether bank capital adequacy regulations formulated by regulators have any effect on the capital decisions of commercial banks. They used a much larger sample of banks and a different time period. The regressions were estimated using annual data for a sample of more than 10,000 banks for the years 1971 to 1975. Their findings, which are similar to those of Peltzman, suggest that there is no significant relationship between changes in capital and the capital standards imposed by regulators. Dietrich and James explained the conflict with Mingo's findings by expressing Mingo's failure to consider the influence of other bank regulations, particularly the effect of deposit interest rate ceilings\(^\text{13}\), which was not effective in the observation period that Peltzman has investigated.

All of the above mentioned studies investigated the impact of capital regulations by employing single multivariate regression models where the dependent variable is the percentage growth in bank capital. Jackson (1999) criticises these studies from two

\(^{13}\) Dietrich and James (1983) argue that when interest payments are limited by rate ceilings (Regulation Q limited the rate of interest that could be paid on time deposits by banks and savings and loans), banks have an incentive to increase capital to compete for non-insured deposits as an increase in capital results in an increase in the risk-adjusted expected return to depositors.
aspects. Firstly, these studies used capital growth rates instead of focusing on changes in capital levels. Secondly, these studies considered only conditioning variables but not lagged capital or capital growth in contrast to subsequent studies that employed a partial adjustment model.

The studies of Marcus (1983), Keeley (1988), Shrieves and Dahl (1992), Jacques and Nigro (1997) and Aggarwal and Jacques (1998) also investigated the impact of capital regulations on bank capital levels. However, in these studies the changes in bank capital are modelled in a partial adjustment framework, where the change in capital is modelled as the difference between the actual capital level and the capital target level. While these studies investigated the impact of capital regulations on the US banks, Ediz et al. (1998) analysed the impact of capital regulations on the UK banks and Rime (2001) analysed the impact of capital regulations on the Swiss banks by employing a partial adjustment framework.

One of the first studies that employed a partial adjustment framework is the study of Marcus (1983). Criticising the previous studies for using only cross-section data and for not considering the change in capital ratios over time, Marcus employed time series cross-sectional data and market values of capital instead of book values. While Marcus found a significant impact of market factors on the capital ratios, he could not find any impact of regulatory pressure. Keeley (1988) also employed a partial adjustment framework to examine the impact of capital regulations on bank capital levels. Keeley investigated the impact of the minimum capital-to-asset ratio requirements that have replaced the earlier peer group type of capital regulations¹⁴ on the capital positions of the 100 largest bank holding companies (BHCs). In particular, he examined whether the new capital requirements urged banks with low capital ratios to meet these new standards. Keeley found that the uniform capital requirements of the 1980s seemed effective as banks with low capital levels increased their capital ratios. He also found that capital deficient banks increased

¹⁴ Prior to the 1980s, there were subjective capital requirements in the US and these were based on the regulators' examinations of banks. In this framework, regulators were comparing a bank's capital-to-asset ratio with bank peer groups, i.e. banks grouped by common characteristics such as total assets or ownership), and require banks with lower capital ratios to increase their capital. After 1981, banks and BHCs in the US were required to hold at least 5 percent capital-to-asset ratio as a result of the increasing risk exposure due to deteriorating asset quality and increase in OBS activities (Keeley, 1988).
their capital ratios mainly by slowing down the asset growth relative to capital growth, which suggests that the increase in the capital-to-asset ratios reflected a reduction in leverage.

Another study that employed a partial adjustment framework is the study of Shrieves and Dahl (1992). Shrieves and Dahl argue that the presence of leverage and risk-related costs might induce managers and shareholders to increase capital (or decrease leverage) in response to higher levels of asset risk. In particular, they examined the bank behaviour with respect to the observed changes in capital and risk by considering the impact of the 1981 capital regulations on a large sample of US banks. They employed simultaneous equation models to analyse adjustments to bank capital and risk levels. Their findings suggest that banks with lower (below 7 percent) capital to assets ratios responded to the capital regulations by increasing their capital levels. They also found a positive association between the changes in risk and capital.

While the above mentioned studies focused on the impact of capital regulations on bank capital levels prior to 1988, Jacques and Nigro (1997) investigated the impact of the risk-based capital regulations.

Jacques and Nigro (1997) examined the impact of the Basle Committee's risk-based standards on both portfolio risk and bank capital levels. Building on previous research of Shrieves and Dahl (1992), which suggests that increasing regulatory capital standards might cause banks to increase, rather than decrease, their portfolio risk, they employed a three-stage least squares methodology to analyse the relationship between bank capital, portfolio risk, and the risk-based capital standards. The study of Jacques and Nigro covers the first year of the risk-based capital standards were in effect, i.e. 1991. Their findings can be summarised under two headings. Firstly, the risk-based capital standards have a significant positive impact on capital and a negative impact on portfolio risk of well-capitalised banks (no significant impact is found for undercapitalised banks). Secondly, undercapitalised banks showed increases in the equity-asset ratio, but these increases essentially appear to be the result of decreasing portfolio risk and a reduction in total assets.
They conclude that while the overall level of portfolio risk in undercapitalised banks decreased, implementation of the risk-based standards appears to have had little effect on the portfolio risk of these banks.

On the other hand, Aggarwal and Jacques (1998) examined the impact of the Prompt Corrective Action (PCA) on capital ratios and portfolio risk levels of the US banks. They used the model developed by Shrieves and Dahl (1992) and modified by Jacques and Nigro (1997). The results of their study suggest that both adequately capitalised and undercapitalised banks increased their capital ratios in response to the PCA standards. In addition, they found some evidence that the PCA standards led to significant reductions in portfolio risk. They conclude that the PCA has been effective in getting banks to simultaneously increase their capital ratios and reduce their level of portfolio risk.

There are also a number of studies that investigated the relationship between capital and implementation of capital regulations in the US by using methodologies other than a partial adjustment framework. Among these studies, Wall and Peterson (1987) investigated the impact of capital regulations on US banks. They claim that, the US bank regulators issued explicit capital standards in 1981 in order to address the long-term decline in capital ratios of many large banking organisations during the 1970s. Therefore, they investigated whether the 1981 US capital guidelines has any effect on the equity capital to asset ratios of large BHCs'. Wall and Peterson argue that there are six factors that influence the capital policies of BHCs. These are:

1) Capital regulations,
2) Deposit insurance, which tends to decrease the optimal capital by shifting part of the risk of failure from depositors to government,
3) Tax advantages of debt, which encourage lower capital ratios,
4) Diseconomies of scale in producing deposit services, which encourage higher capital ratios,

Prompt Corrective Action (PCA) is one of the key provisions of the FDICIA (Federal Deposit Insurance Corporation Improvement Act), which came into effect in 1991. PCA provisions obliged supervisors to take specific actions when a bank's capital ratios fell below certain trigger levels.
5) Bankruptcy costs, which tend to increase optimal capital,
6) Profitability (banks with high earnings might be in a better position to increase their capital ratios).

Wall and Peterson examined the hypothesis that the primary capital guidelines imposed by regulators influenced the changes in large BHCs' equity capital. They used a disequilibrium estimation procedure\(^{16}\) that allows BHCs to be influenced by binding regulatory capital regulations or by market forces. In this framework, maximum likelihood techniques\(^{17}\) were employed and if the regulatory pressure exceeds market pressure, i.e. regulations are binding, the BHC is assumed to operate in the regulatory model. Their findings suggest that the overwhelming majority of the BHCs were influenced by regulatory forces and only a small number of BHCs were influenced by market forces. They conclude that because regulatory control over bank capital leads to greater risk-taking by banks, the regulators should strengthen their supervision for those BHCs that increase their capital due to regulatory pressures.

Arguing that the changes in bank capital ratios might have been caused by financial markets or regulatory standards, Wall and Peterson (1995) investigated the relative impact of regulations and financial markets on the capital ratios of BHCs. They applied a disequilibrium methodology to estimate the regulatory equation and the financial market optimum equation by maximum likelihood. They argue that analysing whether capital regulations cause banks to maintain higher capital ratios is important from four aspects. These are:

1) Can regulators effectively influence bank behaviour?

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\(^{16}\) Wall and Peterson (1987) argue that “disequilibrium estimation overcomes the shortage in ordinary least squares estimation as it allows each observation of the dependent variable in a cross section to come from one of two regimes. In addition, the probability that an observation came from the first or second regime may be estimated. A disequilibrium framework represents a common dependent variable as the greater (or lesser) of that obtained from two different models”. The regulatory regime is based on the hypothesis that capital regulations cause at least some banks to maintain higher capital levels than they would in the absence of regulation (Wall and Peterson, 1995).

\(^{17}\) The regulatory and financial market equations were estimated by maximum likelihood, which selects the optimal separation of the observations into two regimes by maximising the likelihood function.
2) Do binding capital regulations cause banks to take more risk?
3) Do increased capital ratios cause credit crunch, i.e. a reduction in the growth rate of bank lending?
4) If regulations are not binding, does this suggest that banks are subject to substantial market discipline?

They found that most BHCs are not influenced by the market or regulatory pressure to adjust their leverage ratios in 1989. However, BHCs were found to be influenced by the actual implementation of the risk-based capital regulations after 1990. Therefore, they conclude that regulators influence capital levels.

All the above-mentioned studies investigated the impact of capital regulations on the US banks' capital levels. The only study concerning the UK banks' response to capital regulations is the research of Ediz et al. (1998). In this study, they used confidential supervisory data of British banks and employed both descriptive statistical analysis and a regression model. Their findings suggest that capital requirements affect bank behaviour over and above the influence of the banks' own internally generated capital targets. Furthermore, banks were found to achieve adjustments in their capital ratios primarily by directly boosting their capital rather than through systematic substitution away from assets such as corporate loans. Finally, they conclude that capital requirements are attractive regulatory instruments as they serve the aim of strengthening the stability of the banking system without apparently distorting banks' lending choices.

Building on previous work by Shriever and Dahl (1992), Rime (2001) used simultaneous equation models to analyse adjustments in capital and risk at the Swiss banks. He found that the Swiss banks, which had capital ratios below the minimum regulatory capital requirements, increased their ratio of capital to risk-weighted assets. This result indicates that regulatory pressure has the desired impact on banks' behaviour. Rime argues that the regulatory pressure on the Swiss banks' capital is not larger in amplitude than that reported for comparable studies on the UK and US banks. Although Rime found a positive and significant relationship between the changes in risk and the changes in the ratio of capital to total assets, he failed to find
a significant relationship between the changes in risk and the changes in the ratio of capital to risk-weighted assets. According to Rime, these two findings are consistent in a regime of risk-based capital standards "... as banks constrained by the capital requirements have to increase their ratio of capital to total assets following an increase in risk to keep their risk-adjusted capital ratio constant." He concludes that as the implementation of capital regulation in Switzerland has decreased the capital burden for Swiss banks, the positive relationship between capital and risk is not a result of higher capital requirements.

One of the fundamental arguments concerning capital regulations is that these regulations are effective if they result in an increase in capital levels (Rime, 2001). Therefore, by implementing capital adequacy regulations, bank regulators require additional capital for banks. This is called the regulatory cost hypothesis. Although it is costly for bank managers to increase capital ratios, the regulatory view considers capital as a cushion that absorbs unexpected losses. Therefore, this hypothesis implies that in order to be effective, capital regulations should increase the capital level of banks.

Sheldon (1996) also argues that capital regulations are intended to raise the capital standards of the institutions that they cover. Since these regulations increase the percentage of capital that banks must hold and therefore expand the buffer available to absorb losses to the value of a bank's assets, solid capital requirements are expected to decrease the probability of bank failure. As a result, with an increase in the capital ratio, the protection of depositors and debt-holders increase, as well as the increase in the soundness and stability of the banking system as a whole.

The literature review concerning the impact of capital adequacy regulations on bank capital demonstrates that the earlier studies did not make any distinction between bank short-run and long-run effects of capital regulations. These studies did not employ any lagged capital growth in the models and only regressed capital growth on conditioning variables. However, the recent studies have generally employed a partial adjustment framework. Marcus (1983), Wall and Peterson (1987) and Dahl and Shries (1990) used a partial adjustment framework to model bank capital
decisions. Following them, Shrieves and Dahl (1992) used this model to test the relationship between bank capital levels and portfolio risk. Later, Jacques and Nigro (1997), Aggarwal and Jacques (1998) and Rime (2001) modified the model of Shrieves and Dahl to analyse the impact of the risk-based capital regulations on bank capital and risk levels.

In these studies, recognising that banks may not be able to adjust their desired capital and portfolio risk levels instantaneously, the changes in the capital and risk ratios are modelled by using a partial adjustment framework. In this framework, the discretionary changes in capital and risk are proportional to the difference between the target levels and the levels existing in period $t-1$. The actual changes of capital and risk of a bank are assumed to follow the below process:

\[
K_t - K_{t-1} = \delta(K_t^* - K_{t-1}) + \varepsilon_t
\]

(3.1)

where $K_t$ is the actual capital (or risk) at time $t$, $K_t^*$ is the capital (or risk) target for time $t$, $\delta$ is the coefficient of adjustment and $\varepsilon_t$ is a random error. If the target level is less than the level existing in period $t-1$, then the actual change is on average negative. If the target level is higher than the level existing in period $t-1$, then the actual change is on average positive. Therefore, in the long run the actual level will be likely to converge towards the target level and the extent of the coefficient of adjustment ($\delta$) indicates the rate at which this convergence occurs.

Equation 3.1 indicates that the actual change is decomposed into two components. These are, a discretionary adjustment and a change caused by an exogenously determined random shock. As the target level is not observable, it is assumed that the target level depends upon a set of observable variables. Therefore, in the previous studies the capital (or risk) target was replaced by observable variables indicating the bank’s financial condition, such as bank size, risk variables, and profitability, as well as regulatory and macro economic conditions.
The literature review concerning the impact of capital adequacy regulations also demonstrates that, in general the studies concerning the impact of capital regulations on bank capital levels provide contradictory results. However, banks may also react to the implementation of these regulations by changing their risk-taking. The next section presents the literature review concerning the impact of capital adequacy regulations on bank risk-taking.

3.4 The Impact of Capital Adequacy Regulations on Bank Risk-Taking

Another issue in the literature concerning the impact of capital regulations is whether increased capital standards have any effect on bank risk-taking. The implementation of capital adequacy regulations may influence banks either by increasing capital or by decreasing their risk-taking. On the other hand, banks may also respond to these regulations by increasing their risk-taking. Therefore, it is a very important issue to analyse the impact of capital adequacy regulations on bank risk-taking. Leonard and Biswas (1998) stress that:

"Changes in the regulations governing financial institutions change the opportunities for risk-taking and regulatory costs; therefore, regulatory changes will establish a new equilibrium level of risk-taking that equates the new level of marginal benefits and costs. It is an empirical issue whether changes in the incentives for risk-taking dominate or are dominated by changes in regulatory and risk-related costs and whether changes in regulations lead to increased or decreased risk-taking by banks."

Avery and Berger (1991) also argue that one of the important questions that has been investigated in the bank capital standard literature is whether increased capital standards increase or decrease bank risk-taking. They state that:

"Virtually all authors agree that a mandatory increase in capital has the direct effect of reducing insolvency risk by providing an increased `buffer stock' of reserve funds to absorb losses. (...) However, authors sharply disagree upon whether banks in typical financial conditions will generally increase or decrease portfolio and insolvency risks as a result of increased capital requirements."

Although the aim of implementing capital adequacy regulations is to provide a buffer to absorb unexpected losses, these regulations can also create a moral hazard problem by increasing banks' risk-taking. Whether there is any relationship between capital regulations and bank risk-taking is another issue that has led to a considerable

On the other hand, the studies of Shrieves and Dahl (1992), Jacques and Nigro (1997), Aggarwal and Jacques (1998) and Rime (2001) investigated the impact of capital regulations on capital levels as well as analysing the relationship between capital regulations and bank risk-taking. As explained in the previous section, Shrieves and Dahl (1992) found a positive relationship between changes in risk and capital. On the other hand, Jacques and Nigro (1997) found that the risk-based capital regulations result in a significant increase in capital and decrease in portfolio risk of well-capitalised banks, while the impact is little on undercapitalised banks. Furthermore, Aggarwal and Jacques (1998) demonstrated that the PCA has been effective in getting banks to simultaneously increase their capital ratios and reduce their level of portfolio risk. However, the results of the study of Rime (2001) are not so clear. Rime found a positive and significant relationship between the changes in risk and the changes in the ratio of capital to total assets, but could not find a significant relationship between the changes in risk and the changes in the ratio of capital to risk-weighted assets. As a result, the empirical studies that investigated the relationship between capital and bank risk-taking reach contradictory results.

In addition, the theoretical studies which investigated this issue also provided contradictory results. Among these studies, Kahane (1977), Koehn and Santomero (1980) and Kim and Santomero (1988) concentrated only on the relationship between capital regulations and risk-taking. These studies demonstrated that higher regulatory capital standards have caused banks to increase their risk-taking and therefore might lead to higher probability of failure. On the other hand, the theoretical studies of Furlong and Keeley (1989) and Keeley and Furlong (1990) suggest that increased capital standards would not necessarily cause value-maximising banks to increase their risk-taking.
The studies of Kahane (1977), Koehn and Santomero (1980), and Kim and Santomero (1988) were based on a utility maximising framework in which banks seek to maximise their utilities. In this framework, higher capital ratios lead to an increase in the probability of failure because of the increased asset risk to maintain the same rate of return on the increased capital.\footnote{The utility maximising framework attempts to optimise the shareholder's rate of return on the bank's capital by selecting an optimal portfolio of assets and leverage positions (Sundaresan, 1996).}

Analysing the impact of constraints on asset portfolio composition and capital requirements on the probability of insolvency, Kahane (1977) found that these factors are ineffective in reducing failure probability. Kahane concludes that increased capital requirements lead to increased bank risk.

Using the same framework, i.e. utility maximising, Koehn and Santomero (1980) examined the issue of portfolio reaction to capital requirements by investigating the effect of capital regulation on the portfolio behaviour of commercial banks. They firstly examined the portfolio allocation of a bank and then examined the effects on bank portfolio risk of a regulatory increase in the minimum capital asset ratio. Koehn and Santomero found that banks react by rearranging their asset portfolio towards riskier assets when higher capital requirements are imposed. They conclude that, although the central purpose of bank regulation is to reduce bank risk-taking, so as to reduce the probability of failure in order to protect depositors and the banking system as a whole, when higher capital requirements are imposed an opposite result could be expected. Therefore, regulating bank capital through ratio constraints appears to be an inadequate tool to control the riskiness of banks and the probability of failure.

Employing utility maximisation framework similar to Kahane's and Koehn and Santomero's studies, Kim and Santomero (1988) examined the effectiveness of capital regulations in an environment of fixed rate deposit insurance. They found that the portfolio risk of a bank might increase with higher capital standards and the probability of failure could actually rise with higher capital requirements. They conclude that uniform capital requirements are not effective to control bank failure and therefore to maintain a safe and sound banking system, while risk weights under
risk-based capital requirements are more effective as the weights are chosen optimally.

The studies of Kahane, Koehn and Santomero and Kim and Santomero demonstrate that a more stringent capital requirement may influence financial institutions to substitute riskier assets for less risky ones and therefore may increase the risk of trading portfolios and the probability of default. These studies conclude that the effect of an increased capital asset ratio is therefore contrary to the desired objective.

However, some studies do not support the view that capital requirements play a role in bank risk-taking. Furlong and Keeley (1989), for example, criticise Kahane, Koehn and Santomero and Kim and Santomero as their models do not hold for value maximising banks, for which the liability exposure of the deposit insurance system is especially relevant. According to Furlong and Keeley, these studies have internally inconsistent models and their results cannot be used to support the claim that implementing capital regulations could increase bank risk-taking. Furlong and Keeley analysed the effect of stringent capital requirements in a value maximising framework by studying the impact of changes in banks' incentives for increasing asset risk due to the changes in the capital ratio requirements. Furlong and Keeley used a state-preference model (two periods and two states) to analyse the portfolio and leverage decisions of a bank that is subject to deposit insurance and maximises its current market value of equity. By demonstrating that more stringent capital regulations would reduce bank risk-taking as long as the severity of the regulation of asset portfolio risk remains unchanged, they conclude that higher bank capital ratios do not lead value-maximising banks to increase asset risk. Their results also indicate that instead of selling assets and reducing deposits, a value maximising bank prefers to meet higher required capital ratios by raising additional capital.

Keeley and Furlong (1990) also criticise the utility maximising framework because of questionable assumptions and demonstrate that if banks have diversified portfolios, capital requirements could reduce bank risk-taking. In sum, the studies of Keeley and Furlong demonstrate that higher capital requirements reduce the
incentives to increase asset risk and conclude that more stringent capital regulations reduce the risk exposure to the deposit insurance system.

Empirically analysing the appropriateness of risk-weights in risk-based capital regulations, Avery and Berger (1991) argue that if risk-based capital risk-weights correspond precisely with bank risk-taking, this implicit pricing of risk-taking might offset incentives to increase risk-taking influenced by the increased capital requirements. Therefore, they tried to find an answer to the question of "How do the risk weights correspond to actual bank risk?" Using data on US banks from 1982 to 1989, Avery and Berger regressed historical measures of bank performance, such as portfolio losses and bank failures, on the items in the 1988 Basle Accord's risk categories and examined the efficacy of the relative weights assigned. They also compared the ability of various measures of capital, including both the new and the previous capital standards, to predict future bank performance. In addition, they examined the stringency of the new standards to determine whether they are likely to be effective in changing bank behaviour. Avery and Berger found that the new standards are more stringent not only on large banks but also on small banks. They conclude that the 1988 Basle Accord comprises a significant improvement over the previous capital standards. However, because their results are based on historical associations, conclusions regarding future bank performance and behaviour should be drawn carefully.

Leonard and Biswas (1998) investigated changes in bank risk-taking behaviour of US banks resulting from the regulatory changes. In particular, they tested the regulatory cost hypothesis. This hypothesis predicts that more restrictive enforcement practices (greater regulatory scrutiny that resulted from passage of FIRREA in 1989) increased regulatory costs for banks and therefore reduced the level of risk-taking. Their results indicate that more restrictive enforcement practices limited the excessive risk-taking of banks. In addition, they conducted a two-stage least squares analysis to investigate whether the changes in capital and the changes in credit risk index were determined simultaneously. However, the results of this analysis do not indicate any significant relationship between risk-taking and capital.

\footnote{FIRREA = Financial Institutions Reform, Recovery, and Enforcement Act.}
Sheldon (1996) also investigated the impact of capital regulations on bank risk-taking by using a sample of banks operating in different countries. In particular, Sheldon investigated the impact of the 1988 Basle Accord on a sample of 219 banks drawn from the Basle Committee member countries and his study covers the period from 1987 to 1994. The empirical methodology that Sheldon applied is based on the call option interpretation of firm equity stemming from the Black-Scholes model of option valuation. The results indicate little evidence that implementation of the guidelines had a risk increasing impact on bank portfolios.

In his theoretical study, Blum (1999) also explored whether capital adequacy rules cause an increase in bank risk-taking. By using a two-period model, Blum demonstrates that as capital requirements increase the marginal utility of a unit of capital tomorrow, tighter capital requirements may lead to an increase in risk in an effort to increase the expected return. Blum concludes, "if regulators are mainly concerned about reducing the insolvency risk of banks, introducing capital rules, therefore, may not be such a good idea after all."

Consequently, the studies that have investigated the relationship between bank capital and risk-taking could not reach uniform conclusions. Therefore, whether the implementation of capital adequacy regulations creates a moral hazard problem by increasing banks' risk-taking is an important question that should be answered.

Another important issue concerning the impact of capital adequacy regulations is the relationship between these regulations and OBS activities. In response to the capital regulations, banks can also increase their risk-taking by increasing their OBS activities, in particular, derivative activities. The next section investigates the relationship between capital regulations and OBS activities.
3.5 The Impact of Capital Adequacy Regulations on Bank OBS Activities

The aim of this section is to review the related literature and provide an analytical background for the relationship between capital regulations and off-balance sheet activities, in particular, derivative activities. This review is crucial as it provides the theoretical background to the analysis that tests the impact of the market risk capital regulations on bank derivative activities in the next chapter.

Off-balance sheet (OBS) activities have been increasing dramatically since the 1970s. The growing importance of OBS activities also worried the regulators and led them to propose the risk-based capital standards that also cover credit risk of these activities in 1986 (Baer and Pavel, 1988). Hassan et al. (1994) points out to this issue by stating that "Bank regulators have been concerned that off-balance sheet activities increase the riskiness of banks, and have enacted a risk-based capital requirement for some OBS activities." As a result, the risk-based capital requirements implemented by the Basle Accord in 1988 were set up to cover credit risk of OBS activities as well.

Gunther and Siems (1995) also argue that the growth of derivative activities of banks and highly publicised derivative related losses have led regulators and policy-makers to worry about the potential impact of derivative activities. According to Jagtiani (1996), because the notional amount of derivatives exceeds the equity capital of many banks, losses from derivative activities could potentially wipe out bank’s capital and threaten the safety and soundness of the banking system. These discussions lead to the argument that banks become more risky when they engage in derivative activities.

The existing literature examined the key motivations for the explosive growth in bank OBS activities, including derivatives. A popular explanation for this growth is the avoidance of capital requirements, i.e. capital avoidance hypothesis. This hypothesis indicates that OBS activities of banks increase because of the lack of capital standards (Jagtiani et al., 1995). However, the studies that test this hypothesis provided contradictory results. While Giddy (1985) argues that capital requirements
encourage banks to engage in OBS activities, Koppenhaver (1989) argues that the 'bindingness' of capital constraints is not an important factor in banks' decisions to use OBS activities. The studies of Pavel and Phillis (1987), Baer and Pavel (1988), Koppenhaver (1989) and Koppenhaver and Stover (1994) are among the studies that have empirically investigated the relationship between the implementation of capital regulations and OBS activities.

Pavel and Phillis (1987) investigated the reasons of banks selling their assets. They found that banks are involved in asset securitisation in order to reduce regulatory taxes, such as deposit insurance premiums and reserve requirements. Although they indicated that banks are likely to sell loans when capital ratios are low, they did not find any supporting evidence that the loan sales were caused by the implementation of capital regulations. On the other hand, Baer and Pavel (1988) investigated the determinants of stand-by letters of credit activities and found a positive relationship between the implementation of capital regulations and stand-by letters of credit activities.

Investigating the determinants of US commercial bank activity in the market for OBS guarantees, Koppenhaver (1989) found that a bank's issuance of loan commitments, standby letters of credit, and commercial letters of credit significantly depends on bank credibility as a guarantor, regulatory incentives and the willingness and ability to accommodate customers. However, Koppenhaver could not find any significant relationship between increasing capital requirements and bank OBS activities. On the other hand, he found that a number of other regulatory-based incentives, such as required reserves and loan loss allocations are significant determinants of OBS guarantees. Koppenhaver recommends that if OBS participation is a regulatory concern, a policy option should be to pay market interest rates on reserve requirements to reduce the relative advantage of OBS banking. On the other hand, the results of the Koppenhaver's study indicate a consistent and positive relationship between bank asset size and the issuance of OBS guarantees. Koppenhaver concludes that "although a capital requirement has very little effect on the issuance of off balance sheet guarantees, the imposition of a risk-based capital standard may be useful in protecting the solvency of the deposit insurance fund
because it provides an additional buffer against the loss of market value for banks that engage in the risky activities covered by the standard.”

Koppenhaver and Stover (1994) also investigated the relationship between bank standby letters of credit and capital by employing a simultaneous equation model to capture the joint decision process for standby letters of credit issuance and bank capital. They found that there is a positive relationship between the issuance of OBS activities and bank capital. Therefore their empirical results support the theoretical argument that a feedback system exists between OBS activities and bank capital.

The studies that investigated the relationship between capital regulations and OBS activities provide contradictory results. While the studies of Pavel and Phillis (1987) and Koppenhaver (1989) could not indicate any significant relationship between the implementations of capital regulations and OBS activities, Baer and Pavel (1988) and Koppenhaver and Stover (1994) found a positive relationship between capital and OBS activities. However, these studies examined the relationship between capital and OBS items excluding derivatives.

On the other hand, the growth of derivatives has led to more discussion. Jagtiani (1996) argues that because the notional amount of derivatives exceeds the equity capital of many banks, losses from derivative activities could potentially wipe out banks’ capital and threaten the safety and soundness of the banking system. However, although the determinants of derivative usage have been investigated extensively, there is not much evidence in the literature concerning the impact of capital adequacy regulations and derivative activities.

The studies of Koppenhaver (1990), Sinkey and Carter (1997) and Carter and Sinkey (1998) are among the studies that investigated the determinants of derivative usage. Koppenhaver (1990) analysed the determinants of banks’ futures positions. He found that banks use interest rate futures in order to hedge their balance sheet risks, measured by the maturity gap (the difference between interest bearing assets and liabilities maturing or repricing during the relevant period). Koppenhaver also found that bank size and experience affect the use of derivatives.
Sinkey and Carter (1997) analysed the determinants of derivative usage of US banks from 1989 to 1991. They employed two approaches in their study. First, dividing the sample banks into user and nonuser groups of derivatives, group means of the explanatory variables were compared through descriptive statistics (in particular, the statistical significance of the differences in the means of explanatory variables are determined by t-tests, which are based on unequal group variances). In addition to the descriptive statistics, Sinkey and Carter employed a regression analysis to estimate the relationship between the extent of derivative usage and the explanatory variables. Derivative activities were measured by the notional value of outstanding derivative contracts divided by total assets. The results of the Sinkey and Carter's descriptive study indicate that derivative activities are concentrated on large banks with lower capital ratios, smaller maturity gaps, lower net interest margins, more notes and debentures, greater equity growth, higher dividend payout and greater liquidity. On the other hand, similar results were obtained from the econometric analysis. The results of the econometric model indicate that larger asset size, low capital ratios, low net interest margins, small maturity gaps, high liquidity, high dividend payouts and more capital notes are significant determinants of derivative usage.

Carter and Sinkey (1998) investigated the use of interest rate derivatives of US banks from 1990 to 1993. They used the outstanding notional value of derivatives scaled by total assets to capture the extent of derivative activities by large community banks. They found a positive and significant relationship between the use of interest rate derivatives and exposure to interest rate risk, measured by the absolute value of the one-year maturity gap. Size was also found to be an important factor that positively affects the use of derivative instruments. They also found that banks with strong capital positions involve heavily in derivative transactions. The results of this study support the existence of market discipline, which suggests that external monitoring and pricing prevent banks from being involved in risk-taking activities. In addition, the results of Carter and Sinkey also support the existence of regulatory discipline, which suggests that banks are required to hold more capital because of the capital requirements that cover derivative activities of banks.
The studies that investigated the characteristics of banks that use derivatives indicate that, size is an important factor that determines derivative activities of banks. Booth et al. (1984) argue that large banks are more likely to be involved in derivative transactions. By surveying banks in the US, they found a strong relationship between the size of financial institutions and the usage of derivatives, which is consistent with the existence of significant scale economies because of personnel training, education of management and development of internal control systems. Booth et al. conclude that lack of these considerations is an important obstacle that limits the usage of derivative instruments.

The survey results of Block and Gallagher (1986) also indicate that large size non-bank firms involve more in derivative transactions comparing to small firms. Nance et al. (1993) state that over-the-counter (OTC) derivative markets demonstrate significant scale economies in the structure of transaction costs, which means that large banks are more likely to use these instruments. In addition, Gunther and Siems (1995) claim that only larger banks could gather the necessary resources to participate in derivative activities. Investigating the determinants of derivative usage for a sample of 175 BHCs in the US, Whidbee and Wohar (1999) found a positive relationship between size and the decision to use derivatives. Rogers and Sinkey (1999) also argue that participation in non-traditional banking activities, such as derivatives, requires specialisation in that area. In addition, banks should hire or train their personnel with special work related to derivatives and also acquire advanced technology.

As well as investigating the determinants of derivative usage, the studies of Kim and Koppenhaver (1992), Jagtiani et al. (1995), Jagtiani and Khanthavit (1996) and Jagtiani (1996) have also analysed the impact of capital adequacy regulations on derivative activities.

Kim and Koppenhaver (1992) investigated the characteristics of banks that use interest rate swaps. The likelihood of swap market participation was estimated by a probit model and the dependent variable in the model reflects a binary choice of
bank, i.e. a bank could either engage in a swap transaction or not. In a separate model, Kim and Koppenhaver estimated the swap market participation by banks by employing a regression model in which the dependent variable is the notional value of the ratio of outstanding interest rate swaps to total bank assets. As explanatory variables, they employed the following variables:

- Absolute maturity gap, as a percent of total assets,
- Interest rate expectations,
- Primary capital to asset ratio,
- Market concentration in deposits,
- Size,
- A dummy variable which is equal to 1 if the bank is a swap dealer,
- The ratio of loan portfolio to total assets,
- A dummy variable of futures and forward trading (the use of these instruments indicates the experience of a bank with derivative activities),
- A dummy variable of foreign exchange trading,
- Two dummy variables that represent the impact of capital regulations.

Following the arguments of Benveniste and Berger (1987) and Koppenhaver (1989), Kim and Koppenhaver point out that the implementation of capital requirements might motivate banks to engage in OBS activities. In order to measure the impact of capital regulations, they included two dummy variables in the models. First one is related to the regulatory pressure and takes the value of 1 if a bank’s capital ratio is less than 5.5 percent, which is the established minimum capital ratio. In order to capture the impact of capital regulations on the decisions of banks whose capital ratios are between 5.5 and 7.0 percent (above but close to the uniform standard), another dummy variable is included in the models. Kim and Koppenhaver expect a positive impact on the likelihood and extent of a banks’ swap market participation if undercapitalised banks use OBS activities as intermediaries to generate income and preserve this income on the capital to meet regulatory requirements. On the other hand, if the swap market imposes market discipline on undercapitalised banks, regulatory impact variables should be negatively related to swap transaction involvement.

Kim and Koppenhaver use the primary capital to asset ratio as an independent variable. They argue that as bank capital increases, the ability to bear risk increases.
On the other hand, a high capital position makes a bank an attractive party to a swap transaction because of the higher credibility of high-capitalised banks. In addition, they argue that size is an important factor that determines derivative activities as large banks could make use of specialised management skills needed to effectively use these activities. They also argue that because of the 'too-big-to-fail' doctrine, large banks might be perceived more credible than small banks by the markets and therefore be a party to a derivative transaction.

Kim and Koppenhaver found that the likelihood of swap market participation is directly related to the competitiveness of banks and size. However, they found a negative relationship between swap market participation and capital levels. Expected interest rate change was also found to have a negative relationship with swap market participation. On the other hand, increasing interest rate exposure and the ratio of loans to total assets, were found to be a determinant of swap market participation. Outstanding notional amount of interest rate transactions were also found to be directly related to long-term exposure to interest rates, size, loans and the use of futures trading. Concerning regulatory impact, Kim and Koppenhaver found a negative and significant relationship between the usage of swap transactions and dummy variables that represents regulatory capital pressures. Kim and Koppenhaver conclude that "Efforts to increase bank capitalisation through the risk-based capital guidelines, however, may increase the willingness of banks to bear interest rate risk and decrease swap usage as a risk management tool."

Jagtiani et al. (1995) argue that although several studies have examined the impact of capital requirements and other motivations on the growth of OBS activities, the results are mixed. Therefore, they investigated 'whether OBS activities grow over time as OBS financial technology is diffused among banks'. They also investigated the impact of changes in capital requirements on OBS growth by employing dummy variables. In their study, they modelled the diffusion of bank OBS activities, such as interest rate swaps, standby letters of credit, loan securitisation, interest rate options and interest rate futures and forwards. They tested the issue of capital requirements and OBS activities by modelling each OBS activity as an innovation whose adoption follows a diffusion pattern specific to that activity. The notional dollar amounts of
OBS activities were used in the analysis. As bank characteristics, they employed the logarithm of total assets, foreign currency deposits as a percentage of total deposits, the ratio of non-performing loans to total assets, the ratio of net income to total assets and the ratio of risk-weighted assets to total assets. The implementation of new capital regulations was captured by dummy variables. There were two capital requirement changes during the period of their study. First, in June 1985, the uniform minimum capital ratios (the ratio of capital to total assets), second, in July 1988, the risk-based capital regulations (the Basle Accord) were implemented in the US.

The results of Jagtiani et al.'s study indicate that the implementation of uniform capital requirements in 1985 has had a significant negative impact on derivative activities. However, the implementation of these regulations has had a significant positive impact on standby letters of credit and loan securitisation. They conclude that standby letters of credit and loan sales might have been used by banks to avoid capital requirements. The results concerning the impact of the Basle Accord indicate that the risk-based capital requirements do not reduce the growth of derivative transactions. In addition, the results of the model that investigates the impact of bank characteristics on OBS growth did not produce significant coefficients. Therefore, Jagtiani et al. conclude that "the adoption of OBS derivative products seems to be related to technological and learning factors and overall economic activity".

By employing time series cross-section data over the period 1984 to 1991 for 91 largest banks in the US, Jagtiani and Khanthavit (1996) examined the impact of the risk-based capital regulations. They found that banks do not reduce their OBS activities in response to the regulatory tax imposed by the risk-based capital regulations, which is consistent with Jagtiani et al.'s findings. They also found that the changes in risk-based capital reduce the optimal bank size that achieves maximum scale and scope economies. As a result, following the implementation of capital requirements, some large banks that have been efficient until that time have become too large and inefficient. They conclude that regulations encourage large banks to expand their activities.
Jagtiani (1996) investigated whether capital requirements encourage banks to increase their swap transactions and whether market discipline exists in the swap market. In order to investigate the relationship between a bank’s probability to use swap transactions and capital regulations, a logit analysis was employed (in which the dependent variable is 1 if a bank uses swap transactions). The analysis was performed on panel data from 1985Q2 to 1991Q3. In addition to bank size, dummy variables were employed to measure the impact of capital constraints as explanatory variables in this logit model. Furthermore, in order to investigate the factors that determine the volume of swap transactions, OLS estimation was employed. Jagtiani employed two measures of swap volume in this second analysis; first, each bank’s market share (notional amount of swaps to aggregate notional amount of swaps of all banks in the sample), and second, the ratio of notional amount of swaps to total assets. Six variables were included in this model as explanatory variables. These are; the capital ratio, a dummy variable that represents money centre banks, S&P rating, futures and forward contracts and balance sheet creditworthiness (measured by the ratio of income to total assets and the ratio of non-performing loans to total assets). The results of the logit model suggest that banks that are subject to a binding capital constraint are more likely to be involved in swap transactions. Jagtiani explains these results by stating that “when loan activities are constrained, in order to generate income, banks engage more in swap transactions”. The results of the OLS model also suggest that there is a positive significant relationship between credit-worthiness and the use of swap transactions. Therefore, it is concluded that creditworthy banks will be more involved in swap transactions, which is an evidence of market discipline in the swap market. As a result, Jagtiani underlines that bank creditworthiness plays an important role in the use of swap activities.

As a result, the argument concerning that, OBS activities of banks increase because of the lack of capital standards, has been tested by a number of studies. The studies, which investigated the relationship between capital regulations and OBS activities excluding derivative activities, provide contradictory results. The studies that investigated the relationship between derivative activities and capital regulations also provide contradictory results. While Kim and Koppenhaaver (1992) found a negative and significant relationship between the usage of swap transactions and regulatory
capital pressures, Jagtiani et al. (1995) and Jagtiani and Khanthavit (1996) found that the implementation of the risk-based capital requirements do not reduce the growth of derivative transactions. On the other hand, Jagtiani (1996) found that banks that are subject to a binding capital constraint are more likely to be involved in swap transactions.

As a conclusion, there is an emerging literature that investigates the impact of capital requirements on bank OBS activities. However, rather than investigating the impact of capital adequacy regulations on derivative activities, these studies have generally concentrated on other OBS activities. In addition, the studies that investigated the relationship between derivative activities and capital regulations could not provide uniform evidence.

3.6 Chapter Summary

Among the financial safety nets that policy-makers rely on to ensure the stability of a banking system, deposit insurance and capital adequacy have always played a prominent role. Although policy-makers generally consider that deposit insurance is necessary to protect small depositors and to prevent bank runs, it could also cause a moral hazard problem. Therefore, it is generally accepted that policy-makers implement capital adequacy regulations to overcome the moral hazard problem created by deposit insurance. On the other hand, the literature concerning the interaction between deposit insurance and capital regulations indicates that a deposit insurance scheme may not be necessary if banks have adequate capital.

As a result, bank regulators place so much emphasis on banks' capital adequacy and try to affect bank capital by setting capital adequacy regulations to ensure that banks hold sufficient capital to absorb unexpected losses. However, the impact of these regulations is not clear.

This chapter summarised the literature concerning the impact of capital regulations on bank capital levels, risk-taking, and OBS activities. Despite the fact that capital requirements are accepted as being crucial for the soundness of the financial system,
the discussion regarding the impact of these regulations on financial institutions is still an important issue and attracts both the attention of academics and regulators. The literature review presented in this section demonstrates that in general the studies concerning the impact of capital regulations on bank capital levels provide contradictory results. On the other hand, this review demonstrates that a partial adjustment methodology has been broadly employed to test the impact of capital adequacy regulations on bank capital levels and risk-taking.

The implementation of capital adequacy regulations may influence banks either by increasing their capital or by decreasing their risk-taking. Therefore, banks may also react to the implementation of these regulations by changing their risk-taking. The studies that investigated the relationship between bank capital and risk-taking failed to reach a uniform result concerning the impact of capital adequacy regulations on bank risk-taking. Therefore, whether the implementation of capital adequacy regulations creates a moral hazard problem by increasing banks’ risk-taking is an important question that should be answered.

Another important issue concerning the impact of capital adequacy regulations is the relationship between these regulations and OBS activities. In response to capital regulations, banks can also increase their risk-taking by increasing their OBS activities, in particular, derivative activities. The literature review concerning the relationship between capital regulations and OBS activities provide contradictory results. Although there is an emerging literature that investigates the impact of capital requirements on bank OBS activities, most of these studies have concentrated on OBS activities excluding derivatives. In addition, the studies that investigated the relationship between derivative activities and capital regulations could not provide uniform evidence.

Furthermore, although the impact of capital adequacy regulations has been analysed extensively in the literature, excluding the study of Danielsson et al. (2004), there is not much empirical evidence concerning the impact of the market risk capital regulations. In addition, the impact of these regulations on bank capital levels and derivative activities is an issue that has not yet been investigated in the literature.
In summary, there is an ongoing debate concerning the effects of capital adequacy regulations. Therefore, it is a key question to find out whether the implementation of the market risk capital regulations has created any impact on bank capital levels and derivative activities. In order to analyse this issue, an econometric analysis is carried out in the next chapter.
CHAPTER FOUR

THE IMPACT OF THE MARKET RISK CAPITAL REGULATIONS ON BANK CAPITAL LEVELS AND DERIVATIVE ACTIVITIES

4.1 Introduction

The aim of this chapter is to empirically analyse the impact of the market risk capital regulations on bank activities. The implementation of these regulations can influence banks either by increasing their capital or by decreasing their trading activities and in particular, trading derivatives. Therefore, the analysis provided in this chapter investigates the impact of the market risk capital regulations on the changes of bank capital levels and derivative activities.

The changes in capital levels and derivative activities are modelled by using a partial adjustment framework. In these models, the changes in the capital and derivative usage ratios depend on the lagged level of the capital and derivative usage ratios. In addition, a range of variables describing banks' activities and risk-taking are assumed to have an impact on these variables. The study focuses on the large US BHCs, as they are more involved in trading activities and therefore subject to the market risk capital regulations. Using quarterly data for the period 1995Q4 to 1999Q4, a panel data analysis is employed to obtain the estimates.

One of the fundamental arguments concerning capital regulations is that these regulations are effective if they result in an increase in capital levels. Accordingly, by implementing the market risk capital regulations, bank regulators require additional capital for banks that are heavily involved in trading activities. Therefore, the effectiveness of these regulations can be tested by examining to what extent the implementation of these regulations has an impact on bank capital levels.
The first research question of this analysis is whether the implementation of market risk capital regulations has an effect on capital levels. Accordingly, the first hypothesis that is tested in this study is the regulatory cost hypothesis. Although it is costly for bank managers to increase capital levels, the regulatory view considers capital as a cushion that absorbs unexpected losses. Therefore, this hypothesis implies that in order to be effective, capital regulations should increase the capital levels of banks.

In order to test the regulatory cost hypothesis, the impact of the market risk capital regulations on bank capital levels is analysed. This analysis indicates whether the market risk capital regulations are effective by causing an increase in the capital level. A finding of 'no relationship' between the implementation of these regulations and the change in capital ratios should indicate that the market risk capital regulations are not effective, as there is no regulatory influence on the capital decisions of banks. On the other hand, a significant positive coefficient of the variable that proxies for the implementation of the market risk capital regulations should indicate that these particular regulations are effective.

The second research question of this analysis is whether there is a relationship between the implementation of the market risk capital regulations and the usage of derivatives. To find an answer to this question, the capital avoidance hypothesis is tested. According to this hypothesis, OBS activities of banks increase because of the lack of capital standards. In order to test this hypothesis, the impact of the market risk capital regulations on derivative activities is investigated. A finding of a negative relationship between the implementation of the market risk regulations and the change in derivative usage ratios could demonstrate that with the existence of capital regulations banks' derivative activities decrease. On the other hand, a significant positive coefficient of the variable indicates that there is no capital avoidance that causes a decrease in derivative usage by the implementation of these regulations.

The two main hypotheses that are tested in this study in order to investigate the impact of the market risk capital regulations are presented below.
1) H1: The implementation of the market risk capital regulations increases capital levels of banks (the regulatory cost hypothesis).

2) H1: The implementation of the market risk capital regulations decreases the usage of derivatives (the capital avoidance hypothesis).

There are four additional hypotheses that are tested within this analysis. These are; the economies of scale hypothesis, the moral hazard hypothesis, the regulatory discipline hypothesis, and the market discipline hypothesis.

The research questions related to the economies of scale theory are; whether there is a relationship between i) bank capital and asset size, and ii) level of derivative activities and asset size. The size of a bank might influence its capital level in more than one way. The prediction of economies of scale in the production of deposit services suggests a negative relationship between size and capital level as larger institutions attract more deposits. Furthermore, because larger banks could better diversify their portfolios, they have lower bankruptcy risks. In addition, depositors and debt-holders believe that large banks are protected from failure by implicit guarantees of regulators, and this belief rises with size. This argument is known as the 'too-big-to-fail' doctrine. According to this doctrine, bank regulators could be more committed to bailout larger banks that are considered 'too-big-to-fail' in the event of distress and insolvency. In addition, capital is considered as an expensive source for bank managers. Therefore, large banks are more reluctant to increase their capital levels. These arguments suggest a negative relationship between bank size and capital levels.

Concerning derivative activities, the literature indicates that size is an important factor that determines derivative activities of banks. As large banks are more likely to use derivatives, a positive relationship between bank size and derivative activities is expected.

Another research question is to find out whether there is a relationship between the level of bank capital and derivative activities. In addition to this, the relationship
between the level of bank capital and risk-taking of banks is also investigated. According to the moral hazard hypothesis, banks with low capital invest more in risky portfolios and use more derivative activities. Rogers and Sinkey (1999) argue that because of moral hazard, banks use derivative activities to take advantage of deposit insurance. Therefore, excessive risk-taking arises as deposit insurance allows banks to take more risk without having to pay a risk premium on deposits (Calem and Rob, 1999; Rogers and Sinkey, 1999). Moral hazard might encourage low-capitalised banks to use derivative transactions to increase their risk-taking, as these activities could be used for speculative purposes (Sinkey and Carter, 1997). However, the moral hazard hypothesis is not strongly supported by empirical studies (Park, 1997). In order to test this hypothesis, the relationship between bank capital and derivative activities and the level of risk-taking are examined in this study.

The regulatory discipline hypothesis suggests that banks are required to hold more capital because of the capital requirements that cover derivative activities of banks. Due to the regulatory capital requirements, banks that have relatively higher levels of capital are more likely to participate in derivative markets (Carter and Sinkey, 1998). Therefore, this hypothesis is also tested to determine whether a positive relationship between bank capital levels and derivative activities exists.

On the other hand, market discipline could prevent banks from using derivatives. According to the market discipline hypothesis, external monitoring and pricing prevent banks from being involved in risk-taking activities (Sinkey and Carter, 1997). Therefore, with the decrease of the indicators of creditworthiness, the risk-taking activities of banks are also expected to decrease. This hypothesis suggests a positive relationship between the indicators of credibility and derivative activities.

These arguments lead to the following hypotheses.

1) H1: There is a negative relationship between bank capital levels and asset size (the economies of scale hypothesis).

2) H1: There is a positive relationship between bank derivative activities and asset size (the economies of scale hypothesis).
3) H1: There is a negative relationship between bank capital levels and bank risk-taking (the moral hazard hypothesis).

4) H1: There is a negative relationship between bank capital levels and derivative activities (the moral hazard hypothesis).

5) H1: There is a positive relationship between bank capital levels and derivative activities (the regulatory discipline and market discipline hypotheses).

6) H1: There is a negative relationship between bank derivative activities and risk-taking (the market discipline hypothesis).

This chapter proceeds as follows. The second section explains the methodology. As well as the models that are employed to determine the impact of the market risk capital regulations on bank capital levels and derivative activities, the dependent and independent variables are also presented in this section. The third section introduces the data. The fourth section reports the empirical results. The findings are explained in the fifth section.

4.2 Methodology

In this study, the changes in capital and derivative usage ratios are modelled by using a partial adjustment framework. In this framework, the discretionary changes in capital and derivative usage are proportional to the difference between the target levels and the levels existing in period t-1. The actual changes of capital and derivative usage of a bank are assumed to follow the below process:

$$K_t - K_{t-1} = \delta (K_t^* - K_{t-1}) + \varepsilon_t$$  \hspace{1cm} (4.1)

where $K_t$ is the actual capital ratio (or derivative usage ratio) at time $t$, $K_t^*$ is the target capital ratio (or target derivative usage) for time $t$, $(K_t - K_{t-1})$ is the actual change and $(K_t^* - K_{t-1})$ is the desired change in the capital ratio (or derivative usage ratio), $\delta$ is the coefficient of adjustment, which is $(0 < \delta \leq 1)$, and $\varepsilon_t$ is a random error. If $K_t^*$ is less than $K_{t-1}$, then $(K_t - K_{t-1})$ is on average negative. If $K_t^*$ is
higher than $K_{t-1}$, then $(K_t - K_{t-1})$ is on average positive. In the long run, $K_t$ will be likely to converge towards $K_t^*$ and the extent of the coefficient of adjustment ($\delta$) indicates the rate at which this convergence occurs.

Equation 4.1 indicates that the actual change is decomposed into two components. These are, a discretionary adjustment and a change caused by an exogenously determined random shock. As $K_t^*$ is not observable in Equation 4.1, it is assumed to depend upon a set of observable variables.

The major assumptions and limitations of using this framework are presented below:

1) This framework assumes that banks do not adjust their target capital levels and derivative activities instantaneously. In this framework, banks adjust their desired levels with a lag that is approximated by a partial adjustment specification.

2) This framework assumes that banks adjust their portfolios as the actual holding of an asset grows further away from what is desired. However, banks may not forcefully adjust their portfolios if they are not in danger of hitting their minimum required capital levels.

3) As bank capital and derivative targets (with or without any capital regulation) are difficult to observe, they are assumed to depend upon a set of observable independent variables. This framework offers a practical advantage, as the formulation is fundamentally linear in the parameters. However, the actual changes could be determined nonlinearly by the independent variables. Therefore, assuming that the actual changes of capital and derivatives linearly depend upon a set of observable independent variables is an important limitation of the study.

4) The impact of capital regulations is measured by the coefficient of a dummy variable. However, this is another limitation of this framework as the dummy variable may be influenced by any omitted variable.

The models based on this framework are explained in the following sub-section.
4.2.1 Model Specification

In order to investigate the impact of the market risk capital regulations, the actual changes in capital and derivatives usage ratios are modelled by using a partial adjustment framework.

The actual changes in capital and derivative usage ratios are the changes in the bank \( j \)'s capital and derivative usage ratios during the period \( t \), such that:

\[
\Delta \text{CAP}_{j,t} = \text{CAP}_{j,t} - \text{CAP}_{j,t-1}
\]  
(4.2)

and

\[
\Delta \text{DER}_{j,t} = \text{DER}_{j,t} - \text{DER}_{j,t-1}
\]  
(4.3)

where \( \Delta \text{CAP}_{j,t} \) and \( \Delta \text{DER}_{j,t} \) are the total actual changes in the capital and derivative usage ratios during the period \( t \) for bank \( j \), respectively. \( \text{CAP}_{j,t-1} \) and \( \text{DER}_{j,t-1} \) represent the bank \( j \)'s capital and derivative usage ratios at the beginning of period \( t \), and \( \text{CAP}_{j,t} \) and \( \text{DER}_{j,t} \) represent the end of period \( t \) levels for bank \( j \), respectively.

The actual changes in capital ratios are formulated as:

\[
\Delta \text{CAP}_{j,t} = \Delta \text{CAP}_{j,t}^d + \tilde{E}_{j,t}
\]  
(4.4)

where \( \Delta \text{CAP}_{j,t}^d \) represents the endogenously determined (discretionary) adjustment in capital, and \( \tilde{E}_{j,t} \) represents the exogenously determined factors (random shock) for bank \( j \) in period \( t \).
The changes in derivative usage ratios are formulated as:

$$\Delta \text{DER}_{j,t} = \Delta \text{DER}_{j,t}^d + \bar{U}_{j,t}$$  

(4.5)

where $\Delta \text{DER}_{j,t}^d$ is the discretionary adjustment in derivative usage and, $\bar{U}_{j,t}$ represents the exogenously determined random shocks.

Considering capital, exogenous changes could be the result of enforced increases in the required capital by regulators or unanticipated changes in earnings. Considering derivative usage, exogenous changes could be the result of unanticipated shocks.

The behaviour of banks is modelled by using the partial adjustment framework, such that:

$$\Delta \text{CAP}_{j,t}^d = \alpha (\text{CAP}_{j,t}^* - \text{CAP}_{j,t-1})$$  

(4.6)

and

$$\Delta \text{DER}_{j,t}^d = \beta (\text{DER}_{j,t}^* - \text{DER}_{j,t-1})$$  

(4.7)

where $\text{CAP}_{j,t}^*$ and $\text{DER}_{j,t}^*$ are bank j's target capital and derivative usage ratios, respectively. In a partial adjustment framework, the discretionary changes in capital and derivatives are proportional to the difference between the target level and the level at the beginning of the period, which is the desired change. $\alpha$ and $\beta$ are the coefficients that indicate the proportion of the desired level of change. Equations (4.7) and (4.8) postulate that the actual changes in period $t$ is some fraction $\alpha$ (or $\beta$) of the desired change for that period. These equations can be alternatively written as:

$$\Delta \text{CAP}_{j,t}^d = \alpha \text{CAP}_{j,t}^* + (1 - \alpha) \text{CAP}_{j,t-1}$$  

(4.8)

and

$$\Delta \text{DER}_{j,t}^d = \beta \text{DER}_{j,t}^* + (1 - \beta) \text{DER}_{j,t-1}$$  

(4.9)
By substituting the equations (4.8) and (4.9) into the equations (4.4) and (4.5), the actual changes in capital and derivatives are formulated as:

\[ \Delta CAP_{jj} = \alpha CAP^*_{jj} + (1 - \alpha) CAP_{jj-1} + E_{jj} \]  (4.10)

and

\[ \Delta DER_{jj} = \beta DER^*_{jj} + (1 - \beta) DER_{jj-1} + U_{jj} \]  (4.11)

These equations suggest that the actual changes in capital and derivative usage ratios in a period for a bank are a function of:

- Target capital and derivative usage ratios,
- Lagged capital and derivative usage ratios,
- Exogenous factors.

As the target levels are unobservable, they are assumed to depend upon a set of observable variables. Bank size, risk variables, and profitability are assumed to substitute for the target capital level. On the other hand, bank size, risk variables, credibility variables, profitability, and trading activities are assumed to substitute for the target level of derivatives. As it is also desirable to investigate the relationship between bank capital and derivatives, derivative activities are included as an independent variable to explain the actual change in capital. Conversely, the actual change in capital is included as an independent variable to explain the actual change in derivatives. In order to account for the exogenous factors of regulatory and macroeconomic conditions, a number of binary variables are employed.

By substituting the target levels and exogenous factors of equations (4.10) and (4.11), the models are structured as:

\[ \Delta CAP_{jj} = c_0 + c_1 SIZE_{jj} + c_2 RWA_{jj} + c_3 NONPERF_{jj} + c_4 GROSSDER_{jj} \]
\[ + c_5 TRADING_{jj} + c_6 INCEXP_{jj} + c_7 DREG_{jj} + c_8 DRUS_{jj} \]
\[ + c_9 DPRES_{jj} + c_{10} LAGCAP_{jj-1} + E_{jj} \]  (4.12)

and
\[
\Delta \text{DER}_{j} = d_0 + d_1 \text{SIZE}_{j} + d_2 \text{RWA}_{j} + d_3 \text{NONPERF}_{j} + d_4 \text{RBC}_{j} \\
+ d_5 \text{TRADING}_{j} + d_6 \text{INCEXP}_{j} + d_7 \text{DREG}_{j} + d_8 \text{DRUS}_{j} \\
+ d_9 \text{LAGDER}_{j-1} + \bar{U}_{j}, \tag{4.13}
\]

where;

- \(\Delta \text{CAP}\) indicates the change in the capital ratio (\(\text{DELTARBC} / \text{DELTATIERI} / \text{DELTALEV} / \text{DELTAEQUITY}\)),
- \(\Delta \text{DER}\) indicates the change in the ratio of derivatives to total assets (\(\text{DELTAFAIRDER} / \text{DELTAGROSSDER}\)),
- \(\text{SIZE}\) is the natural logarithm of total assets,
- \(\text{RWA}\) is the ratio of risk-weighted assets to total assets,
- \(\text{NONPERF}\) is the ratio of non-performing loans to total loans,
- \(\text{GROSSDER}\) is the ratio of gross value of derivatives to total assets,
- \(\text{RBC}\) is the ratio of risk-based capital to risk-adjusted assets,
- \(\text{TRADING}\) is the ratio of total trading assets and liabilities to total assets.
- \(\text{INCEXP}\) is the ratio of total income to total expense,
- \(\text{DREG}\) is the dummy variable that takes the value of one for those periods that the bank is subject to the market risk capital regulations, 0 otherwise,
- \(\text{DRUS}\) is the dummy variable that takes the value of one for those periods that markets face a financial turmoil, 0 otherwise,
- \(\text{DPRES}\) is the dummy variable that takes the value of one for banks that are undercapitalised, 0 otherwise,
- \(\text{LAGCAP}\) indicates the previous period's capital ratio (\(\text{LAGRBC} / \text{LAGTIERI} / \text{LAGLEV} / \text{LAGEQUITY}\)),
- \(\text{LAGDER}\) indicates the previous period's ratio of derivatives to total assets (\(\text{LAGFAIRDER} / \text{LAGGROSSDER}\)).

The dependent and independent variables of the models presented in equations (4.13) and (4.14) and the hypothesised signs of the explanatory variables are explained in the following sub-sections.
4.2.2 Dependent Variables

The observed changes in bank capital ratios and derivative usage ratios are dependent variables of the models. These variables are explained below:

a) Bank Capital

The capital ratio \((CAP)\) is the ratio of capital to total assets. Four different capital indicators are used to calculate this ratio; namely the total risk-based capital ratio \((RBC)\), the tier-1 risk-based capital ratio \((TIER1)\), the leverage ratio \((LEV)\) and the equity capital ratio \((EQUITY)\).

In the US, banks and BHCs are classified into five capital categories based on three capital ratios, namely the total risk-based capital ratio, the tier-1 capital risk-based ratio and the tier-1 leverage ratio. The capital thresholds for these five categories are presented in Table 4.1.

Table 4.1: Capital Thresholds and Bank Classification

<table>
<thead>
<tr>
<th>Capital Threshold</th>
<th>Total Risk-Based Capital</th>
<th>Tier-1 Risk-Based Ratio</th>
<th>Tier-1 Leverage Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Well Capitalised</td>
<td>≥ 10%</td>
<td>≥ 6%</td>
<td>≥ 5%</td>
</tr>
<tr>
<td>Adequately Capitalised</td>
<td>≥ 8%</td>
<td>≥ 4%</td>
<td>≥ 4%</td>
</tr>
<tr>
<td>Undercapitalised</td>
<td>&lt; 8%</td>
<td>&lt; 4%</td>
<td>&lt; 4%</td>
</tr>
<tr>
<td>Significantly Undercapitalised</td>
<td>&lt; 6%</td>
<td>&lt; 3%</td>
<td>&lt; 3%</td>
</tr>
<tr>
<td>Critically Undercapitalised</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tangible Equity ≤ 2%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Aggarwal & Jacques, 1998

The US regulators use all of these three capital ratios as the indicators of bank capital. The total risk-based capital and the tier-1 risk-based ratios are consistent with the Basle Accord, whereas the leverage ratio, which is the ratio of tier-1 capital to average total assets, was implemented in the US in 1990.
Current Basle regulations define three capital elements, namely tier-1, tier-2, and tier-3. Among these tiers, tier-3, introduced by the 1996 amendment, can only be used by banks that are subject to recent market risk capital regulations (Basle Committee, 1996).

Tier-1 capital consists of the following:

- Common stock,
- Perpetual non-cumulative preference shares,
- Disclosed reserves,
- Minority interests in the equity of subsidiaries (in the case of consolidated accounts),
- Less goodwill.

In addition to tier-1 capital, total risk-based capital includes tier-2 and tier-3 capitals. The items that are included in tier-2 and tier-3 capitals are as follows:

- **Tier-2** (limited to a maximum of 100 percent of tier 1)
  - Undisclosed reserves,
  - Asset revaluation reserves,
  - General provisions/loan loss reserves (limited to 1.25 percent of risk weighted assets),
  - Hybrid (debt/equity) capital instruments,
  - Subordinated debt (limited to a maximum of 50 percent of tier-1), which includes unsecured subordinated debt with a minimum original fixed term to maturity of over five years and limited life redeemable preference shares.

- **Tier-3:**
  - Short-term subordinated debt, (limited to 250 percent of tier-1), which includes unsecured subordinated debt with an original maturity of at least two years and which could be used only to support market risk.

Although all of the regulatory capital indicators are used as dependent variables, the risk-based capital has a more fundamental role in the market risk capital regulations, as banks are allowed to include tier-3 capital in the calculation of the required capital against market risk.

As well as the regulatory capital ratios that are explained above, the ratio of equity capital to total assets is also used as a dependent variable. Equity capital is the
difference between the total assets and total liabilities, which is also called the 'net value' or 'net worth', and the ratio of equity capital to total assets has been extensively used in the literature. In this study, equity capital is the sum of common stock, perpetual preferred stock, capital surplus, retained earnings, net unrealised gains on AFS securities, accumulated net gains on cash flow hedges, cumulative foreign currency translation adjustments, less treasury stock. This is consistent with the calculation of equity capital that the Federal Reserve carries out in its FR Y-9C reports.

b) Derivative Activities

'Derivatives' is a general term, which covers a wide range of financial contracts such as swaps, options, forwards and futures. Banks participate in derivative activities in two ways: as 'end-users' and as 'dealers'. 'End-users' employ derivatives either for hedging or speculation purposes. Dealer banks, on the other hand, as well as being an 'end-user', provide OTC derivative products to other banks or clients. While all derivative user banks participate to a certain extent as 'end-users', only a few of the largest institutions are 'dealers' of OTC derivatives.

The focus of this study is the market risk capital regulations that have been assimilated into the risk-based capital guidelines to incorporate a measure for market risk, which is the risk of losses in on and off-balance sheet positions arising from movements in market prices (Basle Committee, 1996). The risks concerning the interest rate related instruments and equities in the trading book and foreign exchange risk and commodities risk of both trading and banking books are the risks that are subject to these regulations.

As these regulations particularly target the trading activities of banks, as an indicator for derivative activities, the ratio of trading derivative activities to total assets (DER) is employed. However, two different measures are used. First, the ratio of total of positive and negative fair value of trading derivatives to total assets (FAIRDER), and

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20 Equity capital is defined by the “Dictionary of Banking Terms” as the value of stockholders' ownership interest in a corporation after all claims have been paid.
second, the ratio of notional gross amount of trading derivatives to total assets (GROSSDER).

While several studies have employed the notional amount of derivative activities in their models (Sinkey and Carter, 1997; Carter and Sinkey, 1998; Jagtiani et al., 1995; Jagtiani, 1996), Whidbee and Wohar (1999) argue that the total notional principal amount of derivative contracts is not a sufficient measure as it aggregates long and short positions. Although Carter and Sinkey (1998) employed notional amounts of derivatives, they also point out the disadvantage of using this variable by stating that:

“We fully recognise, however, that notional values do not reflect either the market value or the risk of the contracts. Since the focus of our empirical investigation is on two decisions, usage and extent of usage, notional values represent reasonable proxies for these two traits regardless of the actual underlying risk exposure.”

Although this study employs the ratio of notional amount of trading derivatives to total assets, due to the disadvantage of using this variable, the ratio of total positive and negative fair value of trading derivatives to total assets is also employed as a dependent variable.

On the other hand, the limitation of this study is that banks could use derivatives not only for speculative purposes, but also for hedging and dealing purposes. In spite of this, there is no available data that separates the speculative derivative activities from the hedging activities. The unavailability of detailed data that separates the nature of derivative transactions is a limitation of this study.

4.2.3 Independent Variables

In this section the independent variables of the equations (4.13) and (4.14) are introduced.

As the implementation of the market risk capital regulations is the cornerstone of this study, a binary variable (DREG) is used to analyse the impact of these regulations. This dummy variable takes the value of one for periods that the BHC is subject to the market risk capital regulations. In the US, the final rule regarding the market risk
capital regulations has been included into the risk-based capital regulation framework for bank holding companies and commercial banks with significant trading activities effective since January 1998. However, it should be noted that not all the BHCs in the sample are subject to these regulations from the beginning of 1998. Two of them have been required to hold capital for their market risk later, when they became subject to these rules.

In this study the implementation effect of the market risk capital regulations is investigated, rather than the announcement effect. Banks could change the composition of their portfolios quickly and the impact appears more clearly after the implementation date (Haubrich and Wachtel, 1993). Following this argument, a binary variable is used as unity for the quarters that these regulations are effective for the sample banks, and 0 otherwise. Due to the regulatory cost hypothesis, a positive relationship is expected between the capital ratios and DREG, and because of the capital avoidance hypothesis, a negative relationship is expected between the derivative ratios and DREG.

SIZE is calculated as the natural logarithm of a bank’s total assets. This variable is included in the equations to proxy the potential for large banks to realise economies of scale. Following the previous empirical studies, the models include size as a standard control variable that captures the potential influence of other variables. A negative relationship between change in the bank capital ratios and asset size and a positive relationship between the change in bank derivative ratios and asset size is expected because of the economies of scale hypothesis.

In order to capture the risk-taking of banks, three variables are included in both of the equations. These are; the ratio of risk-weighted assets to total assets (RWA), the ratio of non-performing loans to total loans (NONPERF) and the ratio of total trading assets and liabilities to total assets (TRADING). More risky banks are assumed to increase the share of their risk-weighted assets, non-performing loans and trading assets and liabilities in total assets. Due to the moral hazard hypothesis, which implies that banks with low capital invest more in risky portfolios, a negative relationship is expected between the change in bank capital ratios and risk proxies.
Risk measures indicate the creditworthiness of banks. Therefore, banks with risky assets and higher non-performing loans may have been disadvantaged in using derivatives due to the lack of credibility (Jagtiani et al., 1995). On the other hand, more creditworthy banks could become involved in derivative activities without difficulty (market discipline hypothesis). This argument leads to a negative relationship between risk measures and derivative usage. On the other hand, Carter and Sinkey (1998) argue that a higher level of risk is expected to lead to a higher level of derivative usage as banks that have significant risk exposures could use derivatives to hedge these risks. Therefore, Carter and Sinkey expect a positive relationship between risk measures and derivative usage. Furthermore, as derivative activities could be used to hedge trading assets and liabilities, it is not unforeseen to expect a positive relationship between derivative usage and trading accounts. Due to these conflicting arguments, the expected signs of RWA, NONPERF and TRADING in the derivative equations are ambiguous.

In order to investigate the relationship between capital and derivatives, the ratio of gross notional values of derivatives to total assets (GROSSDER) is included in the capital equations and the ratio of risk-based capital to risk-weighted assets (RBC) is included in the derivative equations. Considering the moral hazard hypothesis, which implies that low-capitalised banks are involved in derivative activities, a negative relationship is expected between the change in bank capital ratios and derivative usage. On the other hand, as derivatives are subject to the capital regulations, the regulatory discipline hypothesis implies a positive relationship between the change in bank capital ratios and derivative usage. The RBC variable in the derivative equations also indicates creditworthiness, as capital ratios are often considered as an instrument to control bank risk-taking (Bruni and Paterno, 1995). As the higher capital increases the credibility of banks, their derivative activities should increase accordingly. Therefore, a positive relationship is expected between the changes in derivative usage and the ratio of risk-based capital to risk-weighted assets. As a result, a positive relationship between these two variables indicates the existence of not only regulatory discipline but also market discipline. However, since there are
conflicting arguments concerning the relationship between capital and derivative activities, the expected signs of \( RBC \) and \( GROSSDER \) are ambiguous.

\( INCEXP \), which is the ratio of total income to total expense, is included in the equations as the measure of profitability. Profitability could positively affect capital levels of banks if they prefer to increase capital through retained earnings. Rime (2001) argues that banks prefer to increase capital through retained earnings rather than through equity issues as issuing equity might give a negative signal to the market concerning its value in the presence of an asymmetric information. Therefore, in the capital equations, a positive relationship is expected between the changes in capital ratios and the ratio of total income to total expense.

\( INCEXP \) is included in the derivative equations as a measure of creditworthiness. As profitability increases the credibility of banks, their derivative activities should increase accordingly. Therefore, a positive relationship is expected between the changes in derivative usage and the ratio of total income to total expense.

The BHCs might also be affected by macro economic developments that occurred during the time period of the investigation. In order to allow exogenous regulatory and macro economic factors, which might affect the actual changes in dependent variables, binary variables are used. In order to obtain information concerning which factors that have affected the US banks, two main sources were checked. The first source that has been checked is the “Calendar of Main Economic Events”. This source demonstrates the important economic factors that have affected the US economy during the years 1995 to 1999 and this is published as an appendix in the “OECD Economic Surveys of United States”\(^{21}\). The second source that was checked is the “FDIC Banking Review” for the years 1995 to 2000, in which the “Recent Developments Affecting Depository Institutions” are published regularly.

The most important development that might affect the US BHCs was the Russian default and the near collapse of the Long-Term Capital Management (LTCM)\(^{22}\),


\(^{22}\) The LTCM is a hedge fund.
which occurred in August and September 1998, respectively. In August 1998, Russia devalued the ruble and effectively defaulted on some of its debts, which caused the financial markets to seize up. Following this development, financial markets witnessed the near collapse of the LTCM, which is said to have nearly blown up the world’s financial system (Jorion, 1999). The impact of these developments on derivatives can also be seen from Graph 4.1, which shows that during this period the derivative losses of the US banks increased dramatically. In order to account for these extraordinary developments in global financial markets, another binary variable (DRUS) is used and this variable takes the value of one for the third and fourth quarters of 1998.

![Graph 4.1: Derivatives Charge-Offs of US Commercial Banks, 1996-99](source)

The binary variable DRUS is included in both equations. Additionally, in order to account for the regulatory pressure on BHCs that are undercapitalised, another binary variable (DPRES) is included to explain the actual changes in capital levels. However, this variable is only included in the capital equations.

As noted by Aggarwal and Jacques (1998), if a bank falls into one of the three undercapitalised categories, regulators place compulsory restrictions on the activities of banks that become increasingly severe as the bank’s capital ratios decline. In order to account for the pressure of regulators, the DPRES variable is added to the capital equation, which is unity for the observations when the BHC is undercapitalised at the end of the previous period. This variable also sheds some light on the effectiveness
of the regulatory discipline. Therefore, a positive relationship is expected between the \( DPRES \) and capital ratios.

4.3 Data

In order to investigate the impact of the market risk capital regulations on capital levels and derivative activities, as well as the relationship between them, quarterly data for the US BHCs is employed. There are two important reasons to use the US data in the analysis. Firstly, the US banks are leading financial institutions, which dominate the world market for derivative contracts. Secondly, it is possible to obtain detailed information concerning the US individual institutions.

In the US, the final rules regarding the market risk capital regulations were included into the risk-based capital regulations framework for bank holding companies and commercial banks with significant trading activities in September 1996. These regulations took effect in January 1998. In the US, only the largest 18 banks with extensive trading activity were subject to these regulations at the beginning of 1998. The US market risk capital regulations require these banks to use their internal VaR models. This, in fact, distinguishes the US rules from the Basle amendment, as the standardised approach is not taken into consideration. However, this in turn brings an advantage to use US data as it is known that all banks that are subject to these rules are using a VaR methodology to measure the required capital to hold against market risk. In the UK, for example, internal models have been in use since September 1998 (www.fsa.gov.uk). However, because of the confidentiality it is not possible to separate the banks that are using the standardised approach from the ones that are using internal models.

The data is utilised from the quarterly Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) reports for the periods from the last quarter of 1995 to the fourth quarter of 1999\(^{23}\) (17 quarters). FR Y-9C reports provide financial data from BHCs on a consolidated basis in the form of a balance sheet, an income statement, and detailed supporting schedules, including the schedules of OBS items.

\(^{23}\) Appropriate data for the analysis is available since the third quarter of 1995.
and risk-based capital. These reports were gathered from the National Information Center (NIC) web page (www.ffiec.gov/nic). On this web page, which is supplied by the Board of Governors of the Federal Reserve System, NIC provides comprehensive information on institutions for which the Federal Reserve has a supervisory and regulatory interest.

In the US, the market risk capital rules apply to any bank holding company or commercial bank whose trading activity\(^\text{24}\) equals 10 percent or more of its total assets or USD 1 billion or more, on a world-wide consolidated basis. As the objective of this analysis is to investigate the impact of the market risk capital regulations, the data for the BHCs that are subject to these regulations as of 31.12.1999 were gathered. In order to determine which BHCs are relevant, peer 1 and peer 2 groups of the US BHCs\(^\text{25}\) that are subject to the market risk capital regulations are considered.

This information was gathered from the FR Y-9C Schedule HC-I-Risk-Based Capital reports in which only the BHCs subject to these rules report the amount of market risk equivalent assets, while other BHCs do not report any information\(^\text{26}\). As of 31.12.1999, there were 166 BHCs with consolidated asset size more than USD 3 billion. However, in peer 2, there is no BHC that is subject to these rules, whereas in peer 1 there are 18 BHCs, which are subject to these rules. Among them, three BHCs do not have available data for the entire period; therefore they are excluded from the sample. The final data set contains quarterly detailed consolidated data from 15 US BHCs. Among them, 13 BHCs have been subject to the market risk capital regulations since January 1998. The list of the BHCs that are included in the sample and their total assets are provided in Table 4.2.

\(^{24}\) US regulators define a banking organisation’s trading activity as the sum of its trading assets and trading liabilities.

\(^{25}\) FED classifies BHCs into 8 peer groups, considering the consolidated asset size at the end of the quarter. BHCs with consolidated assets size $10 billion and over constitutes peer 1 group, whereas peer 2 consists of BHC with asset size between $3-10 billion.

Table 4.2: Total Assets of Sample Banks as of Year-end 1999, Millions USD

<table>
<thead>
<tr>
<th>Bank No</th>
<th>Name of the BHIC</th>
<th>Total Assets</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>BANK OF AMERICA CORPORATION</td>
<td>632,574</td>
</tr>
<tr>
<td>2</td>
<td>CHASE MANHATTAN CORPORATION</td>
<td>406,105</td>
</tr>
<tr>
<td>3</td>
<td>CITICORP</td>
<td>388,570</td>
</tr>
<tr>
<td>4</td>
<td>BANK ONE CORPORATION</td>
<td>269,425</td>
</tr>
<tr>
<td>5</td>
<td>J.P. MORGAN &amp; CO. INCORPORATED</td>
<td>260,898</td>
</tr>
<tr>
<td>6</td>
<td>FIRST UNION CORPORATION</td>
<td>253,024</td>
</tr>
<tr>
<td>7</td>
<td>WELLS FARGO &amp; COMPANY</td>
<td>218,102</td>
</tr>
<tr>
<td>8</td>
<td>FLEETBOSTON FINANCIAL CORPORATION</td>
<td>190,692</td>
</tr>
<tr>
<td>9</td>
<td>HSBC USA INC.</td>
<td>90,240</td>
</tr>
<tr>
<td>10</td>
<td>KEYCORP</td>
<td>83,344</td>
</tr>
<tr>
<td>11</td>
<td>BANK OF NEW YORK COMPANY, INC.</td>
<td>74,756</td>
</tr>
<tr>
<td>12</td>
<td>BANKERS TRUST CORPORATION</td>
<td>68,157</td>
</tr>
<tr>
<td>13</td>
<td>STATE STREET CORPORATION</td>
<td>60,899</td>
</tr>
<tr>
<td>14</td>
<td>MELLON FINANCIAL CORPORATION</td>
<td>48,227</td>
</tr>
<tr>
<td>15</td>
<td>BANKMONT FINANCIAL CORPORATION</td>
<td>42,246</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td></td>
<td><strong>3,087,259</strong></td>
</tr>
</tbody>
</table>

Graph 4.2 demonstrates the shares of assets of sample banks as of year-end 1999. While the total assets of these 15 banks is more than USD 3,000 trillion, the Bank of America, Chase Manhattan and Citicorp have the largest asset size as of year-end 1999, respectively.

Graph 4.2: Total Assets (as of year-end 1999)

Using data from the last quarter of 1995 to the last quarter of 1999, Graph 4.3 illustrates the increase of total assets for sample banks. While the total asset size of the sample banks was USD 1,500 trillion as of year-end 1995, in four years time total
assets were increased by almost 100 percent and exceeded the level of USD 3,000 trillion.

Graph 4.4 demonstrates the shares of equity of sample banks as of year-end 1999 and using data from the last quarter of 1995 to the last quarter of 1999, Graph 4.5 illustrates the increase of total equity for sample banks.
During the period of 1995-1999, total equity capital of sample banks increased more than 100 percent from USD 105 billion to USD 214 billion. As of year-end 1999, the Bank of America, Citicorp, and Chase Manhattan have the largest equity, respectively.

Derivative activities of the sample banks also increased substantially during the examination period. Graph 4.6 demonstrates the instrument types of derivative contracts. In the sample, the share of swap transactions is 51 percent, the share of futures and forwards is 28 percent, and the share of options is 21 percent of the total notional amount of derivative contracts as of year-end 1999. Graph 4.7 demonstrates the growth in the use of derivatives of the sample banks. The notional amount of derivative contracts increased dramatically from USD 12.6 billion in year-end 1995 to USD 33.6 billion in year-end 1999, which indicates a 166 percent increase.
Furthermore, Graph 4.8 demonstrates the risk types of derivative contracts. Interest rate risk derivative contracts have the highest share and these contracts constitute 80 percent of the total notional amount of derivative contracts. Graph 4.9 illustrates the increase of gross derivatives by considering risk types.

As mentioned above, one of the main reasons for including only large US BHCs in the sample is that the US banks are generally accepted to be significant users of financial derivative instruments, which provides a proper background to this analysis. Another reason is the availability of detailed quarterly data for the US banks and the significant number of banks that met the criteria to be subject to the market risk capital regulations. Since only large banks present the greatest market risk that could affect the financial stability, it is also meaningful to put these banks in
the focal point of the study. The next section provides the results of the empirical study.

4.4 Empirical Results

In order to analyse the impact of the market risk capital regulations on bank capital, a partial adjustment methodology is used. The sample includes all the US BHCs that are subject to these particular regulations and for which complete Y9C data is available for the period 1995Q3 to 1999Q4. The sample contains information on 15 US BHCs.

The equations 4.13 and 4.14 are estimated by employing a panel data analysis. Instead of using an ordinary least squares (OLS) analysis, a panel data model (pooled cross section, time series model) is employed to allow for simultaneous consideration of the intertemporal movements and cross sectional differences (Greene, 2003). The panel data set, or longitudinal data set, is a data set that combines time series and cross sections. In this study, 15 cross-sectional units, which are BHCs, are observed over 17 quarters. A balanced panel is constructed from banks with no missing data for each quarter.

Heteroskedasticity, which refers to a non-random pattern in the residual error term (i.e., variability in the error term), is a common problem that arises in the analysis of cross-section data. This problem could affect the size of the standard error of the regression coefficient and cause biased hypothesis test results. Therefore, in order to obtain reliable t-ratios, White’s heteroskedasticity-consistent standard errors and covariance is applied. Furthermore, autocorrelation or serial correlation could also influence the outcome of the hypothesis-testing procedure. However, since autocorrelation coefficients could vary across groups, the existence of

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27 Furthermore, because of the limited number of observations, using the cross section or time series data alone does not yield sufficient degrees of freedom in OLS analysis.

28 Heteroskedasticity-consistent covariance matrix estimator is suggested by White and this approach provides correct estimates of the coefficient covariances in the presence of heteroskedasticity of unknown form.
autocorrelation is not investigated by treating each group of observations as a sample.

In order to evaluate the statistical significance of the variables, the level of significance is reported in the tables, as well as the adjusted multiple coefficients of determination, adjusted $R^2$'s, which signify how well the model fits the population. In addition, in order to evaluate the models, $F$ tests are performed and reported in the tables. The $F$ statistics reported for all models indicate that the hypotheses that the coefficients on the independent variables are not jointly significantly different from zero are rejected at the 1 percent significance level.

The following sub-section presents the results of the estimation of equations that analyse the impact of the market risk capital regulations on bank capital levels. The empirical results of the econometric analyses are presented in Tables 4.3-4.8.

4.4.1 Results of the Capital Equations

Tables 4.3-4.6 demonstrate the pooled least squares estimates of the capital equations. When the change in the ratio of risk-based capital to risk-weighted assets is employed as the dependent variable in the capital equation (DELTARBC), most of the variables are found to be significant. In this equation, SIZE, RWA, NONPERF, TRADING, DREG and LAGRBC variables have statistically significant coefficients. In the equation which employs the change in the ratio of tier-1 capital to risk-weighted assets as the dependent variable (DELTATIER1), the variables RWVA, DREG and LAGTIER1; and in the equation which employs the change in the ratio of total equity to total assets as the dependent variable (DELTAEQUITY), the variables TRADING, INCEXP and LAGEQUITY are found to be statistically significant. The previous periods' capital ratios are found to be highly significant with a negative coefficient in all of these three equations. However, in the equation that employs the change in the ratio of tier-1 capital to average total assets (DELTALEV), none of the variables are found to be significant, even at the 10 percent significance level (Table 4.5).
### Table 4.3: Fixed Effect Pooled Least Squares Estimates of Capital Equation

**Dependent Variable: DELTARBC**

(Change in the Ratio of Risk-Based Capital to Risk-Weighted Assets)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Coefficients</th>
<th>t-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIZE</td>
<td>-4.592756</td>
<td>-2.236348**</td>
</tr>
<tr>
<td>RWA</td>
<td>-0.165312</td>
<td>-1.996430**</td>
</tr>
<tr>
<td>NONPERF</td>
<td>4.320498</td>
<td>1.657092*</td>
</tr>
<tr>
<td>GROSSDER</td>
<td>-0.001208</td>
<td>-0.703880</td>
</tr>
<tr>
<td>TRADING</td>
<td>-0.278383</td>
<td>-1.958075*</td>
</tr>
<tr>
<td>INCEXP</td>
<td>-0.057219</td>
<td>-0.351557*</td>
</tr>
<tr>
<td>DREG</td>
<td>2.230915</td>
<td>2.301185**</td>
</tr>
<tr>
<td>DRUS</td>
<td>-1.513709</td>
<td>-1.370155</td>
</tr>
<tr>
<td>DPRES</td>
<td>0.476818</td>
<td>0.208452</td>
</tr>
<tr>
<td>LAGRBC</td>
<td>-3.670264</td>
<td>-5.325487***</td>
</tr>
</tbody>
</table>

Adjusted $R^2$ 0.219057
F statistic 10.58311***
Number of observations 225
Number of Banks 15

Note: The t-statistics that are starred emphasise that the coefficients are significantly different from 0 at the 10% (*), 5% (**), and 1% (***), levels.

### Table 4.4: Fixed Effect Pooled Least Squares Estimates of Capital Equation

**Dependent Variable: DELTATIERI**

(Change in the Ratio of Tier 1 Capital to Risk-Weighted Assets)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Coefficients</th>
<th>t-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIZE</td>
<td>-2.851662</td>
<td>-0.815680</td>
</tr>
<tr>
<td>RWA</td>
<td>-0.223373</td>
<td>-1.880412*</td>
</tr>
<tr>
<td>NONPERF</td>
<td>2.370726</td>
<td>0.536812</td>
</tr>
<tr>
<td>GROSSDER</td>
<td>0.000156</td>
<td>-0.066353</td>
</tr>
<tr>
<td>TRADING</td>
<td>-0.344177</td>
<td>-1.620812</td>
</tr>
<tr>
<td>INCEXP</td>
<td>-0.029548</td>
<td>-0.115068</td>
</tr>
<tr>
<td>DREG</td>
<td>2.312288</td>
<td>1.826627*</td>
</tr>
<tr>
<td>DRUS</td>
<td>-2.139804</td>
<td>-1.333599</td>
</tr>
<tr>
<td>DPRES</td>
<td>-0.755293</td>
<td>-0.227610</td>
</tr>
<tr>
<td>LAGTIERI</td>
<td>-5.412285</td>
<td>-4.879391***</td>
</tr>
</tbody>
</table>

Adjusted $R^2$ 0.187926
F statistic 9.197713***
Number of observations 225
Number of Banks 15

Note: The t-statistics that are starred emphasise that the coefficients are significantly different from 0 at the 10% (*), 5% (**), and 1% (***), levels.
Table 4.5: Fixed Effect Pooled Least Squares Estimates of Capital Equation  
Dependent Variable: DELTALEV  
(Change in the Ratio of Tier 1 Capital to Average Total Assets)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Coefficients</th>
<th>t-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIZE</td>
<td>10.05515</td>
<td>0.819120</td>
</tr>
<tr>
<td>RIVA</td>
<td>0.043924</td>
<td>0.185329</td>
</tr>
<tr>
<td>NONPERF</td>
<td>-11.15595</td>
<td>-0.690380</td>
</tr>
<tr>
<td>GROSSDER</td>
<td>0.004324</td>
<td>0.811069</td>
</tr>
<tr>
<td>TRADING</td>
<td>-0.621322</td>
<td>-1.483054</td>
</tr>
<tr>
<td>INCEXP</td>
<td>-0.674347</td>
<td>-0.877058</td>
</tr>
<tr>
<td>DREG</td>
<td>-0.388120</td>
<td>-0.130546</td>
</tr>
<tr>
<td>DRUS</td>
<td>-5.843741</td>
<td>-1.191958</td>
</tr>
<tr>
<td>DPRES</td>
<td>-0.895408</td>
<td>-0.129454</td>
</tr>
<tr>
<td>LAGLEV</td>
<td>-3.713142</td>
<td>-1.490193</td>
</tr>
</tbody>
</table>

Adjusted $R^2$: 0.060321  
F statistic: 4.478346***  
Number of observations: 225  
Number of Banks: 15

Note: The t-statistics that are starred emphasise that the coefficients are significantly different from 0 at the 10% (*), 5% (**) and 1% (***) levels.

Table 4.6: Fixed Effect Pooled Least Squares Estimates of Capital Equation  
Dependent Variable: DELTAEQUITY  
(Change in the Ratio of Total Equity to Total Assets)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Coefficients</th>
<th>t-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIZE</td>
<td>1.664544</td>
<td>0.360748</td>
</tr>
<tr>
<td>RWA</td>
<td>0.230595</td>
<td>1.618647</td>
</tr>
<tr>
<td>NONPERF</td>
<td>1.110720</td>
<td>0.168255</td>
</tr>
<tr>
<td>GROSSDER</td>
<td>0.003740</td>
<td>1.410766</td>
</tr>
<tr>
<td>TRADING</td>
<td>-0.433577</td>
<td>-1.724039*</td>
</tr>
<tr>
<td>INCEXP</td>
<td>-0.496727</td>
<td>-1.820311*</td>
</tr>
<tr>
<td>DREG</td>
<td>-0.820402</td>
<td>-0.552241</td>
</tr>
<tr>
<td>DRUS</td>
<td>0.190586</td>
<td>0.084796</td>
</tr>
<tr>
<td>DPRES</td>
<td>2.374151</td>
<td>0.514245</td>
</tr>
<tr>
<td>LAGEQUITY</td>
<td>-4.109527</td>
<td>-2.971449***</td>
</tr>
</tbody>
</table>

Adjusted $R^2$: 0.172012  
F statistic: 8.529753***  
Number of observations: 225  
Number of Banks: 15

Note: The t-statistics that are starred emphasise that the coefficients are significantly different from 0 at the 10% (*), 5% (**) and 1% (***) levels.
The positive and highly significant coefficient of the $DREG$ variable in the first equation (Table 4.3) indicates that with the implementation of the market risk capital regulations, banks increase their risk-based capital to risk-weighted assets ratios substantially. The variable $DREG$ is also found to be significant in the equation, which employs the ratio of tier-1 capital to risk-weighted assets as the dependent variable. However, $DREG$ is significant at the 10 percent level in the latter equation. These findings are consistent with the regulatory cost hypothesis. Therefore, it may be concluded that from a regulatory perspective, the market risk capital regulations are effective as the implementation of these regulations result in an increase in the capital ratios of banks.

Due to the economies of scale and too-big-to-fail theories, the capital ratios are expected to have a negative relationship with bank size. In the equation with the dependent variable $DELTARBC$, a negative relationship between bank capital levels and asset size is found, which supports the economies of scale hypothesis. However, the variable $SIZE$ is not found to be significant in other equations. Conversely, in the equations with dependent variables $DELTALEV$ and $DELTAEQUITY$, $SIZE$ even does not have the expected negative sign. Therefore, the evidence on the economies of scale hypothesis is not robust.

In the capital equations, there are three variables ($RIVA$, $NONPERF$ and $TRADING$) that are included in the models to proxy for bank risk-taking and a negative relationship between bank capital levels and bank risk-taking is hypothesised because of the moral hazard hypothesis. The results indicate that $RVA$ has a negative significant coefficient in the equations with dependent variables $DELTARBC$ and $DELTATIER1$. The second risk variable, $NONPERF$, is found to be significant only in the first equation. However, the sign of $NONPERF$ in this equation is positive, which indicates a positive relationship between the ratio of non-performing loans to total loans and the ratio of risk-based capital to risk-weighted assets.

On the other hand, the variable $TRADING$ is found to be significant in two of the equations. In the equation with dependent variable $DELTARBC$ and in the equation with dependent variable $DELTAEQUITY$, the ratio of total trading assets and
liabilities to total assets is found to have an expected negative sign with a statistically significant coefficient. As the variables $RWA$ and $TRADING$ have the expected negative statistically significant coefficients, these results indicate an association of riskier activities with low capitalisation, which supports the moral hazard hypothesis. However, the findings do not support any significant relationship between bank capital ratios and derivative activities. These findings provide conflicting results concerning the moral hazard hypothesis.

However, the regulatory pressure ($DPRES$) is also not found to have any significant association with the change in capital ratios. In addition, the financial turmoil during 1998 and profitability variables are also not found to have any association with the change in capital ratios.

The results of the estimation of equations that analyse the impact of the market risk capital regulations on derivative activities are presented in the following sub-section.

### 4.4.2 Results of the Derivative Equations

Tables 4.7 and 4.8 demonstrate the pooled least squares estimates of the derivative equations. In Table 4.7, the coefficients of asset size ($SIZE$), the ratio of trading assets and liabilities to total assets ($TRADING$), and the ratio of total income to total expense ($INCEXP$) are found to be statistically significant determinants of the change in the ratio of gross fair values of derivative contracts to total assets ($DELTAFAIRDER$). However, in Table 4.8, none of the coefficients are found to be statistically significant. Adjusted $R^2$ of the equation in which the dependent variable is the change in the ratio of total gross amount of trading derivative activities to total assets ($DELTAGROSSDER$) is also found to be relatively low.
Table 4.7: Fixed Effect Pooled Least Squares Estimates of Derivatives Equation
Dependent Variable: DELTAFAIRDER
(Change in the Ratio of Gross Fair Values of Derivatives to Total Assets)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Coefficients</th>
<th>t-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIZE</td>
<td>240.5396</td>
<td>1.794353*</td>
</tr>
<tr>
<td>RIVA</td>
<td>1.253596</td>
<td>0.969430</td>
</tr>
<tr>
<td>NONPERF</td>
<td>-151.9193</td>
<td>-0.987612</td>
</tr>
<tr>
<td>RBC</td>
<td>36.54482</td>
<td>1.246148</td>
</tr>
<tr>
<td>TRADING</td>
<td>8.582017</td>
<td>2.081277**</td>
</tr>
<tr>
<td>INCEXP</td>
<td>-8.356514</td>
<td>-1.886904*</td>
</tr>
<tr>
<td>DREG</td>
<td>-42.15188</td>
<td>-1.473765</td>
</tr>
<tr>
<td>DRUS</td>
<td>57.83696</td>
<td>0.988862</td>
</tr>
<tr>
<td>LAGFAIRDER</td>
<td>-1.917752</td>
<td>-1.484026</td>
</tr>
</tbody>
</table>

Adjusted $R^2$ 0.151695
F statistic 8.552593***
Number of observations 225
Number of Banks 15

Note: The t-statistics that are starred emphasise that the coefficients are significantly different from 0 at the 10% (*), 5% (**) and 1% (***) levels.

Table 4.8: Fixed Effect Pooled Least Squares Estimates of Derivatives Equation
Dependent Variable: DELTAGROSSDER
(Change in the Ratio of Notional Amount of Derivatives to Total Assets)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Coefficients</th>
<th>t-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIZE</td>
<td>3676.792</td>
<td>1.226079</td>
</tr>
<tr>
<td>RIVA</td>
<td>11.25255</td>
<td>0.510290</td>
</tr>
<tr>
<td>NONPERF</td>
<td>2060.280</td>
<td>0.851986</td>
</tr>
<tr>
<td>RBC</td>
<td>-119.3854</td>
<td>-0.467431</td>
</tr>
<tr>
<td>TRADING</td>
<td>141.7283</td>
<td>1.145798</td>
</tr>
<tr>
<td>INCEXP</td>
<td>-109.3104</td>
<td>-1.181686</td>
</tr>
<tr>
<td>DREG</td>
<td>-623.2707</td>
<td>-1.100982</td>
</tr>
<tr>
<td>DRUS</td>
<td>2188.796</td>
<td>1.046431</td>
</tr>
<tr>
<td>LAGGROSSDER</td>
<td>-1.308945</td>
<td>-0.945914</td>
</tr>
</tbody>
</table>

Adjusted $R^2$ 0.037036
F statistic 4.096125***
Number of observations 225
Number of Banks 15

Note: The t-statistics that are starred emphasise that the coefficients are significantly different from 0 at the 10% (*), 5% (**) and 1% (***) levels.
The empirical analysis could not provide any support for the capital avoidance hypothesis. Considering the capital avoidance hypothesis, a negative relationship is hypothesised between the implementation of the market risk capital regulations and derivative activities. In both equations, the coefficients of DREG are found to be negative, as expected. However, the coefficients are not significant, which indicates that the implementation of the market risk capital regulations does not have a significant impact on derivative usage. When the variable RBC is replaced with the variable TIERI (the ratio of tier 1 capital to risk-weighted assets) in the equation with dependent variable DELTAFAIRDER, a significant impact of the implementation is found at only 10 percent significance level\(^{29}\). Therefore, the results do not indicate a robust evidence of the capital avoidance hypothesis.

The results suggest that size is an important factor that determines the change in the usage of derivatives. In the equation in which the dependent variable is DELTAFAIRDER and in the equation in which the dependent variable is DELTAGROSSDER, size is found to have a positive effect on derivative usage. However, the coefficient of size is only found to be statistically significant in the equation in which the dependent variable is the change in the ratio of gross fair values of derivative contracts to total assets. This finding supports the economies of scale hypothesis, which indicates that large banks are expected to use more derivatives.

The positive relationship between the change in derivative usage and risk-based capital is an indicator of regulatory and market discipline in the use of derivatives, as demonstrated by the studies of Gunther and Siems (1995), Jagtiani \textit{et al.} (1995), Jagtiani (1996) and Carter and Sinkey (1998). While the ratio of risk-based capital to risk-weighted assets (RBC) has the expected positive sign in the DELTAFAIRDER equation, this variable has an unexpected negative coefficient in the DELTAGROSSDER equation. However, the coefficients of RBC are not significant in these equations.

\(^{29}\) This is not shown in the study.
Although a positive relationship is hypothesised between profitability and derivative usage, the results indicate a negative significant coefficient, which is significant at the 10 percent significance level. As a matter of fact, credibility measures other than TRADING do not provide any significant coefficient. Therefore, it may be concluded that the credibility of a bank does not have any impact on the use of derivative activities\footnote{It should be noted that credibility could only have an impact on OTC derivatives (swaps, futures and OTC options) as exchange traded futures and options do not have any credit risk.}.

When fair values of derivative contracts is used as the dependent variable, a positive and significant relationship is found between the derivative usage and the ratio of trading assets and liabilities to total assets. This variable has also a positive sign where the dependent variable is the notional amount of derivative contracts. However, in this case the variable is not significant.

The relationship between derivative usage and trading activities is hypothesised as a negative relationship considering the TRADING variable as a proxy of risk. Therefore, it is not unforeseen to observe such a positive association as derivative transactions could be used to hedge trading assets and liabilities, as well as the risk of the existing portfolio.

During the turmoil that financial markets witnessed as a result of the Russian crisis and the LTCM case, the US BHCs seem to increase their derivative usage as the coefficient of the variable DRUS is found to be positive. However, this variable is not statistically significant. In addition, similar to the findings of the capital equations, no significant relationship is found between capital and derivative usage.

4.5 Conclusions

In this chapter, the impact of the market risk capital regulations was analysed. The changes in capital and derivatives usage were modelled by using a partial adjustment framework. In these models, the changes in the capital ratios and derivative usage depend on the lagged level of the capital ratios and derivative usage. In addition, a
range of variables describing banks' activities and risk-taking are assumed to have an impact on these variables. The study focuses on the large US BIICs as they are more involved in trading activities and therefore subject to the market risk capital regulations. Using quarterly data for the period 1995Q4 to 1999Q4, the estimates are obtained by the panel data analysis.

Although the main objective of this analysis is to investigate the impact of the market risk capital regulations on bank capital levels and derivative usage; the economies of scale, moral hazard, regulatory and market discipline hypotheses were also tested.

The principal findings of the empirical analysis indicate that the implementation of the market risk capital regulations has had a significant positive impact on bank capital levels. This finding displays the effectiveness of the market risk capital regulations from a regulatory perspective. On the other hand, no significant relationship was found between the implementation of these regulations and the usage of derivatives. In addition, the results of the study do not provide any evidence of the capital avoidance hypothesis, which explains the growth of off-balance sheet activities due to the lack of capital regulations. Furthermore, the empirical results fail to demonstrate any significant relationship between the capital levels and derivative activities. However, large banks were found to be more active in the use of derivatives, which demonstrates that larger banks have the specialised management skills needed to participate actively in derivative markets.

The analysis that was provided in this chapter empirically investigated the impact of the market risk capital regulations on bank capital levels and derivatives activities. However, as explained in the first chapter of this thesis, it is also aimed to evaluate the use of value at risk methodologies in the framework of the market risk capital regulations. In order to provide a background to the simulations that are carried out in the eighth chapter of this thesis, the next chapter explains the value at risk methodology, which is an important concept of the market risk management framework.
5.1 Introduction

In the previous chapter, the impact of the market risk capital regulations on bank capital levels and derivative activities were analysed empirically. The results indicate that the US banks react to these regulations by increasing their capital levels. However, the results do not indicate any relationship between the implementation of the market risk capital regulations and bank derivative activities.

The market risk capital regulations require banks to hold capital for their market risk and banks are allowed to use their own internal Value at Risk (VaR) models under this framework. The basic concept of VaR is well described by Linsmeier and Pearson (1996):

"Value at risk is a single summary, statistical measure of possible portfolio losses. Specifically, value at risk is a measure of losses due to 'normal' market movements. Losses greater than the value at risk are suffered only with a specified small probability. Subject to the simplifying assumptions used in its calculation, value at risk aggregates all of the risks in a portfolio into a single number suitable for use in the boardroom, reporting to regulators, or disclosure in an annual report. Once one crosses the hurdle of using a statistical measure, the concept of value at risk is straightforward to understand. It is a simple way to describe the magnitude of the likely losses on the portfolio."

As one of the objectives of this research is to evaluate different methodologies that are allowed to be used by the market risk capital regulations, it is crucial to understand the background, underlying assumptions, and advantages and disadvantages of this concept. Therefore, this chapter introduces the concept of Value at Risk (VaR), which was implemented in the capital regulatory framework
following the developments in bank practices. The understanding of this concept and in particular the understanding of different methodologies that are used to calculate VaR is essential, as these methodologies are applied to the foreign exchange portfolios to evaluate the market risk capital regulations in the eighth chapter.

This chapter also introduces the literature review concerning the applications of VaR methodologies. Although there is an extensive VaR literature, the literature review is limited to the studies that particularly analyse the impact of choosing different VaR methodologies.

The chapter is organised as follows. In the second section, the background of VaR is presented, which is followed by describing the underlying assumptions of VaR in the third section. The uses and limitations of VaR are explained in the fourth and fifth sections, respectively. According to the modelling literature, there are three basic approaches to calculate VaR. These are, the variance-covariance (parametric), historical simulation, and Monte Carlo simulation methodologies. These methodologies are explained in the sixth section. The sixth section also discusses the concept of volatility and correlation of financial asset returns, which are essential factors to calculate the VaR estimates in the parametric approach. The first six sections of this chapter explain the VaR concept and the VaR methodologies. Although these issues are extensively documented in the literature, it is important to explain these issues as these were used in the simulations that were conducted in the eighth chapter of this thesis. In the seventh section, the literature associated with the use of different VaR methodologies is reviewed. The chapter is concluded with a summary of discussions.

5.2 The Background of VaR

Financial investment risk is a fact of life and since the earliest trading days, the trade-off between risk and reward has been the basis of virtually every investment decision. Therefore, the financial investment risk, which can be defined as the possible unfavourable deviation from the expected in future, is at the core of the business of finance.
As a result of increasing risks that financial institutions face in their operations, measurement and management of financial risks have become very important. The examples of mismeasurement and mismanagement of the financial risks, such as Orange County, Barings, Metalgesellschaft, LTCM, and Sumitomo, have also attracted attention to financial risks and the management of them. Correspondingly, risk management has been of growing interest in recent years as a result of the well-publicised losses among banks, hedge funds, pension funds, and municipalities (Simons, 2000).

As well as the recent financial disasters, the turbulence in emerging markets, starting in Mexico in 1995, continuing in Asia in 1997 and spreading to Russia and other emerging economies in 1998, has also extended the interest in risk management. It is generally accepted that these financial disasters could have been avoided if there were adequate risk management systems and internal controls in place. These developments accelerated the need of financial market participants to implement properly functioning risk management systems that accurately measure financial risks. At the same time, these developments also attracted the attention of regulators whose main concern is the financial stability.

While there are several types of risks which financial institutions are exposed to, with the increased emphasis on trading activities and considerable volatilities in foreign exchange and interest rates, market risk has become a more important risk element in banking. Therefore, the need for a better understanding of measuring market risk is of crucial importance for risk managers, chief executives, boards of directors, and regulators.

Consequently, measuring the risks incurred by financial market participants and financial institutions has become the main focus of modern finance theory. With the improvement of financial theory and technology, institutions began to measure and manage their risks more effectively. Christoffersen et al. (1999) argue that, there are two important developments that facilitated the advancement in knowledge concerning risk management. These are; the development of volatility models for
measuring and forecasting volatility dynamics that began during the 1980s, and the RiskMetrics methodology that was published by JP Morgan in 1995. The introduction of the RiskMetrics methodology enabled companies to compute similar measures of market risk for a given portfolio of assets.

The risk management methods could be classified under three headings; firstly, traditional risk management tools (such as gap analysis\textsuperscript{31}, and duration analysis\textsuperscript{32}), secondly, the portfolio theory which was developed by Markowitz during the 1950s\textsuperscript{33} (Markowitz, 1952 and 1959) and thirdly, the Value at Risk methodology, which has its philosophical roots in the portfolio theory.

In particular, the risk measurement technique, which is known as Value at Risk, abbreviated as VaR\textsuperscript{34}, has received great attention and is now applied widely by the financial institutions for risk assessment, risk-adjusted performance measurement, and risk-based capital controls. VaR has now become a standard approach for measuring the market risk of financial instruments. Although VaR gained an important role in the risk management of financial institutions in recent years, the origin of today’s VaR systems goes back to the late 1970s and early 1980s. During that time, as a result of the increase in trading activities, especially in derivatives, the major financial institutions operating internationally developed new risk management techniques to monitor their market risk and trader performances.

Bankers Trust and JP Morgan, both U.S. investments banks, were two pioneer institutions that developed financial risk measurement techniques (Jorion, 1997). However, among the VaR methodologies, JP Morgan’s RiskMetrics is one of the best-known models since JP Morgan published this model in 1995. It is interesting how VaR has developed since the 1970s and became a major tool in the JP Morgan’s

\textsuperscript{31} Gap analysis measures the interest rate exposure by considering the difference in the repricing sensitivities of interest bearing assets and liabilities.

\textsuperscript{32} Duration analysis measures the interest rate exposure of a bond, and the duration of a bond can be regarded as the term to maturity of the security, adjusted for the maturities of interim coupon payments.

\textsuperscript{33} The portfolio theory is based on variations from the mean and indicates that investors want a portfolio with maximum expected return and low standard deviation.

\textsuperscript{34} While VaR is a general name, there are also other specific names given by different institutions to the same concept, such as Capital at Risk (CaR) and Daily Earnings at Risk (DeaR).

"By 1990 the data, methodologies and mechanics for risk reporting against limits had become reasonably stable. So Marcus Meier, then head of international trading, requested a daily management report to show aggregated P&Ls and risks – ready for the daily 4:15pm Treasury meeting in New York. With the group’s comments, the report was then forwarded to the chairman, Sir Dennis Weatherstone. (...) The regular daily reporting of risks and returns, side by side, consistent across all trading activities, had a major effect. It sensitised senior management to risk-return trade-offs and led over time to a much more efficient allocation of risks across the trading businesses."

The underlying theory of the RiskMetrics methodology is to calculate the maximum likely loss over the next trading day by using the estimates of the standard deviations and correlations between the returns of trading instruments. However, this approach, which is generally called the parametric approach, is only one of the VaR methodologies that are used in the market risk measurements. VaR can also be estimated by using non-parametric approaches.

The concept of VaR appears to be straightforward. However, as Dowd (1998) points out, the devil is in the detail. Before explaining the methodologies that are used to measure VaR, first the underlying assumptions of VaR are explained and then uses and limitations of VaR are discussed in the following sections.

5.3 The Underlying Assumptions of VaR

VaR is a straightforward concept that measures the maximum expected loss over a given horizon period and at a given level of confidence. As a result of the increased market risk, which is the uncertainty of future returns due to the fluctuations of financial asset quantities such as stock prices, interest rates, exchange rates and commodity rates, measuring and managing these risks is under the focus of market participants. Consequently, VaR has become a common standard in the market risk management. Therefore, in recent years many financial institutions implemented risk management systems based on VaR.

According to Jorion (1997), VaR became popular because of two main reasons; first,
it is a method for measuring market risk that is easy to understand, and second, VaR provides users, especially top managers and shareholders, with a single summary measure of market risk. Furthermore, VaR was also officially accepted and promoted by regulators not only as a sound risk management practice, but also as a methodology that is used in the measurement of market risk for the capital requirement purposes.

By describing VaR as a measure of the worst expected loss over a given horizon under normal market conditions at a given level of confidence, Jorion (1997) illustrates this concept by giving the following example:

"For instance, a bank might say that the daily VaR of its trading portfolio is $1 million at the 99 percent confidence level. In other words, under normal market conditions, only one percent of the time, the daily loss will exceed $1 million."

VaR is a statistical measure of risk exposure with a function of two key factors; the time horizon and the confidence level. Although the choice of these two key quantitative factors has a significant impact on the VaR calculation, there is no consensus among the market participants on these factors. For example, RiskMetrics uses a 95 percent confidence interval over one day and the Basel Committee requires a 99 percent confidence interval over ten days. These two fundamental issues, namely the time horizon and the confidence interval, are discussed in the next two sub-sections.

5.3.1 Time Horizon

Financial institutions calculate VaR based on different time horizons ranging from one day to longer periods as long as one year. Stambaugh (1996) argues that the choice of time horizon has a vital importance on the outcome and states that:

"Longer holding periods are generally associated with greater risk. Clearly, in order for the risk measurement to be meaningful, one would choose a holding period that approximates one's trading behaviour. Active traders in liquid markets, such as banks, will typically find their portfolios change dramatically from one day to the next, and so consider a one-day holding period to be an appropriate one. Other actors, such as investors, will typically maintain a portfolio intact for a longer period, perhaps as long as a month, in which case that would be the better holding period."
The time horizon used to calculate VaR should depend on the liquidity of assets in the portfolio and how frequently they are traded. For example, because it is difficult to liquidate relatively less liquid assets, a longer time horizon is required while calculating VaR for the portfolios that consist of illiquid assets. Therefore, the choice of time horizon depends upon the characteristics of the portfolio and liquidity of its positions. For trading and market making operations, VaR is typically computed using one-day, five-day, or ten-day time horizons, while longer time horizons are often used by institutional investors and corporations.

Despite the fact that a number of institutions can operate on longer holding periods such as one-quarter or one-year, the usual holding periods are one-day or one-month (Dowd, 1998). Although one-day is the shortest holding period at the moment, by employing high frequency data, it is theoretically possible for institutions to work with holding periods less than a day. Dowd argues the liquidity of the markets in which the institution operates is the most important factor that affects the choice of the holding period. If a position can be liquidated quickly in an orderly fashion, that position’s VaR might be preferred to be based on a short target period. However, when orderly liquidation takes time because of thin market conditions and difficulty in finding counterparties, a longer holding period might be more appropriate. On the other hand, because liquidating a position in an orderly manner could differ among markets, it is normal for an institution to choose a common holding period. Therefore, an institution should choose a holding period that best reflects its trading positions, taking into account the markets in which it is mostly involved.

As a result, the time horizon could be a one-day period, i.e. the next trading day, or a longer period. While traders and financial risk managers are generally interested in a one-day time horizon, regulators and market participants, considering illiquid markets, generally prefer multiple-day time horizons while calculating market risk by using VaR methodologies.
5.3.2 Confidence Interval

The confidence interval defines the time frame over which an institution should not lose more than the VaR amount. As a matter of fact, when the implications of the confidence interval are understood, the actual choice of it is not important. While the Basle Committee requires a 99 percent confidence interval, commonly used confidence intervals range from 90 to 99 percent. Often the VaR confidence level is chosen as 99 percent. The 99 percent confidence level implies that there is only a 1 percent probability of losing a larger amount over the period in question. Therefore, on average, at any day during a 100-day period, it can be expected to lose more than the amount of VaR in only one day of the 100-day period. However, other confidence levels such as 95 percent or 98 percent are also used in practice.

Although there are a number of factors that should be taken into consideration while choosing the confidence level and the time horizon, the Basle Committee amendment requires banks to employ a holding period of two weeks (ten trading days) and a 99 percent confidence level when using VaR models to set aside capital for the market risk of their trading operations.

5.4 Uses of VaR

VaR has emerged as a standard tool for measuring and reporting financial market risk. In the last decade, both practitioners and regulators have made increasing use of VaR as a tool for market risk management. Today, VaR has been widely accepted and has become an industry standard in the risk management framework of financial institutions.

As VaR is a measure of a financial institution’s overall exposure to market risk, it is used as a trading and control tool. According to Jorion (1997), many companies in financial markets have lost billions of dollars because of the deficient monitoring of their exposure to market risk. For that reason, in the late 1990s several financial firms began to use VaR for calculating and controlling market risk.
The concept of VaR was first explicitly endorsed in the Group of Thirty's 1993 report entitled "Derivatives: Practices and Principles", where VaR is considered as the best practice for market risk measurement. As VaR estimates provide information concerning the exposure of a company's financial instruments to gain or loss, in 1995, the US Securities and Exchange Commission (SEC) adopted VaR as an acceptable method of providing required information concerning a company's derivatives activity. In 1995, the International Swap and Derivatives Association (ISDA) also approved VaR as a market risk measurement tool.

The popularity and strength of VaR could be explained in its simplicity, because it is a quantitative measure reported in units that everybody could understand. Therefore, the most important contribution of the VaR concept is that the entire distribution of a portfolio's return is summarised in terms of a single number which investors find useful and can easily understand. As VaR measures the market risk of a portfolio as a total value in a single monetary unit, the idea behind VaR is easily explained even for those who do not have special knowledge of different instruments, including chief executives that seek a better understanding of market risk.

The flexibility of VaR as a risk measurement tool also generates its own popularity, as VaR can be specified for various horizons (generally between 1 day and 1 month) and confidence levels (generally between 90 percent and 99 percent).

Although VaR was initially introduced for measuring market risk, it serves a number of other purposes in financial institutions, such as to report information, to allocate economic capital, to trade-off risk and return and to set trading limits for traders. These are explained below:

1) Information reporting: One of the greatest attractions of VaR is that it can be used as a summary measure of market risk to both internal bodies, such as senior management and board of directors, and external bodies, such as shareholders, regulators and investors. This information enables these parties to be informed of the risks run by the trading and investment operations of the institution.
2) Economic capital allocation: The VaR models could be used by the management to gain an idea of the positional risk for the whole or part of the institution (El Jahel et al., 1998). By using VaR information, risk takers are able to make more informed decisions concerning their investment strategies. Therefore, profit objectives across businesses can become a function of the risk incurred and the management could use profit to risk ratios in order to allocate resources to specific businesses (JP Morgan, 1996).

3) Performance evaluation: The remuneration paid to a dealer or a dealer desk can be based on their efforts both in terms of risk and return (El Jahel et al., 1998). However, given that high rewards bestowed on outstanding trading talent may bias the trading professionals towards taking excessive risks, if these risks are not properly measured and the returns are not adjusted effectively for the amount of risk taken, the interest of the firm may not be in line with the interest of the risk-taking individual (JP Morgan, 1996).

4) Setting trading limits: Position limits of traders could also be determined by using the VaR figures. Position limits have traditionally been expressed in nominal terms, future equivalents or other denominators unrelated to the amount of risk effectively incurred (JP Morgan, 1996). However, setting limits in terms of VaR has significant advantages. First, position limits become a function of risk and positions in different markets or products can be compared through a common measure. Second, limits become meaningful for management as they represent a reasonable estimate of how much could be lost. Finally, setting limits motivates managers of multiple risk activities to favour risk reducing diversification strategies.

As a result, VaR is particularly useful for measuring market risk of a multi-asset class portfolio as it can measure the exposure to stocks, bonds, commodities, foreign exchange, structured products such as asset-backed securities and collateralised mortgage obligations, as well as derivative instruments such as forwards, futures, options and swaps.
5.5 Limitations and Drawbacks of VaR

Although the VaR concept is generally accepted, it should be seen as nothing more than a high quality tool for managers because of its limitations and drawbacks. For example, the implementation of VaR is harder than understanding the simplicity of its concept. Beder (1995) points out three issues, which she believes that make VaR difficult to implement. First, the VaR estimates are dependent upon the VaR methodology. Second, vast quantities of data and significant modelling or systems efforts may be required. Finally, firms must design and implement risk management add-ons to address VaR's limitations and weaknesses.

Nugee (2001) argues that, those considering using the VaR techniques need to be aware of its strengths as well as its drawbacks. These weaknesses are as follows:

1) The VaR techniques predict the future by considering the calculations of volatility and correlations based on historical data. However, past performance cannot always be a good guide to future performance. The use of historical data is always limited by the assumption that past trends are replicated.

2) Although the volatility numbers can be derived for each historical period, they may vary from day to day. In addition, the length of the historical data and whether a weighting factor should be applied to give greater weight to recent data should be considered carefully (too little past data or a too fast decay factor could lead to much emphasis on the most recent figures and a volatility input series can jump significantly). On the other hand, long moving averages with little decay in the weighting process could lead to an input series that is slow to change and late in reacting to changes in the prices.

3) Applying a normal distribution of price movements is one of the central assumptions of the parametric approaches. This means that up and down movements of price are broadly equal and the distribution of those movements are consistent with the normal statistical distribution.
However, the distribution of financial price movements generally demonstrates that market movements are not normal but have 'fat tails'. Therefore, a VaR analysis that is based on the normal distribution could lead to an underestimate of the likelihood of extreme events. However, supporters of VaR claim that the gains obtained by assuming the simplicity of the normal distribution are more advantageous than any disadvantages.

4) The use of VaR techniques requires expensive 'information technology' (IT) investment. The amount of data required to calculate and then put to use all the volatilities and cross-correlations could be enormous and could consume computing power and IT resources on a commensurate scale.

5) Users of the VaR models, especially senior managers, should be aware of the fact that the VaR numbers could mislead them concerning the movements in the financial markets and should not forget that the VaR numbers are dependent on the statistical assumptions and the confidence level chosen for the statistical part of the process. For example, considering a confidence level of 98 percent could sound safe. However, this indicates that one day in every 20 working days there is a possibility of losing more than the VaR number. In addition, using VaR models does not make a risky portfolio safer and there is always a possibility of a three or even four standard deviation move in the market to throw a portfolio into heavy loss. It should not be forgotten that no VaR statistic could guide a manager when the basic ground rules change in the market and using VaR statistics is not a substitute for assessing more basic risks, such as whether markets would continue to function at all.

VaR is also criticised for reducing all the information down to a single number, which indicates the loss of information that could in turn create misleading interpretations of the analytical results (Tsai, 2004). Tsai argues that VaR is of limited use at the strategic level as it is difficult to allow meaningful comparisons across various financial markets by reducing everything to a single number.
5.6 VaR Methodologies

Although there is one definition of VaR, there are three fundamental methodologies for estimating VaR that financial institutions use in their market risk management systems. These are:

- The variance-covariance (parametric) methodology,
- The historical simulation methodology,
- The Monte Carlo simulation methodology.

The variance-covariance and historical simulation methodologies forecast risk by analysing historical movements of market variables. However, methodologies that use historical data assume that the relationships between market rates and prices that have been observed over the observation period are valid for estimating risk over the next holding period. In the variance-covariance methodology, VaR is estimated with an equation that specifies the parameters such as volatility and correlation. On the other hand, the historical simulation methodology estimates VaR by revolving positions for each change in the market. The Monte Carlo simulation methodology also estimates VaR by revolving positions in a portfolio. However, the Monte Carlo methodology simulates random hypothetical scenarios rather than using actual historical market movements.

The variance-covariance methodology is the most common method of VaR calculation that financial institutions use, unless the portfolio consists of options in the portfolio, in which case they also use simulations (Simons, 2000). However, choosing the most appropriate model and its associated assumptions to use is one of the first and most important features of the VaR measurement decisions that an institution faces.

As each of these approaches has its own set of assumptions and therefore their own strengths and weaknesses, they should not be considered as competitors, but as alternatives. The intention of this section is to provide the theoretical background of
basic VaR methodologies. These methodologies are explained below along with their strengths and weaknesses.

### 5.6.1 The Variance-Covariance Methodology

The variance-covariance methodology is the most popular VaR approach where the distribution of returns (profit and loss) is specified and used to figure out the VaR number. Also called the parametric approach, this methodology depends on a statistical analysis of past price movements that determine returns on the assets. By quantifying financial risks with the help of statistical techniques, this approach evaluates how return volatility behaved in the past and measures the worst expected loss over a given horizon at a given confidence level.

In this methodology, the VaR estimates are based on the statistical estimates of the volatility, i.e. the variances of returns and the covariances among returns are used to summarise the overall market risk faced by the institution. By using the volatility and covariance estimates, this methodology generates a matrix of possible market movements under the time period and to the probability distribution specified at the outset, where the matrix is then used to calculate the variance of the portfolio return. If it is known that portfolio returns show a certain random behaviour, a normal probability distribution can be used to calculate VaR.

This methodology assumes that the variance-covariance matrix completely describes the distribution. Therefore, the assumption concerning the probability distribution is crucial. A normal probability distribution is characterised by two variables. These are; the mean (expected value) and the variance (spread around the mean). The variance can be defined as the weighted sum of squared deviations around the mean, and the square root of the variance is called the standard deviation, or volatility.

Therefore, the first step in the calculation of a VaR estimate in the variance-covariance methodology is to decide on the probability distribution of the returns of the underlying assets. Then, calculating VaR by using the variance-covariance approach is the estimation of the volatility for each risk factor and the covariances
for the risk factors. The volatilities and covariances are then combined in a covariance matrix, which is followed by the calculation of risk weights for each factor. Then, by using matrix algebra, portfolio volatility is calculated. Finally, the portfolio volatility is scaled by a factor according to the selected confidence level of the assumed probability distribution.

 VaR describes the quantile of the probability distribution of gains and losses over the target horizon. \( f_{\Delta P} \) being the probability density function (pdf) of \( \Delta P \) (portfolio return) and \( c \) being the confidence interval, the VaR number over some time horizon is:

\[
1 - c = \int_{-\infty}^{-\text{VaR}} f_{\Delta P}(x) dx \quad (5.1)
\]

As \( c \) is selected as the confidence level, VaR corresponds to the 1-\( c \) lower-tail level (left tail) and therefore the cut line is \( -\alpha \). If the portfolio return is normally distributed, the VaR number could be obtained by applying the standard deviation \( \alpha = \frac{z - \mu}{\sigma} \) with \( z = -\text{VaR} \); so VaR is calculated by:

\[
\text{VaR} = -\alpha \sigma - \mu \quad (5.2)
\]

where \( \alpha \) is a parameter reflecting the confidence level, \( \sigma \) is the standard deviation of return and \( \mu \) is the mean return. As \( \sigma \) and \( \mu \) are unknown, the estimate of VaR is obtained by replacing them with their estimates \( s \) and \( \bar{x} \), respectively. Then:

\[
\text{VaR} = -\alpha s - \bar{x} \quad (5.3)
\]

If the value of a risk factor \( X \) for a particular day is \( P \), then VaR of this asset factor for that day is:
$$VaR(X) = -\alpha sP - \bar{x}$$  \hspace{1cm} (5.4)

The advantage of the normal distribution assumption is that VaR is expressed as a simple function of the portfolio return's volatility, i.e. standard deviation.

Assuming that the statistical distribution of asset returns is normally distributed, \( \alpha \) corresponding to the confidence level, \( c \), could be obtained from the standard normal table. For example, if the confidence level is chosen to be 95 percent, the corresponding \( \alpha \) is 1.65 (Graph 5.1), and if the confidence level is chosen to be 99 percent, then \( \alpha \) is 2.33 (if confidence level is 98 percent, then \( \alpha \) is 2.054 and 2.054 standard deviations leave 2 percent of the normal distribution in its left tail, where 1.65 standard deviations leave 5 percent of the normal distribution in the left tail).

Graph 5.1: Normal Distribution

For a single financial asset, if it is assumed that returns of that asset are normally distributed, calculating VaR requires only the calculation of volatility of that asset. For a given confidence level of \( \alpha \), for example 5 percent, and assuming a zero mean, VaR equals to \( 1.65\sigma \). Then the calculation of VaR is reduced to estimating the volatility, i.e. standard deviation (\( \sigma \)), of the financial asset's return.
When calculating VaR for a portfolio of assets, while the concept remains the same, the computation of VaR becomes a more complex process, as the VaR of the whole portfolio is not merely the summation of the VaRs of the individual assets because of the inter-correlation among all the assets in the portfolio.

In the variance-covariance approach, calculating the standard deviation of a portfolio requires calculating the standard deviation of each component asset in the portfolio and the covariance between the return on different assets. When returns are assumed to be normally distributed, the standard deviation of a portfolio consisting of two assets is given by:

$$\sigma_{AB} = \sqrt{a^2\sigma_A^2 + b^2\sigma_B^2 + 2ab\rho_{AB}\sigma_A\sigma_B}$$

(5.5)

where $\sigma_A, \sigma_B$ are standard deviations of assets $A$ and $B$, $\rho_{AB}$ is the correlation between those two assets and $a$, $b$ is the amount invested in assets $A$ and $B$, respectively.

In the variance-covariance approach, the portfolio VaR measures are based on the variance-covariance matrix. In equation 5.4, VaR for a risk factor is formulated. Assuming that the mean is zero, then VaR of the risk factor $X$ equals to:

$$\text{VaR}(X) = -\alpha s \rho$$

(5.6)

When the value of the risk factor is known and the desired confidence level ($\alpha$) is chosen, then the only variable that should be estimated is the standard deviation ($s$) of the return of the risk factor. Similarly, for a portfolio containing many risk factors, the standard deviation of the portfolio should be estimated.

Although there are different approaches that have been employed by banks to measure VaR, JP Morgan’s RiskMetrics is the best-known system that uses the variance-covariance methodology. During 1994, JP Morgan launched RiskMetrics$^{35}$

$^{35}$ JP Morgan’s RiskMetrics system was first unveiled in October 1994.
technical document, which is a set of tools allowing the users to estimate their exposure to market risk under the VaR framework. According to this document, RiskMetrics build normal distributions for historic price changes and aggregate the results into a diversified VaR number for a 95 percent confidence level. This means that the volatility estimates generated by RiskMetrics are below the actual figure in 5 percent of cases. RiskMetrics also suggest that the volatility for a certain point in time can be estimated by extracting the square root from a weighted average of lagged, squared portfolio returns (as the average return is assumed to be zero, this is equal to the weighted standard deviation). The weights used decrease exponentially at a given rate, so that only the very latest squared returns contribute significantly to the estimated volatility.

RiskMetrics uses the exponentially smoothed historical data to estimate the volatility series, which allows capturing the time varying, persistent volatility observed in the financial markets. There are two fundamental assumptions that the RiskMetrics method builds upon: First, the value of all positions can be linearly approximated from the underlying prices. Second, log returns are distributed according to the conditional normal distribution\(^{36}\). RiskMetrics considers that the variance of each return and the correlation between returns are a function of time and the returns follow a conditional normal distribution.

Despite its usefulness, such as being straightforward, industry standard, and least computational intensiveness, there are some disadvantages of the variance-covariance approach. This methodology is inadequate for measuring the risk of derivatives such as options. This approach assumes that instrument payouts are symmetrical, which could create problems for institutions whose portfolios contain many options or other instruments whose return profiles are not symmetrical. When dealing with products presenting non-linear payoffs (like options), it is not a reasonable assumption to admit a linear relationship between the value of the instrument and the value of its underlying asset. However, the market risk of financial instruments, which are non-linearly dependent on the price level (such as

\(^{36}\) In addition, RiskMetrics sets the mean return to zero.
options), can only be included as a linear approximation in the variance-covariance methodology.

Furthermore, most of the variance-covariance models, including RiskMetrics, assume that risk factors are normally distributed. However, this assumption could create some problems as the distribution of financial asset price increments is known to be heavy tailed and significantly non-Gaussian (Neftci, 2000). This phenomenon is known as 'fat tails' and indicates that the VaR figures could not sufficiently capture the possibility of extreme market moves. Tsai (2004) also argues that methods such as RiskMetrics that heavily depends on a multivariate normality could produce substantial bias if the distributional assumption is violated significantly.

The normality assumption of the variance-covariance approach is discussed in the following sub-section.

5.6.1.1 Normality Assumption of the Variance-Covariance Methodology

While estimating VaR numbers, the parametric approaches generally assume that returns are normally distributed, which makes the VaR calculation straightforward. However, assuming normality is one of the most important weaknesses of the parametric VaR as it underestimates the frequency of extreme events of asset returns that exhibit 'fat tails'. Since the main objective of the risk management models is to measure the probability of losses in the tails, this assumption is an important one that should be considered.

Although the variance-covariance approach uses the normal distribution as a statistical basis, many empirical studies of time series data have shown that financial asset returns are not normally distributed and these series tend to be skewed and leptokurtic (Neftci, 2000). The degree of fat-tailness of a distribution is assessed by the kurtosis, which measures the relative peakedness or flatness of a given distribution compared to a normal distribution. The leptokurtosis (high kurtosis) indicates that there are more occurrences far away from the mean than is predicted
by a standard normal distribution. The kurtosis is defined as the fourth moment of the
distribution, i.e. the mean to the power of four, divided by the square of the variance;

$$k = \frac{\sum r_i^4}{n(\sigma^2)^2}$$ \hspace{1cm} (5.7)

where \(k\) is the kurtosis, \(r_i\) is the return on day \(i\), and \(\sigma^2\) is the variance. The normal
distribution has a kurtosis of three. Any distribution that has a kurtosis greater than
three is said to be leptokurtotic, i.e. fatter tails and lower central hump than the
normal distribution.

The skewness parameter indicates deviation from the normal distribution, which is
symmetric around the mean. The coefficient parameter of the skewness can be
expressed as;

$$sk = \frac{\sum r_i^3}{n(\sigma^2)^{3/2}}$$ \hspace{1cm} (5.8)

For the normal distribution skewness is zero. While a positive skewness indicates an
asymmetric tail extending toward right side, a negative skewness indicates an
asymmetric tail extending toward left. The parametric VaR is based on the
volatilities and correlations that work well under normal market conditions.
However, this approach could not be successful in times of market crisis. In order to
correct for the weaknesses of parametric VaR, stress tests, such as extreme effects of
financial crises that occurred in the past, and scenario simulations, such as
hypothetical future events (increase in oil prices or in inflation), should be employed.

Despite its disadvantages, the variance-covariance approach is one of the most
popular VaR methodologies in practice. Therefore, users of VaR should consider the
weaknesses of this approach when assessing the market risk of an institution.
However, capturing only linear instruments is not the only problem that the users of
VaR should consider. As VaR relies on the calculation of the volatility and
covariance estimates and the volatilities and correlations could vary through time, the accurate estimates of these parameters are crucial in calculating VaR. The next section discusses estimating volatility in the variance-covariance methodology.

5.6.1.2 Estimation of Volatility

Producing the estimates of volatility and correlation has an essential role in calculating VaR. Therefore, this section explains some fundamental models that are in use while producing the estimates of volatility and correlations.

The volatility of a financial asset's return and risk are almost synonymous in finance. The volatility of a financial asset creates financial risk, which can be defined as the dispersion of unexpected outcomes as a result of the changes in asset prices. The volatility is measured by the standard deviation of these unexpected outcomes. An asset, which has no volatility, has no risk, as there is no unexpected outcome for that asset. Therefore, an asset without volatility needs no measurement and control.

The volatility forecasts are one of the most important factors that affect the parametric VaR, as there are different types of volatility models ranging from historical and exponentially smoothed to GARCH models. While some basic models consider constant volatility, models like exponentially weighted moving average (EWMA) and GARCH attempt to keep track of the variations in the volatility and correlation over time.

Whether to use a static or conditional variance\(^{37}\) is an important issue that should be considered in the variance-covariance methodology. It is generally accepted that as variance changes over time horizons, the VaR estimates should not rely on the unconditional variances. Financial asset returns generally exhibit volatility

\(^{37}\) The conditional volatility means that the volatility can be decomposed into predictable and unpredictable components and the predictable component in a return series is the conditional variance \(\sigma_t^2\) of the series. By modelling a conditional variance, the relationship between the information available at time \(t\) and future volatility can be found.
clustering, or persistence\(^\text{38}\), which means that large changes tend to follow large changes and small changes tend to follow small changes.

The problem with the constant volatility method is that, as indicated by the empirical evidence, the volatility is not constant but varies over time. Figlewski (1997) argues that because volatility changes randomly over time, optimal forecasting must take this into account. Therefore, the accurate forecasting of volatility is of vital interest to traders, investors and risk managers, as well as researchers seeking to understand market dynamics.

There are several methods in the literature that are used to forecast volatility. The simplest one is the random walk, which says that the best forecast of the volatility of today is yesterday’s realised volatility. Another simple model is the historical mean model, which indicates that the best forecast of the volatility today is an equally weighted average of all past volatility observations. Similar to the historical mean model, the moving average model also takes into consideration the past volatility observations. However, unlike the historical mean model, the moving average model employs a moving window of fixed length to estimate the volatility. While the above-mentioned models presume constant volatility, assuming that the volatility of an underlying asset is constant is far from perfect as the volatility of an asset price is a stochastic variable (Hull, 2000).

Graph 5.2 demonstrates the return series of the EUR/USD parity from 1999 to 2003. As it can be seen from this graph, the volatility tends to cluster\(^\text{39}\). While high volatility in the exchange rate returns tends to follow each other, low volatility also tends to follow each other. Therefore, it would be misleading to use constant volatility in VaR calculations as the volatility clustering implies that recent observations should receive more weight.

\(^{38}\) ‘Persistence’ measures the length of clustering. A series that has quite long clusters of unusual events is said to exhibit persistence. This feature implies a non-linear dependency between returns.

\(^{39}\) A statistical approach for detecting volatility clusters is based on the Ljung-Box statistic calculated on the squared returns. This statistic reveals whether the size of the movement today has any predictability for the size of the movement in the future.
While the equally weighted models give the same weight to all observations, in the exponential weighted and GARCH(1,1) models, the weights assigned to observations decrease exponentially as the observations become older. The GARCH(1,1) model differs from the exponentially weighted moving average (EWMA) model as it also assigns some weight to the long-run average variance rate (Hull, 2000). The fundamental methodologies that are used to forecast volatility, namely equally weighted moving average, exponentially weighted moving average and GARCH type models are presented below.

5.6.1.2.1 Equally Weighted Moving Averages

The equally weighted averaging is a standard statistical method to estimate unconditional variances and covariances. However, when they are applied to financial markets, the 'ghost features', which result from the conditional heteroskedasticity characteristic of financial data, could pose substantial problems (Alexander, 1996).
In the equally weighted moving average model (EqWMA), a moving window of fixed length is employed to estimate volatility. The volatility estimate constructed from the moving average is:

\[
\sigma_t^2 = \frac{1}{(n-1)} \sum_{i=1}^{n-1} (r_{t-i} - \mu)^2
\]  

(5.9)

where \( \sigma_t^2 \) denotes the estimated standard deviation of the portfolio at the beginning of day \( t \), \( n \) is the observation period, \( r_{t-i} \) is the change in the portfolio value (return), and \( \mu \) is the mean of returns. Equation 5.9 gives equal weights to all observations on past returns (all weights are equal and set to \( 1/n \)) and calculation is updated by adding new data and dropping the oldest information.

However, although this modeling of volatility is simple to implement, it has some drawbacks. These are:

1) The EqWMA methodology ignores the dynamic ordering of observations because it receives the same weight as the older information (although recent data should be more relevant).

2) As the window moves forward one by one, dropping a large return from the sample could substantially affect the volatility estimate.

Indeed, financial asset returns do not show evidence of random process but exhibit conditional heteroskedasticity. This means that the return of the previous day influences the behaviour of the return on the following day, and this relevance decays with time. The further the data goes into the past, the less relevant it becomes to today’s events. Furthermore, because each observation is equally weighted in the EqWMA approach, a large market move could significantly distort volatility. For example, when using a one-year historic volatility, a market shock that drops from the sample could cause a significant change in the VaR estimation. Alexander (1996) explains this phenomenon of ‘ghost features’ by stating that:

“When there is a large movement in the underlying time series such as a jump in market price, an equally weighted average of squared returns will jump up
to the very next day. This is an accurate reflection of the 'clustering' behaviour of volatility in financial markets. However, there are problems: Firstly, that one, large, squared return will continue to keep volatility estimates high for exactly one year (or however long the moving average) whereas the underlying volatility will have long ago returned to normal levels. Secondly, one year (or whatever) after a major market event the equally weighted volatility estimate will jump down again as abruptly as it jumped up. But there is nothing special about that day – what is seen is just a ghost of what happened one year ago, a correction in the estimate which is by then long over due. Because the average is taken over fewer observations, this correction will be much bigger in short-term volatility estimates.”

A more sophisticated approach to modelling volatility is the exponentially weighted moving average (EWMA) and GARCH type models, where more weight is given to the recent observations. These models overcome the problem of the EqWMA approach. The EWMA and GARCH type models recognise that volatilities are not constant and the variance of the random process depends upon time. These models attempt to keep track of the variations in the volatility through time, as during some periods a particular volatility may be relatively low where as during some other periods it may be relatively high (Hull, 2000). The EWMA and GARCH models are introduced in the next two sub-sections.

5.6.1.2.2 Exponentially Weighted Moving Averages

In the exponentially weighted moving average (EWMA) methodology, which is also called as the exponential smoothing, the forecast of volatility depends on the immediate past observed volatility. In the EqWMA method, in order to estimate the variance, different observations in the sample are given equal weights. They are regarded as equally important in the estimate, since it is assumed that they come from the same distribution. A shock could increase the volatility sharply and volatility would be high until the particular observation drops out of the sample as it moves forward. The decline in volatility would then be just as sharp as the initial increase. However, in the EWMA methodologies, past observations are weighted by a smoothing constant, the decay factor ($\lambda$). For the EWMA models, the variance is calculated as:
\[ \sigma_i^2 = (1 - \lambda) \sum_{n=1}^{n-1} \lambda^{n-1} (r_{i,t} - \mu)^2 \]  

(5.10)

In this model, the exponentially weighted average on a given day is a combination of the weighted average on the previous day, which receives a weight of \( \lambda \) and yesterday's squared deviation, which receives a weight of \( (1 - \lambda) \). The smoothing parameter \( (\lambda) \) is between 0 and 1. The decay factor determines the rate at which the influence of past observations decays as they become more distant. When the decay factor equals zero \( (\lambda = 0) \), the EWMA model becomes an EqWMA. While lower \( \lambda \) indicates faster decay in the influence of past observations, if \( \lambda \) approaches to 1, then a higher weight is given to the last observations.

The RiskMetrics model employs an exponentially weighted moving average in order to model variances and uses only one decay factor for all series. In RiskMetrics, the value of the decay parameter is fixed at \( \lambda = 0.94 \) for daily data and \( \lambda = 0.97 \) for monthly data (25 trading days). As RiskMetrics use an exponential weighting scheme where the weight of past observations declines geometrically, a relatively short time period\(^{40}\) is required. The decay factor could be found from maximizing the likelihood function\(^{41}\). However, in practice, because there are several assets in a portfolio, it is a very difficult task to calculate decay factors for a portfolio (Jorion, 1997). In addition, the decay factor could not only vary across series but also over time.

The EWMA approach is a special case of the GARCH(1,1) process, where \( \alpha_0 \) is zero and \( \alpha_1 \) and \( \beta \) sum to unity (Jorion, 1997). Compared to GARCH, the estimation of the exponential model is relatively straightforward as it relies on only one parameter, i.e. the decay factor \( (\lambda) \). These restrictions reduce the GARCH(1,1)

\(^{40}\) RiskMetrics uses data series consist of six months of daily observations.

\(^{41}\) Actually, maximum likelihood for GARCH model is more reliable than for RiskMetrics as maximum likelihood assigns more weights on large return squares for GARCH models (the bigger value the return square \( (r_i^2) \), the more the algorithm tries bring \( \sigma_i^2 \) close to \( r_i^2 \)). However, maximum likelihood for RiskMetrics assigns equal weight to each data (no matter the value of \( r_i^2 \), it tries to bring \( \sigma_i^2 \) as close to \( r_i^2 \) as possible).
to a one parameter model only and make it significantly easier to estimate volatility. The GARCH models are explained in the next sub-section.

5.6.1.2.3 GARCH Models

Volatility clustering suggests that the disturbances of financial asset returns are serially correlated. This problem could be captured through modelling conditional heteroskedasticity by assuming normality of the conditional distribution of financial asset returns (ARCH/GARCH models). This class of models are specifically designed to model and forecast conditional variances. In these models, the variance of the dependent variable is modelled as a function of past values of the dependent variable and independent, or exogenous, variables. These models also handle the serial correlation of disturbances as well as capturing to a great extent the fat tail effect. The aim of this sub-section is to describe the basic GARCH model.

ARCH is the acronym for autoregressive conditional heteroskedasticity that was introduced by Engle (1982) as a model for macroeconomic uncertainty. As the volatility of asset returns appears to be serially correlated, in order to capture the serial correlation of volatility, Engle proposed ARCH models. The basic ARCH model is a moving average (MA) model where the variance is a function of previous squared error terms. In the ARCH specification, the expected volatility of today depends on the data (squared forecast errors) of the previous \( n \) days:

\[
\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i}^2
\]  

(5.11)

In the ARCH\((q)\) process, the standard deviation at time \( t \) is a function of the observed data at \( t-1, t-2, t-3, \ldots, t-q \).

---

42 The conditional variance means that the forecast of the variance of a time series at time \( t \) is based on the previous data.

43 Heteroskedasticity means changing variance and indicates the lack of stationary volatility, i.e. the presence of periods of large standard deviation alternating with periods of small standard deviation.
Bollerslev (1986) extended ARCH into generalised ARCH, i.e. GARCH, which is the model extended to a full ARMA\((p,q)\) model that includes both an autoregressive and a moving average polynomial. GARCH is a general approach to modelling volatility by not considering it as a parameter but as a process that evolves over time in random (Engle and Mezrich, 1995). The task of any volatility model is to describe the typical historical pattern of volatility and use this to forecast future episodes. The idea of GARCH modelling is that a set of parameters is used to compute the volatility for every day over the sample and if these volatilities fail to match the observed volatility clusters, new parameters are chosen.

The GARCH model, which is the most popular class of the stochastic volatility models (Simons, 1997), assumes that the variance of returns follows a predictable process, where the return at time \(t\) \((r_t)\) is normally distributed with mean \(\mu\) and variance \(\sigma_r^2\). In a GARCH\((p,q)\) process, which is stationary\(^44\), the standard deviation at time \(t\) depends on observed data at \(t-1, t-2, t-3, \ldots, t-q\), as well as observed standard deviation at \(t-1, t-2, t-3, \ldots, t-p\), and conditional variance is a function of conditional variance up to time \(t-p\) and previous returns up to \(t-q\).

\[
\sigma_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + \alpha_2 r_{t-2}^2 + \ldots + \alpha_q r_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \ldots + \beta_p \sigma_{t-p}^2
\]  

(5.12)

where, \(\sigma^2\) is the conditional variance and \(r\) is the return.

In the GARCH\((1,1)\) model, which is the most popular type of GARCH\(^45\) (Simons, 1997), the conditional variance depends not only on the latest return but also on the previous conditional variance. The GARCH \((1,1)\) can be expressed by:

\[
\sigma_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + \beta \sigma_{t-1}^2
\]  

(5.13)

---

\(^44\) The stationary assumption means that the mean, variance, skew and kurtosis of the underlying population distribution are taken to be stable through time, i.e. dynamics are assumed to be constant through time.

\(^45\) The integrated GARCH (IGARCH) model is the non-stationary form (non-stationary is a statistical warning that the past is not necessarily a guide to the future) of the GARCH model. The exponential GARCH (EGARCH), on the other hand, diverges from other models by not being linear.
Empirical studies indicate that the GARCH(1,1) models better forecast volatility of foreign exchange returns. Examining twenty time series volatility models across a wide variety of markets (including the stock market, equities, interest rates and foreign exchange rates), Ederington and Guan (1999) found that GARCH(1,1) yields better out-of-sample forecasts than the historical standard deviation. However, it is not always necessary that GARCH type models always produce better estimates. For example, Figlewski (1997) found that while the GARCH(1,1) model has a lower root mean square error in predicting the S&P index volatilities, the forecasts produced by the historical variance models are better for the interest rate and foreign exchange assets.

Since the GARCH model is non-linear, in order to estimate parameters $\alpha_0$, $\alpha_1$ and $\beta$ in a GARCH(1,1) model, the maximum likelihood method should be applied to do a numerical optimisation, which involves using an iterative procedure to determine the parameter values that maximise the chance or likelihood that the historical data would occur (Hull, 2000).

Similar to the GARCH approach, the EWMA models estimate daily volatility by applying a weighted average of past squared returns, with recent squared returns weighted more heavily. However, while the EWMA model uses the same weights to calculate different class of assets, the GARCH approach computes different weights for each volatility calculation. The GARCH(1,1) model is also different from the exponential smoother as these models include a third term, which is a constant that has all the information for long run forecasting and contains the concept of mean reversion.

The GARCH models have advantages compared to the EWMA and EqWMA models, which are relatively straightforward to implement. However, because of the computational complexity, it is very difficult to estimate volatilities and variances by applying the GARCH models (Alexander, 1996).

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46 In the historical variance, i.e. EqWMA, all observations in the sample period back to a chosen cut-off point are weighted equally and observations before that time are ignored. However, in the GARCH model, the weights attached to successive observations decline exponentially and there is no cut-off date.
5.6.1.3 Estimation of the Covariances and Correlations

For portfolios consisting from more than one risk factor, which are assumed to be correlated, VaR can be estimated by the portfolio volatility. In order to estimate the portfolio volatility, first the covariance matrix of the returns of these risk factors should be established by using the volatilities and correlations of the risk factors in the portfolio.

The correlation between two return series, $X$ and $Y$, can be written as \[ \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y}, \]
where $\sigma_X$ and $\sigma_Y$ are the standard deviations of $X$ and $Y$ and $\text{cov}(X,Y)$ is the covariance between $X$ and $Y$. The covariance between $X$ and $Y$ can be written as $E[(X-\mu_X)(Y-\mu_Y)]$, where $\mu_X$ and $\mu_Y$ are the means of $X$ and $Y$, and $E$ denotes the expected value. The correlation always lies between +1 and -1. A positive value indicates that returns move linearly in the same direction and a greater value indicates greater association between return series. On the other hand, a negative value indicates that returns move linearly in the opposite direction.

However, because the magnitude of correlation depends on the variances of the individual components, using the covariance is a more convenient approach in calculating VaR. The covariance measures the strength and direction between two random variables. If two variables are independent, the covariance is zero. A positive covariance means that the two variables move in the same direction and a negative covariance means that the variables move in the opposite direction.

It should be taken into account that calculating covariances (and correlations) becomes more difficult with the increase in the number of risk factors in the portfolio. If there are two risk factors in a portfolio, only one covariance should be calculated. For ten risk factors, the number of covariances that should be calculated increases to 45.

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47 If there are $n$ risk factors in a portfolio, $n(n-1)/2$ correlations should be calculated.
On the other hand, as in the case of the volatility estimation, various methods such as the equally weighted moving average, exponential weighted moving average and GARCH can be used to capture the time variation in covariance (and correlation).

Equation 5.14 shows the estimate for the covariance between returns in \( X \) and \( Y \) calculated on day \( n \) by using an equally weighted method (it is assumed that the means of returns of these factors, \( x \), and \( y \), are zero).

\[
\text{cov}_n = \frac{1}{m} \sum_{i=1}^{m} x_{n-i} y_{n-i} \tag{5.14}
\]

An alternative to the equally weighted method is the exponential weighted method, which could be used to determine the estimate for the covariance between returns in \( X \) and \( Y \), where weights are given to the observations on \( x, y \)'s decline as time passes.

\[
\text{cov}_n = \lambda \text{cov}_{n-1} + (1 - \lambda) x_{n-1} y_{n-1} \tag{5.15}
\]

The GARCH models can also be used for updating covariance estimates and forecasting the future level of covariances. For example, the GARCH (1,1) model for updating a covariance is \( \text{cov}_n = \omega + \alpha \text{cov}_{n-1} + \beta y_{n-1} \) and the long term covariance is \( \frac{\omega}{1 - \alpha - \beta} \).

Accordingly, calculating the covariance and correlation coefficient statistics that measure the extent of the linear relationship between two variables are very important in estimating VaR under the parametric approach. However, as stated earlier in this chapter, the parametric approach is not the only methodology to calculate VaR. There are two more basic methodologies to calculate VaR, namely the historical simulation and Monte Carlo simulation methodologies.
5.6.2 The Historical Simulation Methodology

In the previous section, the variance-covariance methodology was explained. The objective of this section is to provide an understanding of the historical simulation methodology, which is an alternative approach to the parametric VaR.

Based on the historical data, this approach generates the distribution of the profit and loss of the portfolio and calculates potential portfolio losses using actual historical returns of the risk factors. The variance-covariance methodology assumes normality. Therefore, applying this approach requires an estimate of the standard deviation. However, because the financial asset prices are leptokurtic and skewed as well as indicating a high degree of serial independence, the variance-covariance models could produce unreliable estimates.

However, the historical simulation methodology does not require explicit assumptions concerning the distribution of asset returns. Instead, the historical simulation methodology takes a portfolio and values the portfolio as if each price change occurred from today's portfolio value by applying historical data for a certain observation period. Then, gains and losses of the portfolio are simulated for each day and then ranked in order. The VaR estimate is the lowest return corresponding to the desired confidence level.

For example, if a 99 percent confidence interval is used, the VaR measure is equal to the largest loss corresponding to one percent, which means that the loss is not expected to exceed the VaR figure in more than 1 percent of cases. As a result, this approach estimates the VaR figure by using percentiles of the actual historical portfolio returns of a certain observation period.

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48 Assuming serial independence means that what happened yesterday or the day before has no implications for what will happen today or tomorrow.
49 The only assumption that historical simulation makes is that returns are independent and identically distributed over time, which means that today's return is not dependent upon yesterday's return and the returns are generated by the same probability distribution.
The historical simulation methodology offers a number of advantages. First, because this approach estimates VaR on the basis of past data, it does not assume any specific statistical distribution of asset returns and therefore it does not face the leptokurtosis problem. Second, unlike the variance-covariance and Monte Carlo simulation methodologies, the historical simulation methodology does not depend on the volatility and covariance estimates. Therefore, this methodology captures the dynamic nature of volatilities and covariances as it uses the historical data of actual price movements to determine the actual portfolio distribution. The third advantage of this approach is that it could be applied for both linear and non-linear assets as risk factors are revalued by using the historical data. Finally, historical simulation also considers stress testing as it actually reflects the stress experienced by a portfolio during chaotic periods.

However, the main disadvantage of this methodology is that there should be sufficient available past data to consider cyclical events. Therefore, the length of the data set is crucial in the historical simulation approach. While the length of the data set should be long enough to form a reliable estimate of the distribution, it should not be too long to create paradigm shifts. El Jahel et al. (1998), for example, do not recommend using a large number of observations because when a large number of observations are applied, the assumption that the observations are identically distributed will be less realistic as it is hardly likely that the distribution of the returns will not change over time.

Another disadvantage of the historical simulation methodology is that it is more computationally intensive than the variance-covariance approach. Papageorgiou and Paskov (1999) specify three disadvantages of the historical simulation methodology:

1) It assumes that the past represents the immediate future, i.e. the distribution is assumed to be stationary,

2) The results are highly sensitive to the length of the time horizon. As this approach applies a fixed window of historical data, when extreme market moves are dropped from the window, there could be sharp changes in the VaR estimates.
3) It is difficult to collect consistent historical data. In particular, for new instruments the calculation of VaR under the historical simulation approach is very difficult because of the lack of data.

As the problem of ‘ghost features’ also appears to be valid for the historical simulation approach, simply by giving more weight to more recent data points in the historical distribution, an exponential weighting model could be used in a historical simulation methodology.

Boudoukh et al. (1998) proposed an approach that combines the exponentially weighted variance-covariance methodology with the historical simulation methodology. This hybrid approach estimates the VaR of a portfolio by applying exponentially declining weights to past returns and then finds the appropriate percentile of this time weighted empirical distribution. Boudoukh et al. argue that as EWMA applies exponentially declining weights to past returns in order to calculate conditional volatility, the use of declining weights allows the user to capture the cyclical behaviour of the return volatility. On the other hand, in order to obtain VaR, the historical simulation methodology estimates the percentiles directly by using the empirical percentiles of the historical return distribution. This approach captures fat tails directly. However, there are two problems associated with historical simulation. The first problem is that the extreme percentiles of the distribution are especially difficult to estimate with small datasets, which should be solved by extending the observation period. The second problem is that this approach essentially assumes that returns are independent and identically distributed and therefore does not allow for time varying volatility and correlation. However, if a large observation period is chosen to solve the first problem, then the second problem gets worse as the value of the recent information diminishes. Therefore, by combining the EWMA model and the historical simulation approach, it is possible to overcome these problems.

In the hybrid approach, exponentially declining weights are attributed to historical returns while the historical approach attributes equal weights to each observation in establishing the return distribution. To obtain the VaR estimate by using the hybrid approach, Boudoukh et al. employ three steps. In the first step, to each of the most
recent returns a weight is assigned (the weight given to the observation \( n+1 \) days before is, \( \lambda \) times the weight given to the observation \( n \) days before, where \( 0 < \lambda < 1 \)). In the second step, the returns are ordered in ascending order. Finally, starting from the lowest return, weights are accumulated until the desired percentile is obtained.

5.6.3 The Monte Carlo Simulation Methodology

The second approach of the VaR calculation based on a simulation is the Monte Carlo simulation methodology. In particular, this approach is used in the pricing and risk management of the complex financial instruments, such as options.

Similar to the historical simulation methodology, this approach generates a large number of price samples from a return distribution to value the financial assets in the portfolio. However, while the historical changes in prices are used in the historical simulation methodology, in this approach the portfolio return distribution is generated by a Monte Carlo simulation. By using the actual historical returns of the risk factors, the Monte Carlo simulation methodology randomly generates a large number of simulations, which are used to calculate the volatility and correlation estimates. As the Monte Carlo simulation methodology uses the historic prices to estimate the variances and correlations, it is necessary to employ an assumption concerning the statistical distribution of the returns of the risk factors in the portfolio.

The Monte Carlo simulation methodology is implemented in three steps. The first step corresponds to the scenario generation. In this step, the volatility and correlation matrixes for the risk factors are calculated, which generates a statistical distribution for returns of the underlying risk factors. The second step corresponds to the portfolio valuation. In this step, a large random sample is taken from the statistical distribution to re-price each risk factor and to determine the trial gain and loss. This process is then repeated for each trial, which provides a set of different values for all the risk factors under consideration and each set represents a scenario. In the third step, the scenarios are ordered and the VaR number is obtained according to the desired confidence level (by cutting the list at the desired confidence level). For
example, if a 99 percent confidence level is chosen, then the VaR estimate of the Monte Carlo simulation approach is defined as the result that is exceeded in 99 percent of cases.

While the variance-covariance methodology is not an adequate methodology in capturing the non-linear behaviour of options, the advantage of the Monte Carlo simulation approach is the ability to calculate the VaR estimate for the non-linear financial assets by revaluing them for each trial. Therefore, this approach captures the non-linear effects of securities such as options. While some argue that the Monte Carlo methodology is the most powerful and comprehensive methodology for measuring market risk (Jorion, 1997), the most serious disadvantage of this approach is its high computational cost. As Schreiber et al. (1999) demonstrate, the Monte Carlo simulation methodology produces the highest cost while calculating VaR. On the other hand, while the computational cost of the variance-covariance methodology is not extensive, there is not much difference concerning the cost between the historical simulation and variance-covariance methodologies.

While choosing the appropriate method for calculating VaR, it is crucial to consider the cost of constructing and maintaining a model. Therefore, the cost benefit analysis of the VaR calculation through the Monte Carlo simulation methodology should be carefully considered. In addition, Minnich (1998) argues that for the portfolios consisting of linear financial assets, not much additional benefit could be obtained by using the Monte Carlo simulation methodology compared with the variance-covariance methodology.

Another problem with the Monte Carlo simulation methodology is to determine the necessary number of scenarios to reasonably estimate VaR. In this approach, the accuracy of the estimated VaR increases with the square root of the number of simulation runs and in order to have a stable VaR result with a 99 percent confidence level, a large sample is needed, which makes the Monte Carlo approach a quite expensive practice.
5.7 A Review of VaR Literature

Since the second half of the 1990s, a large amount of research related to VaR has emerged and various aspects of VaR have been extensively documented. However, the aim of this section is not to review all these studies but to review the studies in which the outcomes of choosing different VaR methodologies were analysed.

The choice of the methodology that is used in the VaR estimation process gives rise to very different results. The studies of Beder (1995), Hendricks (1996), Jackson et al. (1998), Boudoukh et al. (1998), Hull and White (1998) and Vlaar (2000) are among the works, which highlighted large variations in the VaR estimates depending on the methodology that is used to calculate VaR.

Beder's (1995) study entitled 'Seductive but Dangerous' is one of the most referenced studies in the VaR literature. In the article, Beder applied eight common VaR methodologies to three hypothetical portfolios. The differences in common VaRs emphasise the fact that no single set of parameters, data, assumptions and methodology can be accepted as the correct approach. Beder used the historical and Monte Carlo simulation methodologies. For each methodology, VaR was calculated for a one-day and a ten-day time horizons. The first methodology, historical simulation, was performed twice, changing the database used from the past 100 trading days to the past 250 trading days. The second methodology, Monte Carlo simulation, was also performed twice, changing the correlation estimates from the JP Morgan RiskMetrics data set to those from the Basle Committee approach.

The VaR calculations were performed for three portfolios. Portfolio 1 exclusively consists of US Treasury strips, and portfolio 2 consists of outright and options positions on the S&P equity index contract. The third portfolio consists of the combination of portfolio 1 and portfolio 2, which are equally weighted. Beder shows that the VaR calculations differ significantly for the same portfolio. VaRs are found to be extremely dependent on parameters, data assumptions, and methodology. Beder calculated eight common VaRs for three hypothetical portfolios for the same portfolio and the calculated VaR ranged from a base level of 100 to 1,400, or up to a
fourteen-fold variation. The result of this study highlighted the picture of expected capital at risk is dependent upon the VaR methodology and the assumptions behind the specific calculation.

Another study that investigates the performance of the VaR technique in practice was carried out by Hendricks (1996). Hendricks applied 12 VaR models to one thousand randomly chosen foreign exchange portfolios and compared the results. These models include; five equally weighted moving average approaches (50 days, 125 days, 250 days, 500 days and 1,250 days); three exponentially weighted moving average approaches ($\lambda = 0.94$, $\lambda = 0.97$, $\lambda = 0.99$) and four historical simulation approaches (125 days, 250 days, 500 days and 1,250 days). In the study the 95 and 99 percent confidence levels over a one-day holding period were used. The data consists of daily exchange rates of eight currencies against the US dollar and the historical sample covers the period 1983-1994.

Leaving the question of which methodology produces capital saving open, Hendricks aimed to understand how each VaR approach would have performed over a realistic range of portfolios containing the eight currencies over the sample period. The overall assessment of Hendricks is that the VaR approaches using longer observation periods tend to produce less variable results than those using shorter observation periods or weighting recent observations more heavily. He states:

"The use of longer time periods may produce larger value-at-risk measures. For historical simulation approaches, this result may occur because longer horizons provide better estimates of the tail of the distribution. The equally weighted approaches, however, may require a different explanation. Nevertheless, in our simulations the time period effect is small, suggesting that its economic significance is probably low."

Hendricks found that none of the twelve models he examined is superior on every count and the choice of confidence level has a substantial impact on the performance of VaR models. Almost all the approaches produce accurate 95th percentile risk measures. However, he found that the 99th percentile risk measures are somewhat less reliable as they generally cover between 98.2th percent and 98.5th percent of the outcomes.
While Beder (1995) and Hendricks (1996) used hypothetical portfolios, the study of Jackson et al. (1998) was one of the first studies that compared the VaR methodologies by employing real life bank data. By using data on actual trading books from a bank with sizable trading exposure, covering equity, interest and foreign exchange risks, the study examined the various aspects of VaR analysis and its use as an instrument of banking regulation. In particular, they analysed the impact of the observation period (window length) and the impact of weighting returns data in the parametric VaR calculations. Furthermore, they also compared the empirical performance of the parametric and simulation based VaR models. They argue that as the Basle Committee amendment does not specify any model that banks should use to generate capital requirements, the penalties envisaged for banks whose models fail to forecast loss probabilities accurately make this analysis crucial.

The data of the Jackson et al.'s study covers the period from July 1987 to April 1995 and the VaR estimates were calculated for the period from June 1989. They found that while various approaches of VaR modelling differ widely in the accuracy with which they predict the fraction of times that a given loss would be exceeded, the historical simulation models produce more accurate VaR estimates. The advantage of the study of Jackson et al. is the use of actual portfolios. They state that, "using actual books ensure that the pattern of risk exposures along the yield curve and between markets is realistic and the amount of exposure taken at different points on the yield curve and between markets clearly reflects a bank's investment decisions". They also claim that randomly generated portfolios cannot be representative and it would be difficult to build stylised books that were representative without basing them on actual books.

While the above-mentioned studies employed most common VaR methodologies, which are variance-covariance, historical simulation and Monte Carlo simulation, Boudoukh et al. (1998) and Hull and White (1998) propose the use of some combined approaches in the VaR calculations and compare this approach to other most common VaR methodologies.
Boudoukh et al. (1998) found that by using a hybrid approach that combines the exponentially weighted variance-covariance and historical simulation methodologies, a significant improvement in the precision of the VaR forecasts occurs. They estimated the VaR figures for four series by applying six models. These models are; the equally weighted variance-covariance, historical simulation, exponentially weighted variance-covariance (0.97 and 0.99 decay factors), and hybrid approaches (0.97 and 0.99 decay factors). They calculated VaR estimates for the DEM/USD exchange rate, crude oil, S&P 500 index, and a general Brady bond index by using 250 observations and the 95 and 99 percent confidence levels. They found that the hybrid approach provides an absolute error, which is 30 to 43 percent lower than the exponentially weighted variance-covariance approach and 14 to 28 percent lower than the historical simulation approach. Therefore, they recommend the use of this method as it combines the benefits of the two key VaR methodologies.

Hull and White (1998) also compared the historical simulation methodology, the hybrid approach that is proposed by Boudoukh et al. (1998), and a new approach (Hull and White - HW) that they proposed as a straightforward extension of the traditional historical simulation. Hull and White used daily data on 12 currencies (between 4 January 1988 and 15 August 1997) and 5 stock indices (between 11 July 1988 and 10 February 1998). For the hybrid approach they applied a 0.98 decay factor and for the HW approach, they applied a 0.94 decay factor. They used the most recent 500 days of data (2 years) and considered the 1 and 5 percentiles of the distribution. They also discussed whether to adjust the mean percentage change to zero in the historical simulation and test all approaches with and without a mean adjustment. They found that the results with mean adjustment are similar to those without mean adjustment. They also found that the HW approach, which involves adjusting observations to reflect the difference between the volatility at the time of the observation and current volatility, provides better 1-percentile estimates of daily returns than the historical simulation and hybrid approaches.

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50 Hull and White explain this methodology by stating: "Suppose that 20 days ago the observed percentage change in a market variable was 1.6% and the daily volatility was estimated to be 1%. If the daily volatility is now estimated to be 1.5%, the sample percentage change corresponding to the observation 20 days ago is 2.4%."
Hull and White also calculated the regulatory capital that would be required for an investment of USD 1 in each currency and stock index. They found that:

1) The capital is significantly more variable under the HW and hybrid approaches than under the historical simulation methodology.

2) In the historical simulation approach the risk capital is unchanged for long periods of time due to the length of the window and it is affected by large observations that appear in and drop off from the window.

3) For long positions in a single foreign currency, they found that the required capital under the HW approach is on average 7.8 percent less than under the historical simulation methodology. For long positions in a stock index, they find that the required capital under the hybrid approach is on average 0.2 percent higher than under the historical simulation methodology and the required capital under the HW approach is on average 6.7 percent higher than under the historical simulation methodology. They comment that the hybrid approach scores higher figures if the objective is to minimise capital.

4) Considering which method provides maximum protection against losses, they found that for currencies the hybrid and HW approaches produce better results than historical simulation while for stock indices the results are unclear.

Vlaar (2000) also investigated the consequences of dynamics in the term structure of Dutch interest rates for the accurateness of VaR models. Using 17 years of daily data, he compared the out-of-sample performance of VaR standards calculated on the basis of the historical simulation, variance-covariance and Monte Carlo simulation models, as well as a combined variance-covariance Monte Carlo approach, for 25 hypothetical portfolios consisting of Dutch government bonds of eight different maturities. He argues that as VaR is supposed to give the amount of money that can be lost with certain (for example 1 percent) probability, VaR is considered adequate if the frequency of actual losses in excess of the calculated VaR is approximately 1 percent. He found that with a 99 percent confidence level and for a ten-day holding period, best results were obtained for a combined variance-covariance Monte Carlo
methodology in which the variance is derived from the Monte Carlo simulation and VaR is subsequently calculated on the variance-covariance methodology. Concerning other methods, he found that while the historical simulation methodology is satisfactory when a long history is studied, the Monte Carlo methodology requires a large number of samples to arrive at the theoretically correct size of the 1 percent exceedance level. Vlaar concludes that the differences in the VaR standards on the basis of different methods vary and accurate VaR calculations lead to higher capital requirements than inaccurate measures, which might not encourage banks to accurately calculate the VaR estimates.

While the above-mentioned studies compared different VaR models, the studies of Dimson and Marsh (1997) and Crouhy et al. (1998) compared the required capitals that are calculated by using the standardised approach and the VaR models.

Dimson and Marsh (1997) discussed a number of potential issues, which a financial institution might face when calculating appropriate levels of capital for multiple positions during periods of stress. In particular, they evaluated the performance of the leading methods for setting capital requirements for securities’ firms trading books and found that the VaR type models are efficient in providing appropriate levels of capital to cover the position risk of equity trading books, while the building block approaches fail to provide effective cover.

Another study that evaluated different VaR models is the study of Crouhy et al. (1998). Crouhy et al. compared the capital charges for market risk by using different approaches. Firstly, they compared the required market risk capital amounts of a bank’s actual positions over a six-month period, where the capital amounts were produced by that bank. They mention that the capital savings, which is the reduction in capital charge realised by adopting an internal model instead of the standardised approach, varies between a low of 60 percent to a high of 85 percent. Secondly, they investigated the same issue, i.e. the extent of the capital charge differences between the standardised method and the internal model for five basic portfolios, which are limited to linear interest rate products. In their study, the amounts regarding the internal VaR method were provided from that bank’s own system and comparisons
were made for only a one-day calculation. In addition, as the details of the bank’s in-house VaR method were not classified in the study, it is not clear whether the requirements of the Basle Committee were met. For the first two portfolios, the adoption of the internal model did not allow any capital savings. On the contrary, the use of internal models generated a capital surcharge of 132 percent for the first and 103 percent for the second portfolios. However, for the third, fourth and fifth portfolios, the use of internal models generate capital savings of 62 percent, 11 percent and 51 percent, respectively.

Reviewing the literature demonstrates that there is no ‘best VaR estimation method’ and the VaR estimates are dependent upon the VaR methodology, parameters and data assumptions. However, the evidence concerning the accuracy of the VaR models that are used in the framework of the market risk capital regulations is limited. Beder (1995) found that not only the VaR estimates for the individual portfolios differ significantly, but also the magnitude of the differences does not follow a clear pattern. However, in her study Beder did not evaluate the accuracy of the VaR estimates that have been calculated by employing various VaR methodologies.

Jackson et al. (1998) evaluated the VaR estimates but they only focused on the regulatory backtesting. Their results indicate that various approaches of VaR modelling differ widely in the accuracy with which they predict the fraction of times that a given loss would be exceeded. However, their conclusions rely on the regulatory backtesting methodology.

Hendricks (1996) also evaluated various VaR models. Hendricks applied nine methods to evaluate VaR models\(^1\). The studies of Dimson and Marsh (1997), Boudoukh et al. (1998), Hull and White (1998), Crouhy et al. (1998) and Vlaar (2000) also evaluated the VaR models by applying a number of tests, including the regulatory backtesting. However, earlier research could not employ more

---

\(^1\) These methods are: mean relative bias, root mean squared relative bias, annualised percentage volatility, fraction of outcomes covered, multiple needed to attain desired coverage, average multiple of tail event to risk measure, minimum multiple of tail event to risk measure, correlation between risk measure and absolute value of outcome, and mean relative bias for risk measure scaled to desired level of coverage.
sophisticated backtests due to the absence of some of these tests when most of these studies were carried out.

However, because the VaR estimates are extremely dependent upon the VaR methodology, parameters and data assumptions, it is crucial to supplement the VaR models with more sophisticated backtesting methodologies to validate the accuracy of these models.

5.8 Chapter Summary

In this chapter, after providing an insight into the concept of VaR, the statistical framework for the derivation of VaR was introduced. In addition, the advantages and disadvantages of VaR and major methodologies for estimating VaR were provided. Furthermore, the related literature on the applications of VaR was reviewed.

Quantifying the financial risk of loss has been a common concern to those who have done business throughout history. However, until very recently, risks of investments were only guessed at, as predicting future events with certainty is not possible. The developments in the finance theory and innovations in technology, allowed those involved in business to start measuring their risks during the twentieth century. Increased volatility in the financial markets after the breakdown of Bretton Woods also accelerated the need for measurement and management of financial risks that the companies have been facing in their operations. The attention to the management and measurement of financial risks increased during the first half of the 1990s, and accelerated in 1995, after the collapse of Barings and the bankruptcy of Orange County. As a result, market risk has become one of the most significant concerns of the participants of the financial markets. These developments made VaR popular for measuring market risk.

The introduction of VaR is a milestone in the development of risk management and VaR has become a key concept in the analysis of market risk. Although the concept of VaR is straightforward, there are two fundamental issues that the users should follow in the VaR calculation process. First, the time horizon over which the user of
VaR wishes to estimate a potential loss should be determined. This time horizon could be a one-day period, i.e. the next trading day, or a longer period. While traders and financial risk managers are generally interested in a one-day time horizon, regulators and participants considering illiquid markets generally prefer a multiple-day time horizon while calculating their market risk with VaR. As a result, in each case the time horizon is required to be specified by the user of VaR. Second, the degree of certainty required, i.e. the confidence interval for the estimate, should be selected.

There are three major methodologies for estimating VaR. These are; the variance-covariance methodologies (equally weighted and exponentially weighted), the historical simulation methodology and the Monte Carlo simulation methodology. Although banks have integrated these models into their market risk management systems, VaR models have some limitations and pitfalls. Table 5.1 summarises the strengths and weaknesses of VaR methodologies.

Table 5.1: Summary of Strengths and Weaknesses of VaR Methodologies

<table>
<thead>
<tr>
<th>Method</th>
<th>Strengths</th>
<th>Weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance-Covariance</td>
<td>• Easy to understand</td>
<td>• Does not properly incorporate options or other non-linear instruments</td>
</tr>
<tr>
<td></td>
<td>• Least computationally intensive</td>
<td>• Fat tails problem</td>
</tr>
<tr>
<td></td>
<td>• Industry standard</td>
<td></td>
</tr>
<tr>
<td>Historical Simulation</td>
<td>• Naturally addresses the fat tail problem</td>
<td>• Computationally intensive</td>
</tr>
<tr>
<td></td>
<td>• Performs well under back-testing</td>
<td>• Relies on history; therefore its output depends heavily on the</td>
</tr>
<tr>
<td></td>
<td>• Can fully capture non-linear risks</td>
<td>time period selected (history must repeat itself)</td>
</tr>
<tr>
<td></td>
<td>• Easiest to explain to the non-mathematically</td>
<td>• Data intensive</td>
</tr>
<tr>
<td></td>
<td>inclined and easiest to implement from a</td>
<td></td>
</tr>
<tr>
<td></td>
<td>systems perspective</td>
<td></td>
</tr>
<tr>
<td>Monte Carlo Simulation</td>
<td>• Incorporates any statistical distribution</td>
<td>• It is computationally intensive</td>
</tr>
<tr>
<td></td>
<td>for the risk factors</td>
<td>• Sampling error</td>
</tr>
<tr>
<td></td>
<td>• Fully captures non-linear instruments</td>
<td></td>
</tr>
</tbody>
</table>

Adopted from Minnich (1998)
This chapter also provided the literature review concerning the applications of VaR. The conclusion that has been arrived at in the literature review is that there is no best VaR estimation method and the VaR estimates are dependent upon the VaR methodology, parameters, and data assumptions. In addition, the evidence concerning the accuracy of the VaR estimates that are obtained by employing various models for different portfolios is limited. In addition to that, it is crucial to validate the accuracy of VaR models with more sophisticated backtesting methodologies. The backtesting methodologies are presented in the following chapter.
CHAPTER SIX

BACKTESTING

6.1 Introduction

In recent years, several financial institutions have employed the VaR methodology to estimate the potential losses that could arise from market risk. In addition, the 1996 Basle Committee amendment has also required international banks to calculate the market risk capital since the beginning of 1998.

The 1996 Basle Committee amendment is a revolution in financial regulation as it allows financial institutions to use their own models to determine required capital to cover market risk. While the original accord imposed capital requirements to cover credit risk based on a uniform approach, the 1996 amendment requires additional minimum capital to cover market risk based on either a standardised approach or any type of internal VaR models approach, of which the latter is subject to the approval of national regulators. If financial institutions choose to determine the required capital on the basis of their own internal VaR models, they are required to report their daily VaR at the 99 percent confidence level and over a ten-day horizon.

On the other hand, verifying the accuracy of internal VaR models is crucial. As described by Hendricks and Hirtle (1997):

"The actual benefits from this information depends crucially on the quality and accuracy of the VaR models on which the estimates are based. To the extent that these models are inaccurate and misstate banks' true risk exposures, then the quality of the information derived from any public disclosure will be degraded. More significantly, inaccurate VaR models or models that do not produce consistent estimates over time will undercut the main benefit of a models-based capital requirement: the closer tie between
capital requirements and true risk exposures. Thus, validation of the accuracy of these models is a key concern and challenge for supervisors."

As it is crucial to have an accurate VaR model that forecasts the maximum portfolio loss that could occur over a given holding period with a specified confidence level, the backtesting of VaR models is essential to risk practitioners and regulators. Therefore, this chapter provides a survey of backtesting methods that are used to validate the VaR models. The understanding of backtesting is essential as the framework that is provided in this chapter is used to evaluate different VaR models in the eighth chapter.

The chapter is organised as follows. The second section introduces the concept of backtesting. The regulatory backtesting required by the Basle Committee amendment is explained in the third section. The statistical backtests are provided in the fourth section. In particular, the binomial frequency tests proposed by Kupiec (1995) and the conditional frequency test proposed by Christoffersen (1998) are explained in this section. The fifth section provides the ranking tests proposed by Lopez (1998) and Blanco and Ihle (1999). Finally, a chapter summary is provided in the sixth section.

6.2 The Concept of Backtesting

Backtesting is an application that can either be used to determine whether the estimates of a VaR model are consistent with the assumptions on which the model is based, or to rank the VaR models against each other (Dowd, 2002). This methodology provides information concerning the quality and accuracy of a VaR model by comparing an institution’s VaR estimates with the actual trading profits and losses of the activities that are subject to the VaR measurement.

In its simplest form, the backtesting procedure consists of calculating the number of times that the observed returns fall below the negative VaR estimate and comparing that number to the confidence level. If the VaR estimate exceeds trading loses at a greater frequency than indicated by the chosen confidence level, this indicates that the model is not an accurate one.
As demonstrated in Figure 6.1, a general backtesting framework consists of 6 steps. To implement a backtesting methodology, first the VaR estimate should be calculated by using an appropriate model. Second, the confidence level should be selected. In practice, it is common to select some arbitrary confidence level such as 95 percent. However, the market risk amendment of the Basle Committee requires banks to predict VaRs on a confidence level of 99 percent.

Figure 6.1: A General Backtesting Framework*

![Diagram of a General Backtesting Framework](image)

*Adopted from Dowd, 2002.

After constructing a VaR model at a certain confidence level, the next step of the backtesting process is the collection of profit and loss data for the backtesting purposes. In backtesting, two types of profit and loss data could be used. These are ‘actual’ and ‘hypothetical’ profits and losses. The actual profit and loss includes all gains and losses from market moves, trading revenues and fee incomes. On the other hand, the hypothetical profit and loss is the profit and loss that would have resulted if the portfolio had stayed constant and excludes trading revenue and fee income. The Basle Committee proposes the use of both methods. However, Dowd (2002) argues that for the risk measurement purposes it is crucial to use the profit and loss data that reflect the underlying volatility rather than the accounting prudence. Therefore, in order to compare VaR against the profit and loss data, components such as fee income, hidden profits and losses from trades carried out at prices different from the
mid bid-ask spread, realised profit and loss and provisions should be omitted from the profit and loss data. Otherwise, a hypothetical profit and loss data that is obtained by revaluing trading positions from one period to the next should be used.

The profit and loss of a portfolio is obtained by applying market data to the positions. For example, for a foreign exchange portfolio that consists of currencies, the profit and loss is calculated by using the appropriate market data on the foreign exchange positions. Then, in order to attain the accuracy of the VaR models, the backtesting procedure is applied and the results are obtained.

Due to the importance of using accurate VaR models in calculating the required market risk capital, one of the qualitative criteria of the internal models approach is the use of backtesting. The method that is required by the Basle Committee is the simplest form of backtesting method, in which penalties are set depending on the frequency of exceptions. However, this method does not provide sufficient information to examine VaR performances. In addition to counting the number of exceptions, there are a variety of tests that have been proposed to determine the accuracy of VaR models. While these tests differ in their details, their base is a particular transformation of VaR and the realised profit and loss.

These tests are classified into two groups: the statistical backtests and ranking tests. In particular, these tests are applied to answer the following questions:

1) Given a VaR model, how could a risk practitioner or regulator statistically test that this model is accurate?

2) Given different VaR models, how could a risk practitioner or regulator compare these models?

In order to answer these questions, a risk practitioner or a regulator could use three general methods, namely, the regulatory backtesting, statistical backtests and ranking tests. These methods are explained in the following sections.
6.3 The Regulatory Backtesting

The Basle Committee explains the supervisory framework for the use of backtesting in conjunction with the internal models approach in its paper published in January 1996. The Basle Committee believes that backtesting offers the best opportunity for incorporating suitable incentives into the internal models approach in a manner that is consistent and that will cover a variety of circumstances.

The regulatory backtesting process requires a financial institution to compare on a quarterly basis its daily net profits and losses to daily VaR measures using a 99 percent confidence level and a one-day period of rate and price movements. Each day, for which net daily trading loss exceeds the VaR estimate, is counted as an exception.

The regulatory backtesting is based on the binomial assumption and it is the simplest backtesting method as it only counts the number of days on which an exception occurs. As a VaR number is reported at the confidence interval, \( c \), the number of exceptions \( E \) in a total of \( n \) observations is \( n(1-c) \). In the regulatory backtesting, the VaR model is accepted or rejected depending on the \( E \). This is what the Basle Committee requires by its amendment to the capital regulations. The Basle Committee recommends national regulators to backtest the financial institutions’ VaR models by evaluating the frequency of exceptions, i.e. the frequency of daily losses exceeding VaR, starting one year after a financial institution initiates calculating the market risk capital charges.

The Basle Committee amendment also sets penalties depending on the frequency of exceptions. For models that systematically underestimate risk exposures, bank regulators charge a multiplication factor. If the frequency of exceptions is high, then regulators should increase the multiplier that is used to determine the market risk charge from three to up to four. Additional corrective actions in response to a high number of exceptions are also left to the discretion of the national regulators.
The Basle Committee has laid down three error levels. These are:

1) Green zone, which means satisfactory (up to four exceptions),
2) Yellow zone, which means a warning signal (up to nine exceptions),
3) Red zone, which requires an immediate adjustment to the capital adequacy multiplier (10 or more exceptions).

The number of exceptions guides the size of potential regulatory action in a financial institution's capital requirement. If a financial institution has five or more exceptions, it is supposed to have an inaccurate VaR model. Then, the financial institution is required to increase the multiplication factor from three up to a maximum of four, depending on the number of exceptions.

It should be noted that while the VaR estimates used for the capital purposes consider a ten-day holding period, backtesting requires a one-day standard. In their amendment, the Basle Committee (1996) explains this by stating that;

"It is often argued that VaR measures cannot be compared against actual trading outcomes, since the actual outcomes will inevitably be 'contaminated' by changes in portfolio composition during the holding period. (...) This argument is persuasive with regard to the use of VaR measures based on price shocks calibrated to longer holding periods. That is, comparing the ten-day, 99th percentile risk measures from the internal models capital requirement with actual ten-day trading outcomes would probably not be a meaningful exercise. In particular, in any given ten-day period, significant changes in portfolio composition relative to the initial positions are common at major trading institutions. For this reason, the backtesting framework described here involves the use of risk measures calibrated to a one-day holding period."

The backtesting process is not only a requirement of the regulatory framework but also a tool that banks use to determine the accuracy of their VaR models. Therefore, banks also exercise more formal statistical tests to validate their models. These are explained below.

6.4 The Statistical Backtests

Counting the number of days that losses exceed the VaR estimate is a simple backtest procedure and does not measure the accuracy of the models. Therefore, the
VaR models should be evaluated through backtesting by employing more formal statistical methodologies.

The first condition of the statistical backtesting is to obtain exceptions (tail losses). When an institution’s loss on the trading activities is less than its ex ante VaR estimate, this is called as an exception. Indicating the portfolio profit and loss over a fixed time interval, the number of losses that exceed VaR is determined by the following hit function;

\[
I_t = \begin{cases} 
1 & \text{if } x_{t,t+1} \leq -\text{VaR}_{t}(\alpha) \\
0 & \text{if } x_{t,t+1} > -\text{VaR}_{t}(\alpha) 
\end{cases} 
\quad t \in \{1,2,\ldots,n\}
\]  
\tag{6.1}

where \(x_{t,t+1}\) represents the profit or loss between the end of date \(t\) and date \(t+1\); \(\text{VaR}_{t}(\alpha)\) represents reported VaR on date \(t\) at a specific confidence level (\(\alpha\)). If an institution’s loss on the trading activities between the end of date \(t\) and date \(t+1\) is less than or is equal to its negative VaR calculated on date \(t\), this is called as a success (1). If an institution’s loss on the trading activities between the end of date \(t\) and date \(t+1\) exceeds the negative VaR calculated on date \(t\), this is called as a failure (0). The negative sign arises from the convention of reporting VaR as a positive number.

The hit function sequence indicates the events when an institution’s loss on the trading activities is less than its ex ante VaR estimate. After constructing the hit function sequence (e.g.; 0,1,0,0,1,0,0,0,0) for all observations, the next step is to specify the null hypothesis. Then, a significance level should be selected and the probability associated with the null hypothesis being true should be estimated. If the estimated value of this probability exceeds the significance level, the null hypothesis is accepted. If the estimated value of this probability does not exceed the significance level, the null hypothesis is rejected.

The basic statistical test based on the frequency of tail losses is a binomial test proposed by Kupiec (1995). This approach tests whether the observed frequency of
losses that exceed VaR is consistent with the frequency of the tail losses that is predicted by the model. Kupiec argues that daily profits and losses determine the outcome of a binomial event. If an institution’s loss on the trading activities is less than its ex ante VaR estimate, this is called as a success. If an institution’s loss on the trading activities exceeds the ex ante VaR estimate, this is called as a failure. When daily forecasts are efficient, potential loss estimates are independent and the performance data are distributed as a series of draws from an independent Bernoulli distribution.

The objective of the binomial test is to test whether the observed frequency of exceptions is consistent with the predicted frequency of exceptions. Under the null hypothesis that a model is correct, the number of exceptions follows a binomial distribution. Therefore, the probability of observing $x$ exceptions in a sample of size $n$ is:

$$\text{binomial}[n, x] = \binom{n}{x}(1-p)^{n-x} p^x = \frac{n!}{x!(n-x)!}(1-p)^{n-x} p^x$$

(6.2)

where $\text{binomial}[n, x]$ signifies the binomial coefficient for $n$ objects taken $x$ at a time, $x$ is the number of successes, $n$ is the number of observations, $p$ is the predicted probability of a success on any one of the independent trials (which equals to 1 minus the confidence level).

For example, for 1,000 observations and at the 99 percent confidence level, the model predicts that $p = 1 - \alpha = 0.01$, which indicates that the null hypothesis is $H_0: p = 0.01$. Therefore, the model predicts 10 exceptions ($n*p = 1,000*0.01 = 10$) for this sample. If there are 15 exceptions in the sample, this indicates that observed frequency ($\hat{p} = 0.015$) exceeds $p$ (0.01) and for that reason a one-sided alternative hypothesis should be specified ($H_1: p > 0.01$). The probability value of the test is then the probability under the null that $x \geq 15$ and this could be calculated as $1 - \Pr[x < 15]$. For $n=1,000$ observations and at the 1 percent significance level, the cumulative probability of 15 or fewer exceptions is 0.95 and therefore.
$1 - \text{Pr}[x < 15] = 0.05$. As this value is higher than $p$, the model is acceptable. Table 6.1 demonstrates the non-rejection level of exceptions for alternative sample sizes for a one-sided test.

<table>
<thead>
<tr>
<th>Null Hypothesis Probability Level ($p$)</th>
<th>Non-Rejection for $x \ n = 250$ days</th>
<th>Non-Rejection for $x \ n = 500$ days</th>
<th>Non-Rejection for $x \ n = 1,000$ days</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.010</td>
<td>$x \leq 6$</td>
<td>$x \leq 10$</td>
<td>$x \leq 17$</td>
</tr>
<tr>
<td>0.025</td>
<td>$x \leq 10$</td>
<td>$x \leq 19$</td>
<td>$x \leq 34$</td>
</tr>
<tr>
<td>0.050</td>
<td>$x \leq 17$</td>
<td>$x \leq 32$</td>
<td>$x \leq 61$</td>
</tr>
<tr>
<td>0.075</td>
<td>$x \leq 24$</td>
<td>$x \leq 45$</td>
<td>$x \leq 86$</td>
</tr>
<tr>
<td>0.100</td>
<td>$x \leq 30$</td>
<td>$x \leq 58$</td>
<td>$x \leq 111$</td>
</tr>
</tbody>
</table>

As an example, Table 6.1 demonstrates that when $p = 0.01$ and $n = 1,000$, then the model will not be rejected as long as $x \leq 17$. However, a value of $x$ greater than 17 indicates that the VaR model is not acceptable and the null hypothesis is rejected.

While a one-sided binomial test provides a single cut-off point, testing a two-sided alternative hypothesis estimates a confidence interval for the number of exceptions and then controls whether the observed number of exceptions lies within this interval. This approach tests the hypothesis that $E[I, I] = p$ against the alternative $E[I, I] \neq p$. Kupiec (1995) presents the use of the likelihood ratio (LR) test in order to test the null hypothesis, as this test is the uniformly most powerful test for a given sample.

The likelihood under the null hypothesis is;

$$L(p; I_1, I_2, ..., I_n) = (1 - p)^{n-x} p^x$$  \hspace{1cm} (6.3)

and under the alternative;

$$L(\pi; I_1, I_2, ..., I_n) = (1 - \pi)^{n-x} \pi^x$$  \hspace{1cm} (6.4)

Under the null hypothesis, the likelihood ratio test statistic is given by;
\[
LR = -2 \ln \left[ \frac{L(p; I_1, I_2, \ldots, I_n)}{L(H; I_1, I_2, \ldots, I_n)} \right] \sim \chi^2(s-1) = \chi^2(1) \quad (6.5)
\]

where \( \hat{\pi} = (x/n) \) is the maximum likelihood estimate of \( \pi \) and \( s=2 \) is the number of possible outcomes of the sequence. By substitution, the following likelihood ratio is obtained;

\[
LR = -2 \ln \left[ (1-p)^{x-n} p^n \right] + 2 \ln \left[ (1-x/n)^{x-n} (x/n)^n \right] \quad (6.6)
\]

where \( p \) is the predicted probability of a failure, \( x \) is the number of exceptions in the sample, \( n \) is the number of observations and \( x/n \) is the observed frequency of exceptions.

Under the null hypothesis that \( p \) is the true probability, the \( LR \) test statistic has an asymptotic \( \chi^2 \) distribution with one degree of freedom. If the test statistic does not exceed the relevant critical \( \chi^2 \) value, the null hypothesis is accepted. However, if the test statistic exceeds the relevant critical \( \chi^2 \) value, the null hypothesis is rejected.

Kupiec (1995) also demonstrates confidence regions for the number of tail losses and then verifies whether the expected number of tail losses lies within this interval. The confidence levels for the number of tail losses are constructed by using the inverse of the tail-loss binomial distribution. Table 6.2 demonstrates the number of failures (\( x \)) that could be observed in a sample size \( n \) without rejecting the indicated null hypothesis that \( p \) is the correct probability at the 95 percent confidence level.
Table 6.2: The Non-Rejection Regions for the Kupiec Test for Alternative Sample Sizes

<table>
<thead>
<tr>
<th>Null Hypothesis Probability Level (p)</th>
<th>Non-Rejection Region for x n = 255 days</th>
<th>Non-Rejection Region for x n = 510 days</th>
<th>Non-Rejection Region for x n = 1,000 days</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.010</td>
<td>x ≤ 6</td>
<td>2 ≤ x ≤ 10</td>
<td>5 ≤ x ≤ 16</td>
</tr>
<tr>
<td>0.025</td>
<td>3 ≤ x ≤ 11</td>
<td>7 ≤ x ≤ 20</td>
<td>16 ≤ x ≤ 35</td>
</tr>
<tr>
<td>0.050</td>
<td>7 ≤ x ≤ 20</td>
<td>17 ≤ x ≤ 35</td>
<td>38 ≤ x ≤ 64</td>
</tr>
<tr>
<td>0.075</td>
<td>12 ≤ x ≤ 27</td>
<td>28 ≤ x ≤ 50</td>
<td>60 ≤ x ≤ 91</td>
</tr>
<tr>
<td>0.100</td>
<td>17 ≤ x ≤ 35</td>
<td>39 ≤ x ≤ 64</td>
<td>82 ≤ x ≤ 119</td>
</tr>
</tbody>
</table>

Source: Kupiec (1995)

For example, if n = 1,000 days (four years of data), then at the 95 percent confidence level the number of exceptions is:

\[ \mu = n(1-c) = 1,000 \times (1-95\%) \approx 50 \]  \hspace{1cm} (6.7)

However, when p=0.05, then the model will not be rejected as long as \( x \in (38, 64) \). For example, if there are \( x=55 \) exceptions out of \( n=1,000 \) observations, then it is expected under the null hypothesis that at the 95 percent confidence interval the model is true and therefore it could be concluded that the VaR model is acceptable. Values of \( x \) greater than 64 indicate that the VaR model underestimates the probability of large losses and values of \( x \) less than 38 indicate that the VaR model overestimates the probability of large losses.

Table 6.2 demonstrates that the interval for exceptions is dependent on the null hypothesis probability level (p). A smaller \( p \) leads to a smaller interval for \( x \), which makes it easier to reject the null hypothesis. Conversely, a larger \( p \) leads to a larger interval for \( x \), and makes it easier to accept the VaR model.

The drawback of the statistical test proposed by Kupiec is that if there is not a relatively long historical performance, there are significant statistical difficulties surrounding the verification of VaR estimates. Therefore, a reliable performance based on the verification techniques requires a relatively long comparison sample period. Dowd (2002) also argues that because the Kupiec approach focuses solely on the frequency of tail losses, it does not use potentially valuable information.
concerning the sizes of tail losses. Furthermore, the Kupiec approach assumes that exceptions are independent of each other and therefore this test does not take into account information concerning the temporal pattern of exceptions. Christoffersen (1998) develops the backtesting methodology proposed by Kupiec and suggests a conditional backtesting procedure.

The Christoffersen approach separates out the particular null hypothesis that the model has the correct frequency of independently distributed exceptions into its constituent parts and then tests each sub-hypothesis separately. These sub-hypotheses are:

a. Coverage hypothesis: The model generates the correct frequency of exceptions.

b. Independence hypothesis: The exceptions are independent; i.e. the exceptions should not be clustered over time.

Even if the model generates the correct frequency of exceptions, the indication of exception clustering would suggest that the model is inaccurate. However, in addition to the frequency of exceptions, a risk practitioner or regulator should be cautious about the clustering of exceptions, which could imply high autocorrelation in risks.

The Christoffersen approach tests both the coverage and independence hypotheses at the same time. If the model fails, where the model failure arises is straightforward to establish as this approach enables the user to test each hypothesis separately.

After setting the hit function sequence, \( \{I_t\} \), which is constructed from a given interval forecast, the second step of the Christoffersen approach is to test the coverage hypothesis. Therefore, the hypothesis that \( E[I_t] = p \) is tested against the alternative \( E[I_t] \neq p \). As demonstrated above while explaining the Kupiec test, the likelihood ratio of the coverage hypothesis is given by;
where \( LR_{uc} \) is the test statistic of the coverage hypothesis.

This test implicitly assumes that the exceptions are independent. However, the clustered exceptions might represent a signal of the model misspecification. Therefore, the next step of the Christoffersen approach is to test the independence of exceptions. The independence hypothesis is tested against an explicit first-order Markov alternative. First, a binary first-order Markov chain, \( \{I_t\} \), is considered, with transition probability matrix;

\[
\Pi_1 = \begin{bmatrix}
1 - \pi_{01} & \pi_{01} \\
1 - \pi_{11} & \pi_{11}
\end{bmatrix}
\]  

(6.9)

where \( \pi_{ij} = \Pr(I_t = j|I_{t-1} = i) \) \( (\pi_{ij} \) is the probability of an \( i \) on date \( t-1 \) being followed by a \( j \) on date \( t \)). The approximate likelihood under the null hypothesis for this process is;

\[
L(\Pi_1; I_1, I_2, \ldots, I_n) = (1 - \pi_{01})^{n_0} \pi_{01}^{n_{01}} (1 - \pi_{11})^{n_0} \pi_{11}^{n_{11}}
\]  

(6.10)

where \( n_{ij} \) is the number of observations with value \( i \) followed by \( j \). The maximum likelihood estimates of \( \pi_{01} \) and \( \pi_{11} \) are presented below;

\[
\pi_{01} = \frac{n_{01}}{n_{00} + n_{01}} \quad \text{and} \quad \pi_{11} = \frac{n_{11}}{n_{10} + n_{11}}
\]  

(6.11)

For a hit function sequence of \( \{I_t\} \) that consists of 0s and 1s, there are only four cases for any two consecutive days. These are; 00, 01, 10 and 11. In order to implement backtesting based on the Christoffersen approach, the hit function sequence is transformed into a duration series and the number of days for the following processes is obtained:
\( n_{00} \): The number of days that date \( t \) and date \( t+1 \) are failures.

\( n_{01} \): The number of days that date \( t \) is a failure and date \( t+1 \) is a success.

\( n_{10} \): The number of days that date \( t \) is a success and date \( t+1 \) is a failure.

\( n_{11} \): The number of days that date \( t \) and date \( t+1 \) are successes.

The next step of the Christoffersen approach is to maximise the log-likelihood function and solve the parameters, which are ratios of the counts of the appropriate cells;

\[
\hat{\Pi}_1 = \begin{bmatrix} 
\frac{n_{00}}{n_{00} + n_{01}} & \frac{n_{01}}{n_{00} + n_{01}} \\
\frac{n_{10}}{n_{10} + n_{11}} & \frac{n_{11}}{n_{10} + n_{11}} 
\end{bmatrix} \tag{6.12}
\]

Then, Christoffersen (1998) considers the output sequence, \( \{I_t\} \), from an interval model and estimates a first-order Markov chain model on the sequence and tests the hypothesis that the sequence is independent by noting that the following matrix corresponds to independence;

\[
\Pi_2 = \begin{bmatrix} 
1 - \pi_2 & \pi_2 \\
1 - \pi_2 & \pi_2 
\end{bmatrix} \tag{6.13}
\]

The approximate likelihood under the null hypothesis for this process is;

\[
L(\Pi_2; I_1, I_2, \ldots, I_n) = (1 - \pi_2)^{n_{00} + n_{01}} \pi_2^{n_{01} + n_{11}} \tag{6.14}
\]

and the maximum likelihood estimate is;

\[
\hat{\Pi}_2 = \hat{\pi}_2 = \frac{n_{01} + n_{11}}{n_{00} + n_{10} + n_{01} + n_{11}} \tag{6.15}
\]
Under the null hypothesis, the likelihood ratio test statistic is given by;

\[ LR_{ind} = -2 \ln \left[ \frac{L(\hat{\Pi}; I_1, I_2, \ldots, I_n)}{L(\Pi; I_1, I_2, \ldots, I_n)} \right] \sim \chi^2(s-1) = \chi^2(1) \] (6.16)

where \( LR_{ind} \) is the test statistic of the independence hypothesis and \( s=2 \) is the number of possible outcomes of the sequence. The \( LR_{ind} \) test statistic has an asymptotic \( \chi^2 \) distribution with one degree of freedom. By substitution, the likelihood ratio test statistic of the independence hypothesis is given by;

\[ LR_{ind} = -2 \ln \left[ (1-\pi_2)^{(n_{r0}+n_{r1})} \pi_2^{(n_{r0}+n_{r1})} \right] + 2 \ln \left[ (1-\pi_{01})^{n_{01}} \pi_{01}^{n_{01}} (1-\pi_{11})^{n_{11}} \pi_{11}^{n_{11}} \right] \] (6.17)

If the sample has \( n_{11} = 0 \), which could be easily observed in small samples and with small coverage rates, then the first-order Markov likelihood is calculated as (Christoffersen and Pelletier, 2003);

\[ LR_{ind} = -2 \ln \left[ (1-\pi_2)^{(n_{r0}+n_{r1})} \pi_2^{(n_{r0}+n_{r1})} \right] + 2 \ln \left[ (1-\pi_{01})^{n_{01}} \pi_{01}^{n_{01}} \right] \] (6.18)

The final step of the Christoffersen approach is to combine the above tests for unconditional coverage and independence to form a combined test of conditional coverage. Effectively, the null of the unconditional coverage test is tested against the alternative of the independence test. Under the null hypothesis, the likelihood ratio test statistic is given by;

\[ LR_{cc} = -2 \ln \left[ L(p; I_1, I_2, \ldots, I_n) \right] \sim \chi^2(s(s-1)) = \chi^2(2) \] (6.19)

where \( LR_{cc} \) is the test statistic of the combined hypothesis of the correct conditional coverage and \( s=2 \) is the number of possible outcomes of the sequence. The \( LR_{cc} \) test statistic has an asymptotic \( \chi^2 \) distribution with two degrees of freedom. Christoffersen (1998) conditions on the first observation in the test for unconditional
coverage and finds \( \hat{\pi} = \hat{\pi}_2 = \Pi_2 \), which implies that if the first observation is ignored, then the test statistic of the combined hypothesis is;

\[
LR_{cc} = LR_{ac} + LR_{imd}
\]  

(6.20)

The advantage of applying a joint full null hypothesis in a standard frequency-of-tail-losses test is that the model generates a correct frequency of exceptions, as well as that the exceptions are independent of each other (Dowd, 2002). However, the disadvantage of this backtesting method is that it has relatively small power in realistic small sample settings (Christoffersen and Pelletier, 2003). In addition, the statistical backtests do not allow the users to rank the VaR models. Therefore, these tests should be supplemented by the ranking tests, which are introduced in the next section.

6.5 The Ranking Tests

The backtests that were discussed in the previous sub-section are the statistical tests that focus on analysing the behaviour of the hit function. However, while the statistical backtests determine the performance of individual VaR models, different models can be compared to each other by giving them a score in terms of a loss function.

Lopez (1998) provides an alternative evaluation method that is not based on a hypothesis-testing framework. Instead, Lopez uses the standard forecast evaluation techniques; the accuracy of the VaR estimates is determined by how well they minimise a loss function that represents regulators’ concerns.

The loss function evaluation method proposed by Lopez is based on assigning a numerical score, which reflects specific regulatory concerns, to the VaR estimates. This approach ranks the models depending on this numerical score. A loss function that gives a score for each observation is obtained by evaluating profit and loss for each period and their associated VaR estimates. The score depends on the
comparison of past data on profits and losses and the correspondent VaR numbers. The general form of this loss function is:

\[
C(VaR_{t(\alpha)}, x_{t+1}) = \begin{cases} 
 f(x_{t+1}, VaR_t) & \text{if } x_{t+1} \leq -VaR_{t(\alpha)} \\
 g(x_{t+1}, VaR_t) & \text{if } x_{t+1} > -VaR_{t(\alpha)} 
\end{cases} \quad t \in \{1, 2, \ldots, n\} \quad (6.21)
\]

where \( f(x_{t+1}, VaR_{t(\alpha)}) \) and \( g(x_{t+1}, VaR_{t(\alpha)}) \) are functions such that \( f(x_{t+1}, VaR_{t(\alpha)}) \geq g(x_{t+1}, VaR_{t(\alpha)}) \), which ensures that tail losses do not receive a lower value than other profit and loss observations; \( x_{t+1} \) represents the loss between the end of date \( t \) and date \( t+1 \), \( VaR_{t(\alpha)} \) represents reported VaR on date \( t \) at a specific confidence level (\( \alpha \)). This general loss function measures how well the VaR model predicts losses when they occur.

One of the most important issues of the ranking process is to specify the loss function. Lopez proposes two loss functions. These are:

a) The loss function implied by the binomial method,

b) The loss function that addresses the magnitude of the exceptions.

The loss function implied by the binomial method is:

\[
C(VaR_{t(\alpha)}, x_{t+1}) = \begin{cases} 
 1 & \text{if } x_{t+1} \leq -VaR_{t(\alpha)} \\
 0 & \text{if } x_{t+1} > -VaR_{t(\alpha)} 
\end{cases} \quad (6.22)
\]

This approach uses the same information that is used in the binomial method; i.e. the number of exceptions, and a score of 1 is imposed for the exceptions and a score of 0 otherwise.

On the other hand, the loss function that addresses the magnitude of the exceptions uses a quadratic term that takes the sum of the number of exceptions and their squared distance from the corresponding VaR;
The advantage of this loss function is that in addition to imposing a score of 1 when an exception occurs, a quadratic term is added based on the magnitude of the exceptions. The numerical score increases with the magnitude of the exception and could provide additional information on how the underlying VaR model forecasts the lower tail of the distribution.

The backtesting is then performed by generating numerical scores for each individual VaR model and the score for any model is based on the sample average loss;

\[
\hat{C} = \frac{1}{n} \sum_{t=1}^{n} C(Var_t^{(a)}, x_{t+1})
\]

Different VaR models could be compared by ranking the models depending on the score (\(\hat{C}\)) of each model and more accurate VaR estimates generate the lowest score.

Lopez also suggests constructing benchmarks to evaluate the performance of a set of VaR estimates after a loss function is defined and (\(\hat{C}\)) is calculated. Therefore, a score function that takes the loss function and a benchmark as its inputs should be established to rank VaR models. The appropriate benchmark for a loss function implied by the binomial method is \(p\) (\(p=1\)-confidence level), which is the expected value of \(E[C]\).

Lopez suggests the following quadratic probability function as the score function implied by the binomial method;

\[
QPS = \frac{2}{n} \sum_{t=1}^{n} (C - p)^2
\]
which takes a value in the range of \([0,2]\) and a lower QPS value indicates a better model.

However, it is more difficult to construct a benchmark for a loss function that addresses the magnitude of the exceptions as the underlying distribution is unknown. Therefore, the benchmark should be estimated by some other means, such as Monte Carlo simulation.

Furthermore, the loss function that addresses the magnitude of the exceptions only takes into account the size of the exceptions and by squaring them the intuition behind the loss function is lost, as squared monetary returns do not have a monetary interpretation.

Blanco and Ihle (1999) suggest an alternative way to deal with the problem of aggregating the frequency with the size of the exceptions. They also stress that it is important to consider both the frequency and the size of the violations. However, they focus on the average size of the exception and create a weighted average indicator that captures both the size and the frequency of the exceptions.

The loss function proposed by Blanco and Ihle gives each exception a weight equal to the difference between the tail loss and the VaR estimate, divided by the VaR estimate.

\[
C_{\text{size}}(VaR_{t(a)}, x_{t,t+1}) = \begin{cases} 
(x_{t,t+1} - VaR_{t(a)})/VaR_{t(a)} & \text{if } x_{t,t+1} \leq -VaR_{t(a)} \\
0 & \text{if } x_{t,t+1} > -VaR_{t(a)} 
\end{cases} \quad (6.26)
\]

The advantage of this loss function is that it ensures that higher tail losses get higher values without the impaired intuition introduced by squaring the tail loss. Blanco and Ihle also suggest a final indicator \((C_m)\) that incorporates both the size and the frequency of the exceptions;

\[
C_m = \lambda C_{\text{size}} + (1 - \lambda) C_{\text{frequency}} \quad (6.27)
\]
where $\lambda$ is a weighting factor that reflects the relative importance of each type of violation, $C_{\text{size}}$ is the Blanco-Ihle size loss function (equation 6.26) and $C_{\text{frequency}}$ is the Lopez frequency loss function (equation 6.22).

The advantage of the loss function methodologies that were explained above is that as they are not statistical tests, forecast evaluation approaches do not suffer from the low power of standard tests (Dowd, 2002) and they provide a measure of relative performance that could be used to monitor the performance of the VaR estimates. However, as these approaches do not consider any statistical inference, the results could not indicate whether the performances of the models are significantly better or worse. Therefore, the backtesting procedures that were described in this chapter are not substitutes for but complements to each other.

As a conclusion, the use of accurate VaR models is very important in the market risk management of banks, as banks use the internal VaR models to calculate the required capital for their market risks. Therefore, regulators require banks to do backtesting in order to determine the accuracy of VaR models.

6.6 Chapter Summary

The simplest test of a VaR model is to count the number of days on which the realised portfolio loss is greater than the VaR estimate. This is the base of the Basle Committee’s regulatory backtesting procedure. However, this approach cannot evaluate the accuracy of a VaR model. As the model validation is a crucial process of checking whether a model is adequate, more formal methodologies, such as the statistical tests and the ranking tests should be used.

As well as the regulatory backtesting, this chapter introduced the statistical tests and the ranking tests. The assessment of these backtesting models has a crucial role as these models are used to evaluate different VaR models in Chapter Eight. Before that, in order to investigate the variations among banks’ VaR methodologies, disclosure practices of a sample of international banks are examined in the next section.
CHAPTER SEVEN

THE DISCLOSURE OF
VALUE AT RISK

7.1 Introduction

In recent years, the ability to understand, measure, and manage market risk has become a competitive necessity for financial institutions. Therefore, financial institutions have begun to reveal more information concerning the market risk in their annual reports. Disclosure of information is a major prerequisite of the market discipline theory. Therefore, the Basle Committee strongly encourages banks to continue their efforts to develop their market-risk disclosures.

On the other hand, although VaR has become a standard in the measurement of market risk, there is still no industry consensus on the methodology for calculating VaR. In addition, within the framework of the market risk capital regulations, banks are not restricted to use any specific type of VaR model.

One of the main objectives of this thesis is to analyse the outcomes of using different VaR methodologies on the required capital amounts. Therefore, it is important to determine the discrepancies in bank VaR methodologies. In order to find out the differences concerning the VaR practices of banks, a documentary analysis is conducted in this chapter. In particular, this analysis addresses the question of ‘What kind of VaR models and parameters do banks use in their market risk measurement framework?’

The chapter is organised as follows. In the second section, the emergence of the disclosure of market risk is explained. In the third section, the annual reports of a
bank are investigated in order to demonstrate how the market risk disclosures have evolved. In the fourth section a documentary analysis is carried out by surveying the annual reports of 25 international banks. The objective of this survey is to assess the dissimilarities between the market risk measurement methodologies of banks. The final section explains the results of the survey.

7.2 Disclosure of Market Risk

Over the last decade, financial institutions have expanded their businesses in derivative and trading activities. Consequently, bank regulatory agencies have recommended disclosure of more information related to quantitative and qualitative market risk measures.

In June 1999, the Basel Committee introduced a proposal for a new capital adequacy framework in order to replace the 1988 Capital Accord. Also known as Basel II, which will be implemented by 2007, this new framework consists of three pillars, namely; the minimum capital requirements, a supervisory review process and effective use of market discipline. Regarding the third pillar of this framework, which is the market discipline, the Basle Committee seeks to encourage high disclosure standards and to enhance the role of market participants to encourage banks to hold adequate capital.

In January 2000, the Basle Committee published detailed guidance concerning market discipline. In this guidance, in order to increase market discipline, the Basle Committee recommends six disclosure practices to enhance effective disclosure, which should be made at least annually by banks. The underlying motive to enhance effective public disclosure is explained by the Basle Committee as:

"Market discipline performs an essential role in ensuring that the capital of banking institutions is maintained at adequate levels. Effective public disclosure enhances market discipline and allows market participants to assess a bank's capital adequacy and can provide strong incentives to banks to conduct their business in a safe, sound and efficient manner."

This guidance presents recommendations regarding disclosure in the areas of capital structure, risk exposures, and capital adequacy. However, because the focus of this
research is on the market risk capital regulations and the VaR methodologies, the recommendations that are related to the market risk management, which gained importance in the second half of the 1990s, are discussed below.

In the Basle Committee guidance, there are two recommendations related to market risk of banks. These are, 'Risk Exposures' and 'Capital Adequacy Measures'. According to the 'Capital Adequacy Measures', banks are requested to disclose measures of risk exposure calculated in accordance with the Basel Committee capital regulations for market risk. In particular, banks are requested to provide relevant information concerning their market risk capital calculations under the standardised or internal models approach, whichever is appropriate, as well as providing capital charges for every risk factor. If a bank prefers to use the internal models approach, there should be sufficient disclosed information to allow outsiders to understand the models used, which at least should cover the broad VaR data, parameters, backtesting, and stress testing information.

The Basle Committee's recommendation concerning the disclosure of 'Risk Exposures', requires banks to publicly disclose qualitative and quantitative information about their risk exposures. In addition, banks are required to provide comparative information concerning the previous years' data. Regarding detailed recommendations on the disclosure of risk exposures, the guidance points out another publication of the Basle Committee as a reference, entitled 'Recommendations for Public Disclosure of Trading and Derivatives Activities of Banks and Securities Firms'. This report, which was published jointly with the Basle Committee and IOSCO Technical Committee in October 1999, makes recommendations for public disclosures of trading and derivatives activities of banks and securities firms. The recommendations regarding market risk in this report are presented in Appendix 7.1.

As a matter of fact, the first regulatory effort that introduced the disclosure of market risk is the 'Discussion Paper on the Public Disclosure of Market and Credit Risks by Financial Intermediaries', which is known as the 'Fisher Report'. Recommended by the Euro-Currency Standing Committee, this report was published by the governors
of the G-10 central banks in September 1994. This report addresses disclosure issues relating to the risk exposures and risk management performance of trading activities of financial intermediaries. In addition, this report complements disclosure formats for financial trading activities to further develop the public debate concerning the disclosure of risk exposures and risk management performances.

The Basel Committee explains the role and the characteristics of public disclosure in another publication entitled 'Enhancing Bank Transparency', published in September 1998. According to this report, in order to establish market discipline, which is based on the recognition that markets contain disciplinary mechanisms by rewarding banks that have effective risk management and by penalising those which do not, market participants should have access to meaningful information that enable them to determine a bank’s financial condition. This report answers the question of 'What makes information meaningful?', by defining the characteristics of transparent information. These are:

- Comprehensiveness,
- Relevance and timeliness,
- Reliability,
- Comparability,
- Materiality.

Considering the objective of this research, the comparability concept is worth detailed examination. According to this concept, the comparability of information across banks should enable users to assess the relative financial position and the performance of banks.

As accurate financial information in annual reports is especially essential for establishing efficient market discipline, bank regulators and in particular the Basle Committee has urged financial institutions to disclose more information. This trend started with the 1996 market risk amendment and continued with Basel II, which strongly recommends that banks should disclose their VaR. Although the disclosure of VaRs by financial institutions increased after 1995 with the recommendations of the Basle Committee, it should be noted that this was a period that was followed by
the collapse of Barings and the announcement of huge losses by some corporations due to their trading activities. These made financial institutions disclose market risk practices in order to convince their investors and shareholders that they have efficient risk management systems, especially for market risk associated with derivatives.

The accuracy of financial risk information in annual reports is extremely important for analysts and investors. Linsmeier and Pearson (1997) point out that a common characteristic of firms reporting large losses arising from their market risk positions is that "... information about (financial or derivative) instruments and their associated risks was not well disclosed. Investors were surprised by the reported derivatives losses and, thus, public (market risk) disclosures became an important topic." Therefore, it is crucial for financial institutions to reveal appropriate and adequate information for market participants. According to the Basle Committee (1996), financial institutions should disclose both qualitative and quantitative information. Qualitative disclosures should include:

a) An overview of the financial institution’s overall business activities and risk-taking philosophy,
b) Major risks arising from the financial institution’s activities and the methods used to manage these risks,
c) The principal internal control procedures, significant valuation, and accounting policies.

Financial institutions should also disclose quantitative information produced by their own risk management systems. This quantitative information should include:

a) The financial institution’s exposure to financial risks (in particular credit and markets risks) and its performance in managing these risks,
b) Summary information concerning the composition of trading portfolios,
c) Disclosures based on internal risk measurement systems, in particular the VaR models and the underlying assumptions of the VaR estimates.

52 As of year-end 1998, the Basle Committee surveyed 71 financial institutions’ annual reports and found that 66 of them disclose the VaR figures (BIS, 1999).
Although regulators encourage banks to continue their efforts to develop their market risk disclosures, there is not much evidence on the efficiency of quantitative and qualitative market risk disclosures as firms generally do not voluntarily provide sufficiently detailed information regarding these issues (Ahmed et al., 1999). Dowd (2000a) examined the disclosure practices on VaR in firms’ annual reports and his findings indicate that while firms vary considerably in the amount of VaR information that they report, even the most detailed reports provide insufficient information.

The findings of Dowd are consistent with the study of Liljestrom et al. (2000) who surveyed the financial risk management information in the annual reports of banks operating in Europe. The findings of Liljestrom et al. indicate that there are substantial differences in the level of disclosure of risk information among European banks. These differences were found to be largely due to the variations in the size of banks and the cultural discrepancies. They also argue that Nordic, British, Irish and German banks tend to disclose more information on risks than others and larger banks disclose more information than smaller banks.

On the other hand, Jorion (2002) provides evidence on the information content of the VaR disclosures by investigating the relation between publicly disclosed quarterly bank VaR measures and the absolute value of the unexpected trading revenue in the subsequent quarter for a small sample of US commercial banks consisting of eight major banks, both cross-sectionally and over-time. In the study, Jorion estimated the volatility in quarterly trading revenues from the daily volatility using the square root of time rule. His findings indicate that especially in cross sections, VaR-based volatility forecasts based on the publicly available VaR disclosures of banks are significantly related to future market risk. His findings also indicate that banks with large VaR measures experience higher fluctuations in the unexpected trading revenues. He argues that the VaR disclosures are informative measures of risks and they could be used to predict the variability of banks trading revenues. He also argues that analysts and investors could use VaR disclosures to compare cross sectional risk profiles of trading portfolios.
Although Jorion converted different reporting time horizons and different confidence levels into a quarterly standard deviation assuming normal distributions and identically and independently distributed returns, the literature on VaR methodologies indicate that employing different VaR methodologies results in significant differences in the VaR estimates. Therefore, if banks use different methodologies, the comparison of bank VaR estimates might be misleading.

In order to assess the usefulness of financial risk disclosures, Woods and Marginson (2004) examined the annual reports of UK banks from a user perspective. They found qualitative disclosures to be general and quantitative disclosures to be incomplete and not always comparable. They also found that there are significant variations in the scale, content, and format of disclosures among the UK banks. They point out the difficulty for a user to combine qualitative and quantitative information in order to understand a bank’s financial risk-taking. They argue that, in relation to the particular market risk disclosures of the UK banks, the usage of market risk information is limited because of three reasons. These are:

1) Reliability of market risk disclosures is not strong because of the potential for bias in the selection of a VaR methodology.

2) Comparability is constrained as the VaR models and the assumptions could vary across institutions.

3) Understandability requires that users of market risk disclosures should be well informed concerning the VaR methodologies and should know how to read disclosed information.

Woods and Marginson (2004) also argue that the existence of fundamental problems concerning the mathematical models used to calculate VaR creates a dangerous environment for users of the financial statements because they could take an inaccurate estimate too seriously while looking for information on which to base an economic decision.
As a result, expanded disclosure concerning financial risk is a major prerequisite of the market discipline theory. However, comparing VaR models could mislead market participants, as the VaR estimates are dependent upon the methodology, parameters, and data assumptions. Therefore, it is not a straightforward task for market participants to assess a financial institution's risk-taking, in particular in relation to market risk, by comparing the VaR models and the assumptions underlying these models.

In recent years, as a result of the importance of managing and measuring market risk, financial institutions have begun to reveal more information concerning the market risk management in their annual reports. In order to demonstrate the improvements of banks disclosure practices, annual reports of HSBC were surveyed. As HSBC is a major international bank and its annual reports were easily accessed, HSBC was chosen as the subject of the case study and the annual reports from 1993 to 1999 were surveyed. This case study is presented in the next section.

7.3 A Case Study: HSBC

Most of the major financial institutions have implemented risk management systems and publish their VaR models and estimates in their annual reports. As an example, the HSBC case was analysed to demonstrate to what extent the market risk disclosures of a bank have evolved. The 1993 annual report of the bank does not have any information related to risk management and value at risk. In the 1994 annual report, the financial review of the company covered the credit risk management, market risk management, liquidity management, and OBS financial instruments. Although there is some information concerning the VaR calculations, no VaR figure is published. Concerning market risk, the bank announced in the 1994 annual report that:

"Market risk is managed within risk limits approved by the Group Executive Committee. (...) Risk limits are determined for each portfolio, subject to restrictions on product, currency, interest rate repricing and market volatility risks. Liquidity considerations are also taken into account in determining the limits set. Only certain offices within major subsidiaries, with sufficient derivative product expertise and appropriate control systems, are authorised to
trade derivative products. Actual risk levels compared with approved limits are monitored daily by each subsidiary and Group Market Risk”.

In addition, the bank states in the 1994 annual report that VaR is computed for principal treasury centres across the group on a regular basis.

In the 1995 annual report the VaR numbers are released for the first time. It is stated in the report that the estimation of potential losses that could occur on risk positions, taken due to the movement in market rates and prices, is a key component of the market risk management. In order to assess the potential loss that could occur due to the change in the value of treasury portfolios, the bank employs the value at risk methodology. Furthermore, it is mentioned that the VaR calculations are augmented by stress testing, both on the individual portfolios and on a consolidated basis.

Compared with the earlier annual reports of the bank, the 1998 annual report has an extensive VaR disclosure. In this report, especially the amount of information concerning the issue of market risk management and VaR methodologies has improved dramatically. In this report, the bank states that VaR is calculated on a variance-covariance basis by using a 95 percent confidence level and historical one-day movements in the market rates and prices. The one-day movement in the market prices is calculated by reference to two years of historical data. The aggregation of VaR from different risk categories is based upon the assumption of independence between risk types. In addition, although the bank uses VaR as a major market risk management tool, the limitations of this methodology are also emphasised in the 1998 report. Indicating that VaR should not be viewed as a maximum amount that the bank can lose on its market risk positions, the bank draws attention to the following limitations and assumptions of the VaR methodology.

- Although the changes in the risk factors follow a normal distribution, this may not be the case in reality and may lead to an underestimation of the probability of extreme market movements,
- Although all positions can be liquidated or hedged in one day, the use of a one-day holding period does not fully capture the market risk arising
from times of illiquidity, when one day liquidation or hedging may not be possible,
- Any loss might occur beyond the 95 percent confidence level,
- The use of historical data as a proxy for estimating future events may not encompass all potential events, particularly those which are extreme in nature,
- The assumption of independence between risk types may be incorrect,
- VaR is calculated at the close of each business day with intraday exposures not being subject to intraday calculations,
- VaR does not necessarily capture all of the higher order market risk and may underestimate VaR.

HSBC recognises these limitations by augmenting the VaR limits with other positions and sensitivity limit structures, as well as with stress testing, both on the individual portfolios and on a consolidated basis. Therefore, they emphasize that their stress-testing regime enables the senior management to assess the impact of extreme events on the market risk exposures.

The case study of HSBC demonstrates how rapidly the VaR disclosures have evolved and how banks have begun to give higher importance to disclose detailed information concerning the market risk management. However, the information that is disclosed by banks concerning their market risk measurements differs widely. Furthermore, the internal VaR models that banks use to measure their market risk exposure and the underlying assumptions of these models also differ widely. This makes it very difficult to compare the risk-taking activities of financial institutions. The next section provides a documentary analysis that demonstrates the differences in the VaR practices of banks.

7.4 A Survey of Bank Annual Reports

In the previous sections, the global standards for the market risk disclosures of financial companies were provided and the evolution of bank market risk disclosures was demonstrated. The remaining part of this chapter is devoted to find out whether
banks use different methodologies for their market risk management purposes. In order to do so, the annual reports of 25 international banks are surveyed. This documentary analysis is not intended to imply recommendations for ‘best practice’ disclosures or to provide evidence on the efficiency of market risk disclosures. Instead, the aim of this section is to demonstrate the differences in VaR practices.

In order to assess the discrepancies among the financial disclosures related to market risk and VaR practices, a documentary analysis was conducted. In this respect, the 1999 year-end annual reports of 25 banks were surveyed. Banks included in the survey are required to be large national banks and an additional precondition is to have easy and prompt access to their annual reports.

The survey is only concentrated on the disclosure of market risk information presented in the annual reports. As well as supplying reliable and valid information, the documentary analysis also provides information on banks operating in different locations. One of the main disadvantages of interviews is the difficulty of reaching institutions in different locations. That is the reason the survey has been conducted by using annual reports.

The annual reports of 25 banks were surveyed. Country distribution of the sample is as follows: 10 US banks, 9 UK banks, 2 German banks, 2 Swiss banks, 1 Canadian bank and 1 Dutch bank (Graph 7.1).
The results of the survey concerning the comparison of differences in VaR methodologies are shown in Table 7.1.

<table>
<thead>
<tr>
<th>Institution</th>
<th>Country</th>
<th>Methodology</th>
<th>Holding Period</th>
<th>Confidence Level (%)</th>
<th>Observation Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Royal Bank of Scotland</td>
<td>UK</td>
<td>Various</td>
<td>1 day</td>
<td>97.5</td>
<td>1 year</td>
</tr>
<tr>
<td>Lloyds TSB</td>
<td>UK</td>
<td>Various</td>
<td>1 day</td>
<td>95</td>
<td>3 years</td>
</tr>
<tr>
<td>HSBC</td>
<td>UK</td>
<td>Variance-Covariance</td>
<td>10 day</td>
<td>99</td>
<td>2 years</td>
</tr>
<tr>
<td>Barclays</td>
<td>UK</td>
<td>Historical Simulation</td>
<td>1 day</td>
<td>98</td>
<td>1 year</td>
</tr>
<tr>
<td>National Westminster</td>
<td>UK</td>
<td>Historical Simulation</td>
<td>1-10 day</td>
<td>95</td>
<td>2 years</td>
</tr>
<tr>
<td>Bank of Scotland</td>
<td>UK</td>
<td>Variance-Covariance</td>
<td>1 day</td>
<td>99</td>
<td>2 years</td>
</tr>
<tr>
<td>Abbey National</td>
<td>UK</td>
<td>Sensitivity Analysis</td>
<td>1 day</td>
<td>95</td>
<td>N/A</td>
</tr>
<tr>
<td>Fleeming</td>
<td>UK</td>
<td>Scenario Analysis</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Schroders</td>
<td>UK</td>
<td>Loss Risk Potential</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chase</td>
<td>US</td>
<td>Historical Simulation</td>
<td>1 day</td>
<td>99</td>
<td>N/A</td>
</tr>
<tr>
<td>Bank of New York</td>
<td>US</td>
<td>Monte Carlo</td>
<td>1 day</td>
<td>99</td>
<td>N/A</td>
</tr>
<tr>
<td>Bank of America</td>
<td>US</td>
<td>Variance-Covariance</td>
<td>1 day</td>
<td>99</td>
<td>N/A</td>
</tr>
<tr>
<td>State Street</td>
<td>US</td>
<td>Historical Simulation</td>
<td>1 day</td>
<td>99</td>
<td>1 year</td>
</tr>
<tr>
<td>Citicorp</td>
<td>US</td>
<td>Variance-Covariance</td>
<td>1 day</td>
<td>99</td>
<td>N/A</td>
</tr>
<tr>
<td>Fleet Boston</td>
<td>US</td>
<td>Variance-Covariance</td>
<td>N/A</td>
<td>99</td>
<td>N/A</td>
</tr>
<tr>
<td>JP Morgan</td>
<td>US</td>
<td>Hist. Sim. (Hybrid)</td>
<td>1 day</td>
<td>95</td>
<td>N/A</td>
</tr>
<tr>
<td>Bank One</td>
<td>US</td>
<td>Variance-Covariance</td>
<td>1 day</td>
<td>99</td>
<td>N/A</td>
</tr>
<tr>
<td>First Union</td>
<td>US</td>
<td>Variance-Covariance</td>
<td>N/A</td>
<td>97.5</td>
<td>1 year</td>
</tr>
<tr>
<td>Key</td>
<td>US</td>
<td>N/A</td>
<td>1 day</td>
<td>95</td>
<td>N/A</td>
</tr>
<tr>
<td>ABN Amro</td>
<td>Holland</td>
<td>Historical Simulation</td>
<td>1 day</td>
<td>99</td>
<td>4 years</td>
</tr>
<tr>
<td>Deutsche Bank</td>
<td>Germany</td>
<td>N/A</td>
<td>1 day</td>
<td>99</td>
<td>N/A</td>
</tr>
<tr>
<td>Nord/LB</td>
<td>Germany</td>
<td>Var-Cov (EqWMA)</td>
<td>10 day-</td>
<td>99</td>
<td>1 year</td>
</tr>
<tr>
<td>Credit Suisse</td>
<td>Switzerland</td>
<td>Var-Cov &amp; Hist. Sim.</td>
<td>10 day-</td>
<td>99</td>
<td>N/A</td>
</tr>
<tr>
<td>UBS</td>
<td>Switzerland</td>
<td>Historical Simulation</td>
<td>10 day-</td>
<td>99</td>
<td>5 years</td>
</tr>
<tr>
<td>Royal Bank of Canada</td>
<td>Canada</td>
<td>Historical Simulation</td>
<td>1 day</td>
<td>99</td>
<td>2 years</td>
</tr>
</tbody>
</table>

Table 7.1 demonstrates the following observations concerning the market risk disclosures of banks:

1) The banks in the sample employ three different methodologies in order to calculate their VaR estimates. These methodologies are; the historical simulation, variance-covariance and Monte Carlo simulation methodologies. Graph 7.2 demonstrates the share of each methodology that is employed by the sample banks to calculate their VaRs.
2) 36 percent of the banks (8 banks) in the sample report that they use only the variance-covariance methodology. While Nord/LB particularly states using the equally weighted variance-covariance methodology and First Union states using the exponentially weighted variance-covariance methodology, other banks do not disclose any specific information concerning the type of the variance-covariance methodology. In addition, the annual reports of the banks that use the variance-covariance methodology do not contain any information concerning the decay factors.

3) 36 percent of the banks (8 banks) in the sample report that they use only the historical simulation methodology. However, one of the banks (JP Morgan) particularly states that it employs the hybrid approach of the historical simulation methodology (exponentially weighted historical simulation methodology).

4) There are two banks that changed their methodology in 1999. Barclays had been using the exponentially weighted variance-covariance methodology, NatWest had been using both the variance-covariance and historical simulation methodologies. In 1999, both of these banks started to use only the historical simulation methodology.

5) There is only one bank (Credit Suisse) that employs both the variance-covariance and historical simulation methodologies.
6) The Bank of New York is the only bank in the sample that uses the Monte Carlo simulation methodology.

7) Two UK banks in the sample, namely the Royal Bank of Scotland and Lloyds TSB, report that they employ various VaR models. However, while specifying the assumptions of the VaR calculations, these banks do not identify any specific model and report that they employ various models.

8) While 22 banks in the sample employ VaR methodologies in their market risk measurement framework, there are 3 banks that employ other methodologies. While the Fleemings Bank reports that it uses the ‘scenario analysis’ in its market risk measurement framework; the Schroders Bank reports that it uses the ‘loss risk potential’. However, these banks do not disclose any particular explanation or assumptions related to their risk measurement frameworks.

9) The Abbey National reports that it uses the ‘sensitivity analysis’ to measure its market risk exposure. The sensitivity analysis measures the impact of the hypothetical changes in interest rates or market prices on banks’ earnings or net assets. The Abbey National reports that it uses a one-day holding period and a 95 percent confidence level in this analysis, however, it does not disclose any information concerning the observation period.

10) As a result, among the banks in the sample that employ VaR methodologies in their market risk measurement framework, most of them (77 percent) employ a historical simulation methodology, a variance-covariance methodology, or both of these.

11) Among the banks in the sample that employ VaR methodologies in their market risk measurement framework, the assumptions such as the holding periods, confidence levels and observation periods that banks use to estimate their VaR also differ significantly.

12) As shown in Graph 7.3, while 68 percent of the banks in the sample (15 banks) report that they estimate the VaR figures by using a one-day holding period, 14 percent of the banks (3 banks) report that they employ a ten-day holding period. There are two banks in the sample that report
using both a one-day and a ten-day holding period. On the other hand, the remaining two banks do not disclose any information concerning the holding period.

13) The banks in the sample that employ VaR methodologies in their market risk measurement framework use 4 different confidence levels ranging from 95 percent to 99 percent. As shown in Graph 7.4, while 68 percent of the banks (15 banks) in the sample employ a 99 percent confidence level, 18 percent of the banks (4 banks) report that they estimate the VaR figures based on a 95 percent confidence level. In addition, 9 percent of the banks (2 banks) report that they employ a 97.5 percent confidence level, while only one bank in the sample reports that it employs a 98 percent confidence level.
14) It is worth mentioning that while some banks in the sample do not provide information concerning the VaR methodology and holding period, all of them disclose information concerning the confidence level. In addition, in line with the Basle Committee regulations, most of the banks use a 99 percent confidence level.

15) As shown in Graph 7.5, while 27 percent of the banks (6 banks) in the sample use a one-year observation period, 18 percent of the banks (4 banks) employ a two-year observation period. In addition, there is one bank that employs a three-year, one bank that employs a four-year and one bank that employs a five-year observation period to calculate their VaR estimates. The banks that employ longer observation periods are also observed to use the historical simulation methodology.

16) While 60 percent of the banks that use a VaR methodology in the sample disclose their observation periods, there are 9 banks (40 percent) that do not report any information concerning the observation period.

As a result, the survey of disclosures concerning the VaR practices presented in the annual reports of 25 banks located in 6 countries reveals that the methodologies and parameters that are used to calculate the VaR estimates differ substantially. However, one of the most important results of this documentary analysis is that, 77 percent of the banks in the sample that employ VaR methodologies in their market risk
measurement framework employ either a historical simulation or a variance-covariance methodology, or both of these. Therefore, it could be claimed that these two methodologies are the most common methodologies that banks use to calculate the VaR estimates.

7.5 Conclusions

In this chapter, the regulatory efforts to increase disclosure concerning the qualitative and quantitative market risk information were introduced. In addition, in order to understand the variations among VaR methodologies of banks, the disclosure practices of a sample of international banks were compared. The sample was chosen from a search of banks that report market risk information in their annual reports. Although there are only 25 annual reports used, what is important for the purpose of this analysis is not to find out the best practice but provide an indication of how VaR models and parameters vary across banks.

The results of this study indicate that in recent years financial institutions were tending to give out more detailed VaR information in their annual reports. On the other hand, the market risk management information gathered from bank annual reports indicates that the VaR systems that financial institutions use differ widely across institutions.

According to the survey results, there are two major VaR methodologies that are in use by banks in their market risk management systems. These are the variance-covariance and historical simulation methodologies. In addition, there are differences in the underlying assumptions, such as the holding period, confidence interval, or historical observation period. These findings are consistent with the studies of Dowd (2000) and Liljestrom et al. (2000) and Woods and Marginson (2004), who find substantial differences in the level of disclosure of risk information by surveying the financial risk management information in the annual reports of financial institutions.

Under the framework of the market risk capital regulations, banks may employ either a standardised approach or their own internal VaR models to calculate the required
capital. Although the market risk capital regulations prescribe some quantitative standards, such as a 99 percent confidence level, a ten-day holding period and at least one-year of historical data, these regulations do not set the specific type of VaR model to be used. However, even when the same parameters are used, applying different methodologies may create different outcomes. As a result, an outsider would not be able to make any comparison as no additional calculation could be made to convert these figures to a common basis when different methodologies are used. Therefore, it is very difficult for financial market participants to make comparisons across institutions and to evaluate the risk-taking of individual banks by looking at single VaR values.

One of the first decisions, and may be the most difficult one that risk practitioners face with regard to VaR is to decide which model is more appropriate for them. The reliance on allowing financial institutions' to choose the VaR methodology could generate an incentive for them to prefer a methodology that calculates the minimum capital requirement. Therefore, it is important to find out whether any methodology results in capital savings for a financial institution. Furthermore, as obtaining accurate VaR estimates is crucial for risk practitioners and regulators, the following chapter also provides a backtesting process to assess the accuracy of VaR models.
CHAPTER EIGHT

AN EVALUATION OF THE STANDARDISED AND THE INTERNAL MODELS APPROACHES OF THE MARKET RISK CAPITAL REGULATIONS

8.1 Introduction

Since 1998, international banks have been required to set aside capital to cover their market risk, either by employing a standardised approach or by using the internal VaR models. The regulatory capital requirements for the market risk exposure of banks are explicitly based on the VaR estimates in the US; however, other industrialised countries allow banks to use either a standardised approach or an internal model.

Although bank regulators integrated the VaR models in the framework of capital adequacy regulations, these models have limitations and pitfalls. The aim of establishing a set of minimum capital levels is not only necessary to strengthen the safety and soundness of the banking system but also necessary to ensure a 'level playing field' for financial institutions in order to eliminate the competitive inequalities. On the other hand, giving an option to banks to determine the VaR methodology could create a moral hazard problem as banks may choose an inaccurate model that provides less required capital amounts. Therefore, it is very important to examine whether different methodologies that are allowed to be used in the market risk capital regulations have any potential to create such a moral hazard problem. Furthermore, as the market risk capital regulations are under close examination in many countries, it is crucial to understand not only the impact but also the limitations and drawbacks of these regulations.
The main problem concerning the use of VaR models is that there is no best VaR estimation method and the VaR estimates are extremely dependent upon the VaR methodology, parameters, and data assumptions. On the other hand, the use of these models differs widely across financial institutions.

The survey results provided in the previous chapter indicate that there are three main VaR methodologies that are used by banks in their market risk management systems. In addition, there are also differences in practice concerning the underlying assumptions, such as the holding period, the confidence interval or the historical observation period. On the other hand, the evidence concerning the accuracy of the VaR models that are used in the framework of the market risk capital regulations is limited. However, it is crucial to validate the accuracy of VaR models with sophisticated backtesting methodologies.

The aim of this chapter is to provide an answer as to whether the market risk capital regulations could create a moral hazard problem as the institutions may have an incentive to choose inaccurate models that report less capital requirements. In order to find an answer to this question, the required capital amounts, based on both the standardised approach and three different VaR methodologies, of two foreign exchange portfolios are compared. The main objective of these simulations is to assess the impact of using different models on capital levels. In addition, the accuracy of VaR models is evaluated by applying three backtesting methodologies.

In particular, the following research questions are answered in this study.

1) To what extent do the approaches of the market risk capital regulations produce different required capital amounts?
2) Do the market risk capital regulations provide a 'level playing field'?
3) Do the internal VaR models provide accurate VaR estimates that reflect banks' market risk exposures?
4) Do the market risk capital regulations create a moral hazard problem?
The chapter is organised as follows. The second section explains the general framework of the analysis. The third section provides the underlying assumptions of the choice of portfolios. The data and data sources are explained in the fourth section. This section also presents the methodology related to the calculation of daily returns of the currencies and the descriptive statistics of daily returns. The fifth section provides the methodologies that are applied to calculate required capital charges for the foreign exchange portfolios. The sixth section provides the empirical results. Then, the VaR models that are used in the analysis are evaluated through backtesting in the seventh section. The final section explains the empirical results of the study.

8.2 The Framework of the Analysis

VaR has become an industry standard for measuring market risk, especially after the recognition of it in the regulatory framework. However, in order to calculate the required capital, the market risk capital regulations allow the use of a standardised approach as well as the use of internal VaR models. The standardised approach is a building block approach, which is relatively more straightforward to use. On the other hand, the VaR approaches require sophisticated models to calculate the market risk of an institution, and its complexity increases with the increase in the number of risk factors. One of the major objectives of this study is to find out the impact of choosing different approaches when calculating the required market risk capital. In order to do so, simulations are carried out. In these simulations, a number of different models are applied to foreign exchange portfolios and the required market risk capitals are calculated accordingly. Furthermore, in order to assess and compare the usefulness of VaR models, the performances of different VaR models are tested through backtesting. The conceptual framework of this analysis is presented in Figure 8.1.
As demonstrated in Figure 8.1, the analysis consists of five steps. These steps are explained below.

1) The analysis process starts with the portfolio setting and data collection. First, the exposure to market risk that corresponds to the market value of the position in the investor base currency is determined as the US dollar. Then, a fixed and an active hypothetical portfolio are set up. Each portfolio consists of 10 foreign exchange rates against the US dollar. As the foreign exchange rate risk is one of the most important risks that financial institutions face in their activities, the foreign exchange...
positions are chosen. The database consists of daily returns of currencies from 2 January 1986 until 30 June 2000.

2) The daily returns of currencies, which are defined as logarithmic changes, are calculated for each day. Furthermore, the descriptive statistics of daily returns are examined.

3) The required market risk capitals are calculated by using both the standardised and internal model approaches. Three major VaR methodologies are used to calculate the required market risk capital. These methodologies are:
   - The equally weighted variance-covariance (EqVCV) methodology (2500-day, 1250-day, 750-day, 500-day, and 250-day),
   - The exponentially weighted variance-covariance (ExpVCV) methodology ($\lambda = 0.93$, $\lambda = 0.94$, $\lambda = 0.95$, $\lambda = 0.96$, $\lambda = 0.97$, $\lambda = 0.98$),
   - The historical simulation (HS) methodology (2500-day, 1250-day, 750-day, 500-day, and 250-day).

4) The performances of the standardised and VaR approaches are assessed by comparing the required capitals. Furthermore, the VaR approaches are evaluated by employing the regulatory backtesting, the statistical tests and the ranking tests.

5) Finally, the empirical results of the study are provided.

8.3 Portfolio Setting

In order to compare the standardised approach and the three most commonly used VaR methodologies, two hypothetical foreign exchange portfolios are set up. The main reason for selecting portfolios consisting of foreign exchange positions is that the foreign exchange rate risk is one of the most important risks that financial institutions face in their activities.

The market risk capital comparison is made for a fixed portfolio and an active portfolio and the modelling of these portfolios are not irrelevant to the market practices. Two small banks are considered (Bank A and Bank B). Each bank has a
similar portfolio consisting of limited exposure in foreign exchange and these banks are subject to the market risk capital regulations. The foreign exchange traders of these banks are allowed to make investments in 10 currencies and to take USD 1 million equivalent exposure (long or short) in each currency.

The trader of Bank A (Trader A) is a conservative trader who is not active in the foreign exchange market. The portfolio of Trader A is named as the fixed portfolio and the amount that is invested in each currency stays constant over the period in question. The trader of Bank B (Trader B) is more active in the foreign exchange market and revises the portfolio every day based on his/her market expectations and forecasts. However, this portfolio generates losses every trading day due to the wrong decisions of Trader B. Therefore, the portfolio of Trader B is called the worst-case portfolio. This assumption allows especially bank regulators to understand the performances of the market risk capital requirements in an unpleasant setting.

The limitation of these models is that while the composition of the fixed portfolio stays constant over the period in question, the composition of the worst-case portfolio is revised daily. However, a financial institution’s risk profile could be significantly altered by intraday changes in positions, as there are buys and sells during a trading day.

The general conditions of these two portfolios are:

1) Time is discrete and indexed by \( t \in \{1,2,3,...,1137\} \) (the total number of trading days covered by the data is 1,137).

2) The traders take positions in 10 assets and all of these assets are currencies.

3) The base currency for calculating the required capital, which is typically the currency of equity capital and reporting currency of a bank, is the USD.

4) \( P_{it} \) is the foreign exchange rate of the \( i^{th} \) currency against USD at time \( t \). The return on \( P_{it} \) between period \( t-1 \) and period \( t \) is denoted by \( r_{it} \) and defined as logarithmic changes.
5) The traders have USD 1 million equivalent exposures (long or short) in each currency and the investment amount of USD 1 million is held constant to keep the discretion at a minimum.

6) The exposures in foreign exchanges are in cash and are not invested in any interest-earning asset; i.e. there is no interest gain on these assets.

7) The positions are marked-to-market every day and the profit or loss is realised.

8) The profit or loss is not added to the investment amount; i.e. the portfolios exclude trading revenues or losses. Therefore, whatever the previous day's profit or loss, the traders have an investment of USD 1 million equivalent exposures (long or short) in each currency every day.

9) The foreign exchange positions are not hedged.

10) At the end of each day, the banks report the required market risk capital charge as well as the actual profit or loss over that reporting day to the regulator. The banks are required to maintain capital for their foreign exchange positions as demanded by the market risk capital regulations.

The specific conditions of the fixed and worst-case portfolios are presented below.

**The Fixed Portfolio:**

The foreign exchange positions are fixed in Trader A's portfolio. The specific conditions of this portfolio are presented below.

1) The trader has a conservative trading approach and does not change his/her portfolio position.

2) The exposure in each currency has a value equivalent to USD 1 million long position.

3) The trader rolls over the same portfolio in each trading day.

4) If the $i^{th}$ currency appreciates against the USD ($r_{ij} > 0$), the bank makes a profit and if the $i^{th}$ currency depreciates against the USD ($r_{ij} < 0$), the bank makes a loss.
The daily actual profits and losses of the fixed portfolio from January 1996 to June 2000 are illustrated in Graph 8.1. This graph demonstrates that the maximum loss of the fixed portfolio is approximately USD 140,000.

![Graph 8.1: Profit and Loss of the Fixed Portfolio](image)

**The Worst-Case Portfolio:**

Trader B’s portfolio builds upon an active hypothetical portfolio and this trader takes long or short positions in currencies based on his/her market expectations and forecasts. This trader reviews his/her trading activity each trading day. However, the simulation is set such that the trader always makes wrong decisions and every day the investment in each currency makes a loss.

This portfolio is called as the worst-case portfolio as it generates losses every trading day. The loss-generating portfolio is set up for two reasons. First, if the capital charges cover the loss of the portfolio, then it could point out that the market risk capital charges are sufficient to cover losses of a portfolio that makes a loss every day. Second, although randomly selected and real portfolios were investigated in the literature, a hypothetical loss-generating portfolio was not considered.

The specific conditions of this portfolio are presented below.

1) The trader has an active trading activity and takes either a long or short foreign exchange position.
2) The trader revises his/her portfolio position each trading day and any asset traded at date \( t-1 \) matures at date \( t \) and is reinvested at date \( t \). However, there are no intraday portfolio changes.

3) The investment amount of each currency has a value equivalent to either USD +1 million (long position) or USD -1 million (short position).

4) If \( r_{i,t+1} > 0 \) (the next trading day the \( i^{th} \) currency appreciates against the USD), in order to allow the portfolio to make a loss on date \( t \), the investment amount of the \( i^{th} \) currency is set as USD -1 million, which indicates a short position in that currency.

5) If \( r_{i,t+1} < 0 \) (the next trading day the \( i^{th} \) currency depreciates against the USD), in order to allow the portfolio to make a loss on date \( t \), the investment amount of the \( i^{th} \) currency is set as USD +1 million, which indicates a long position in that currency.

Graph 8.2 illustrates the daily actual losses of the worst-case portfolio from January 1996 to June 2000. This graph demonstrates that the maximum loss of the worst-case portfolio is approximately USD 210,000.
8.4 Data

In this analysis, the banks take positions in 10 traded assets and all of these assets are currencies. Both of the portfolios consist of currencies against the USD for the following 10 currencies: Deutche mark (DEM), French franc (FRF), Italian lira (ITL), Netherlands guilder (NLG), Belgian franc (BEF), Japanese yen (JPY), British pound (GBP), Canadian dollar (CAD), Swedish krona (SEK) and Swiss franc (CHF). All of these currencies are represented in the US dollar index, which is a weighted basket of world currencies and a trademark of the Financial Instrument Exchange (FINEX) in New York.

The data consists of daily foreign exchange rates against the USD and this data has been gathered from the DataStream database. The data for the;

- JPY, GBP, CAD, SEK and CHF covers the period from 2.1.1986 to 30.6.2000, i.e. 3,635 observations,
- DEM, FRF, ITL, NLG and BEF covers the period from 2.1.1986 to 31.12.1998, i.e. 3,254 observations,
- EUR covers the period from 2.1.1999 to 30.6.2000, i.e. 382 observations.

Daily capital requirements for the standardised approach and VaR methodologies are calculated for the period from 2.1.1996 and to 30.6.2000. The data from the earlier period is used to construct the first VaR estimate. The simulation is repeated for 1,137 days and the analysis period covers the South Asia crisis in 1997 and the LTCM and Russian crises in 1998, which are periods of high market volatility.

The analysis period also covers the introduction of the euro, which is a structural change in the global financial markets. As the euro was introduced at the end of 1998 and replaced 11 currencies, this is an important issue that should be considered in the analysis. When the participating currencies to the European Monetary Union were replaced by the euro, consequently there became only one currency, which does not have any history. On the other hand, the variance-covariance and historical simulation methodologies rely on historical data and without any data for the euro it
is not possible to calculate the VaR estimates by using these methodologies. Therefore, the data history of the Deutche mark was used for the euro; as the Deutche mark money market and swap rates are suitable proxies for a euro history in the respective euro markets for these instruments (Brooks et al., 1998).

Therefore, the history of the Deutche mark replaces the euro in the dataset. As five currencies in the sample, namely DEM, FRF, ITL, NLG and BEF were replaced by the euro, starting from 1999 the euro investment was weighted by the equivalent USD 5 million long or short position in each trading day.

As the VaR estimate depends on the input data, the frequency of data is another important issue that should be considered in the VaR calculation. However, the high frequency data is not necessarily better than the low frequency data due to the noise it may be associated with and the cost of storage. On the other hand, the low frequency data has the possibility of missing some critical events (Tsai, 2004). As the VaR estimate assumes that the portfolio's composition does not change over the holding period, the solution of choosing data frequency depends on the investment strategies. In addition, due to the assumption that the portfolios' position changes daily, daily data of currencies is employed in this study. In addition, as the Basle Committee requires the use of at least one year of data, the minimum data period that is used in the simulations is one year.

8.4.1 The Calculation of Daily Returns

The next step in the analysis is the calculation of daily returns of the currencies. The return of an asset (portfolio), i.e. the profit or loss, which is denoted as $\Delta P$, is the difference between the asset prices (portfolio values). That is, $\Delta P = P_t - P_{t-1}$, where $P_t$ and $P_{t-1}$ are the asset prices (portfolio values) at time $t$ and $t-1$, respectively. However, instead of using the absolute differences in the asset prices, the rate of return should be calculated to demonstrate the magnitude of differences. There are two methodologies to calculate the rate of return. These are, the arithmetic and geometric methodologies.
\[ r_t = \frac{P_t - P_{t-1}}{P_{t-1}}; \] represents the arithmetic returns on an asset, and \[ r_t = \ln(P_t / P_{t-1}); \] represents the logarithmic returns on an asset.

In this study, each series was transformed to a set of continuously compounded changes (logarithmic returns). As an example of the return distribution, Graph 8.3 demonstrates the compounded daily returns of the EUR/USD parity and also the frequency distribution of this parity for the period from January 1999 to June 2000.

Graph 8.3: The EUR/USD Daily Returns and the Frequency Distribution

8.4.2 The Descriptive Statistics of Currency Returns

The descriptive statistics of daily returns are given in Table 8.1 for 10 currencies (USD against DEM, FRF, ITL, NLG, BEF, JPY, GBP, CAD, SEK and CHF) from 2 January 1986 until 30 June 2000 (Panel A) and for the EUR/USD parity from 2 January 1999 to 30 June 2000 (Panel B).
Table 8.1: The Descriptive Statistics on Daily Returns in Risk Factors (%)*

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>DEM/USD</td>
<td>3254</td>
<td>-0.0115</td>
<td>3.4650</td>
<td>-3.5017</td>
<td>0.7071</td>
<td>5.0798</td>
<td>0.0502</td>
<td>587.85</td>
<td>0.0000</td>
</tr>
<tr>
<td>FRF/USD</td>
<td>3254</td>
<td>-0.0087</td>
<td>4.3590</td>
<td>-4.8133</td>
<td>0.6972</td>
<td>7.7670</td>
<td>-0.1271</td>
<td>1932.8</td>
<td>0.0000</td>
</tr>
<tr>
<td>ITL/USD</td>
<td>3254</td>
<td>-0.0001</td>
<td>13.186</td>
<td>-14.478</td>
<td>0.8622</td>
<td>59.301</td>
<td>-0.2109</td>
<td>429792.6</td>
<td>0.0000</td>
</tr>
<tr>
<td>NLG/USD</td>
<td>3254</td>
<td>-0.0116</td>
<td>4.8430</td>
<td>-5.7140</td>
<td>0.7177</td>
<td>7.2545</td>
<td>-0.0698</td>
<td>2456.85</td>
<td>0.0000</td>
</tr>
<tr>
<td>BEF/USD</td>
<td>3254</td>
<td>-0.0112</td>
<td>9.3192</td>
<td>-9.6017</td>
<td>0.7675</td>
<td>20.355</td>
<td>-0.2922</td>
<td>41736.0</td>
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</tr>
<tr>
<td>JPY/USD</td>
<td>3635</td>
<td>-0.0173</td>
<td>5.8305</td>
<td>-7.6773</td>
<td>0.7714</td>
<td>10.545</td>
<td>-0.6262</td>
<td>8859.68</td>
<td>0.0000</td>
</tr>
<tr>
<td>GBP/USD</td>
<td>3635</td>
<td>-0.0015</td>
<td>4.2758</td>
<td>-3.4090</td>
<td>0.6526</td>
<td>5.9919</td>
<td>0.2294</td>
<td>1387.63</td>
<td>0.0000</td>
</tr>
<tr>
<td>CAD/USD</td>
<td>3635</td>
<td>0.0015</td>
<td>1.4555</td>
<td>-1.8811</td>
<td>0.2341</td>
<td>5.9412</td>
<td>0.0234</td>
<td>1310.57</td>
<td>0.0000</td>
</tr>
<tr>
<td>SEK/USD</td>
<td>3635</td>
<td>0.0041</td>
<td>6.8344</td>
<td>-4.1720</td>
<td>0.6609</td>
<td>9.2498</td>
<td>0.4207</td>
<td>6023.29</td>
<td>0.0000</td>
</tr>
<tr>
<td>CHF/USD</td>
<td>3635</td>
<td>-0.0062</td>
<td>4.8500</td>
<td>-5.3882</td>
<td>0.7922</td>
<td>5.8570</td>
<td>-0.1133</td>
<td>1244.05</td>
<td>0.0000</td>
</tr>
<tr>
<td>B) 1/99 - 6/00 Risk Factor</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EUR/USD</td>
<td>382</td>
<td>0.0538</td>
<td>1.8692</td>
<td>-2.0576</td>
<td>0.6531</td>
<td>3.5091</td>
<td>-0.2517</td>
<td>8.1380</td>
<td>0.0171</td>
</tr>
</tbody>
</table>

* The statistics concerning DEM, FRF, ITL, NLG and BEF cover the period up to the introduction of euro.

Table 8.1 demonstrates the following observations for the return series:

1) The means of daily returns vary from +0.05 percent to -0.02 percent and all of them are very close to zero. The ITL/USD parity has the lowest mean (-0.0001) and the EUR/USD parity, which has the lowest observation sample, has the highest mean (0.0538).

2) The ITL/USD parity has the minimum (14.5 percent) and maximum (13.2 percent) daily returns.

3) The CAD/USD parity has the lowest standard deviation (0.2341) and the standard deviations of the other currencies vary from 0.6526 to 0.8622.

4) The kurtosis that is presented in the seventh column measures the relative flatness of the return distribution of currencies compared to a standard normal distribution. The kurtosis is calculated by the expected fourth power of deviations from the mean and the kurtosis estimates are highly sensitive to extreme returns.

5) High kurtosis or leptokurtosis indicates that there are more occurrences far away from the mean than predicted by a standard normal distribution. A distribution with a kurtosis greater than three is called leptokurtic or fat-tailed and the coefficients of kurtosis that are shown in Table 8.1 indicate that all of the returns have kurtosis higher than three.
6) The EUR/USD parity has the minimum kurtosis, which is 3.51 and the Jarque-Bera statistic\textsuperscript{53} is significant at the 5 percent level. The kurtosis of the other 10 currencies varies from 5 to 59 and the Jarque-Bera statistics are significant at the 1 percent level. As the Jarque-Bera test statistics demonstrate that the kurtosis of all currencies are significantly different from zero, normality for all return series is rejected.

7) In particular, the ITL/USD parity has the highest kurtosis. The return series of the ITL/USD parity has a kurtosis coefficient of 59.3, which indicates an extremely heavy tail. The BEF/USD parity also has a very heavy tail (the kurtosis is 20.5).

8) The skewness parameter that is presented in the eighth column characterises the degree of asymmetry of the distribution around its mean and it is measured by the expected third power of deviations from the mean.

9) The coefficients of skewness that are shown in Table 8.1 indicate that all of the returns have non-zero skewness.

10) While the returns on DEM/USD, GBP/USD, CAD/USD and SEK/USD are positively skewed, the returns on FRF/USD, ITL/USD, NLG/USD BEF/USD, JPY/USD, CHF/USD and EUR/USD have negative skewness. The return series that have negative skewness indicate that large negative returns are more likely than large positive returns. The return series that have positive skewness indicate that large positive returns are more likely than large negative returns.

11) As the ‘excess kurtosis’ and the skewness should be zero for a standard normal distribution, none of the currency series exhibits a standard normal distribution. Besides, the Jarque-Bera test statistics reject normality for all return series.

\textsuperscript{53} The Jarque-Bera statistic has an asymptotic $\chi^2$ distribution with two degrees of freedom under the null hypothesis of normally distributed errors. If the residuals are normally distributed, the histogram should be bell-shaped and the Jarque-Bera statistic would not be significant.
One of the most important outcomes of the descriptive statistics of daily returns on currencies is that some return series, such as the return series of ITL/USD, exhibit extremely heavy tails. Extreme heavy tails might suggest a distribution with an infinite variance and in these cases the VaR estimates that are calculated by assuming a normal distribution cannot provide appropriate measures of market risk as the tail behaviour of asset returns is not captured adequately. Therefore, instead of a normal distribution, the use of leptokurtic (fat-tailed) distributions could lead to more prudent risk measures (Lucas and Klaassen, 1998).

The stable distribution is one of the distributions that could be used to deal with the infinite variance as the variance and other higher moments do not exist in this distribution. However, Simons (1997) argues that since the use of stable distributions in finance has always been controversial, the use of jump diffusion and stochastic volatility models are more applicable in practice to deal with extreme heavy tails, as these models produce fat tails while preserving the finite variance.

On the other hand, the stable distribution aims to capture not only the fat tails but also the whole distribution of the returns. Therefore, Nefici (2000) points out that if the distribution of asset returns is heavy tailed, it is likely that the use of a non-parametric procedure based on the extreme value theory of Wilks (1948) will lead to more satisfactory results when applying VaR techniques.

Although the assumption of the normal distribution simplifies the computation of VaR, the descriptive statistics of currency returns indicate that currency returns are fat-tailed, which implies that extreme events occur much more than are predicted based on the assumption of normality. As a matter of fact, the observed non-normality of the currency return distributions provides a strong motivation for not using parametric approaches, where the normal distribution is assumed in the calculation of VaR estimates. On the contrary, the historical simulation methodology does not suffer from the fat tail problem, as it does not rely on the normal distribution assumption. Despite this banks widely use the parametric variance-covariance models in their risk management framework. Therefore, these parametric models are
also simulated in this analysis. The next section presents the methodologies that are applied to calculate required capital charges for the foreign exchange portfolios.

8.5 The Simulation Methodology

The aim of this section is to present the simulation methodology that provides a comparison of the regulatory market risk capital for two foreign currency portfolios. In these simulations, the required capital charges are calculated for each day in the sample, by applying both the standardised and the internal models approaches. As the results of the documentary analysis that was provided in the previous chapter demonstrate, the VaR methodologies of banks differ in a wide range. Therefore, three different VaR techniques and 16 different VaR models are used in the analysis. The simulation methodology that is presented in this section involves all of the steps of the VaR calculation framework that was provided in the fifth chapter of this thesis.

The first step of the simulation is to establish the database of portfolio positions. For each portfolio, a particular database is established. These databases are also used to calculate the daily returns of the portfolios. The change in the market value of the portfolios is simulated by using the returns on the underlying currencies. The second step of the simulation methodology is the calculation of the required capital. The required capital charge is calculated for a time period starting from 1996 and ending at 30.6.2000 (1,137 days) on a rolling basis.

The calculations of the required capital for market risk for the standardised approach and VaR models were made by using the Excel software. First, the required market risk capital is calculated by applying the standardised approach. Then, the required market risk capitals is calculated by applying 16 VaR models.

The first VaR technique, the EqVCV methodology, is performed using five different models by altering the amount of historical data. For this methodology, 250, 500, 750, 1250 and 2500 days of equal weights are applied. The second VaR technique, the ExpVCV methodology, is performed using six different models. For this methodology, decay factors of 0.93, 0.94, 0.95, 0.96, 0.97 and 0.98 are applied. In
addition, a 250-day historical data set is used. The third VaR technique, the historical simulation methodology, is also performed by using five different models by altering the amount of historical data. For this methodology, the same historical data sets that are used in the EqVCV methodology are utilized.

The procedure that is followed to simulate the required capital charges by using both the standardised and the internal models approaches are explained below.

8.5.1 The Standardised Approach

The calculation of the required capital charge for the foreign exchange rate risk under the standardised approach is straightforward. In order to calculate the capital requirement under the standardised approach, firstly the banks' net positions in each currency are calculated after the position in different foreign exchanges are converted into the USD. The net positions in each currency are calculated by using the daily spot rates. Secondly, the net long and net short positions are added separately across currencies. In the standardised approach, the changes in long and short positions for the same currencies offset one another. Then, an eight percent capital charge is applied to the higher of net long or net short position, i.e. net open position.

While the capital charges for the worst-case portfolio vary from USD 400,000 to USD 800,000, capital charges for the fixed portfolio are fixed at USD 800,000, as the value of the portfolio is stable at USD 10 million.

8.5.2 The Internal Models Approaches

Calculating the required capital by utilizing internal model approaches is more complicated. As the financial institutions' VaR practices indicate, the variance-covariance (EqVCV and ExpVCV) and historical simulation methodologies are two broad types of VaR models. Therefore, in this study capital charges for the foreign exchange portfolios are calculated by using the variance-covariance and historical
simulation methodologies\textsuperscript{54}. These methodologies were explained in the fifth chapter of this thesis.

In order to follow the regulatory framework, calculations are made in accordance with the 1996 Basle Committee amendment. Therefore, the holding period is used as 10 holding days and the confidence level is taken as 99 percent.

For the variance-covariance and historical simulation\textsuperscript{55} methodologies, first daily VaRs are calculated. The VaR calculations are based on the returns within the historical window. If the rolling window is set to 250 days, the VaR calculation for the first day ($t=1$) is based on the observed exchange rates within the last year (from date $t-1$ to $t-250$). For the second date ($t=2$), the window is moved one day forward and VaR is calculated by using the data from date $t$ and $t-249$. The VaR estimates are calculated on a daily basis, starting at 2.1.1996 and ending at 30.6.2000 (1,137 days).

Second, the VaR estimates are multiplied by a factor of $\sqrt{10}$. The Basle Accord recommends that multi-period volatility predictions are to be obtained by multiplying the one-day volatility estimates by the square root of the time horizon (in days).

Finally, the VaR estimates are based on a 99 percent confidence level and 10 holding days are multiplied by a multiplication factor of three. The Basle Committee amendment requires that if the market risk capital requirements are calculated by a VaR methodology, a multiplication factor of three should be used. This means that the amount calculated by the VaR model should be multiplied by three. On the other hand, regulators could increase the multiplication factor depending on the backtesting results.

\textsuperscript{54}While the GARCH method has found widespread empirical support from academics, as it requires a complicated computer-intensive procedure in estimating volatilities (Hopper, 1996), this method has not been adopted in this analysis.

\textsuperscript{55}For the historical simulation methodology, the ten-day holding period VaR numbers were also estimated by actual 10 day returns.
According to the Basle Committee amendment, the capital charge for the general market risk should be equal to the greater of the average of the VaR estimates on each of the preceding 60 days, times the scaling factor or the previous day's VaR estimate calculated in accordance with specific quantitative standards. The formula that is used to determine the required capital is presented below:

\[ C_t = \max \left[ \text{VaR}_{t-1}, (\text{MF}) \frac{1}{60} \sum_{j=1}^{60} \text{VaR}_{t-j} \right] \]  

(8.3)

where \( C_t \) is the required capital level at time \( t \), \( MF \) is the multiplication factor, \( \text{VaR}_{t-1} \) is the VaR estimate which is calculated at date \( t-1 \), \( \text{VaR}_{t-j} \) is the VaR estimate which is calculated at date \( t-j \).

Another issue that should be considered when applying the internal models approach is that there is no consensus on the preferred length of the simulation period. However, because the Basle Committee requires at least 1 year of historical data, these VaR calculations are based on this requirement. However, in addition to the 250 days of historical data, four different window lengths are applied for the EqVCV and historical simulation methodologies. These historical rolling windows are; 500 days (two years), 750 days (three years), 1,250 days (five years) and 2,500 days (ten years).

8.5.2.1 The Variance-Covariance Methodologies

There are two major techniques of the variance-covariance methodology. These are the equally weighted moving average and the exponentially weighted moving average techniques. In this analysis, both of these techniques are used to estimate VaRs. The equally weighted moving average (EqVCV) methodology is performed using five different models by altering the amount of historical data. For this methodology, 250, 500, 750, 1250 and 2500 days of equal weights are applied. The second technique is the exponentially moving average methodology (ExpVCV), in which exponentially weighted moving averages with different smoothing parameters
(including those of RiskMetrics use) are used to estimate VaRs. The calculations of VaRs for the ExpVCV methodology are carried out by applying six decay factors (0.93, 0.94, 0.95, 0.96, 0.97 and 0.98) and a window of 250 lagged daily returns.

In order to calculate the required capital under the variance-covariance methodologies, first the estimates of the variance and covariance of risk factors are calculated. Then, in order to calculate the variance of the portfolio's profit and loss, matrixes of the estimates of variance and covariance are generated. In this calculation, the variance-covariance matrix is obtained by taking the standard deviation matrix and multiplying it by the covariance matrix. The advantage of using matrixes is that, a weighted matrix for several assets that has only one row could be easily set up from a covariance coefficient matrix and a volatility matrix. As pointed out by Hull (2000), the variances and covariances are calculated consistently. This means that, when VaR is calculated by applying the equally weighted variance-covariance methodology, the variances and covariances are both calculated by giving an equal weight to the last 250 observations for a one year data set. When VaR is calculated by applying the exponentially weighted variance-covariance methodology, the variances and covariances are updated by using the identical decay factor.

In the ExpVCV methodology, past observations are weighted by using six smoothing constants, i.e. decay factors ($\lambda$), which vary from 0.93 to 0.98. In this methodology, the observation of $n$ days before in the historical data set is multiplied by $\lambda$. Therefore, as the decay factor decreases, the earlier observations have a smaller impact, although information contained in more lagged observations is not totally ignored. As a result, as Alexander (1996) points out, "Extreme events have less of an impact on variances and covariances as they move further into the past, and the 'ghost features' should no longer appear."

In the simulation of the variance-covariance methodologies, the means ($\mu$) are fixed at zero. Jackson et al. (1998) state that "Fixing the means at zero might seem an unconventional statistical procedure, but the estimation error associated with badly determined mean estimates in relatively small samples may reduce the efficiency of the estimated volatilities." Furthermore, Figlewski (1997) argues that if the true mean
returns are very close to zero, fixing them at zero could enhance the forecasts. Figlewski also shows that, by setting the average daily return to zero, over the entire data period better forecasts are obtained. Therefore, while calculating VaRs by applying the variance-covariance methodologies, the mean of the currency returns are assumed to be zero.

8.5.2.2 The Historical Simulation Methodology

The historical simulation methodology calculates the VaR estimates by using a past period of the historical returns of the portfolios over one-day and ten-day holding periods. The returns exceeded in 99 percent of the cases are taken out as the VaR estimate. In this approach, the scenarios are directly drawn from the historical data and the portfolio returns are calculated for each date represented in the historical data set. As the historical simulation approach does not make any assumptions of normality or serial dependence, VaR has to be recalculated for each confidence level. This means that the 99 percent and 95 percent confidence levels are not constant multiples of each other and the holding periods other than one day are not fixed multiples of the one-day VaR estimate. The calculations of VaRs by applying the historical simulation methodology are carried out by using five historical rolling windows (250 days, 500 days, 750 days, 1,250 days and 2,500 days).

8.6 Empirical Results

In the previous section, the simulations that are used in the calculation of the required capital charges for two foreign exchange portfolios were explained. In these simulations, the required capital charges are calculated by applying the standardised and 16 VaR models. These VaR models are 5 EqVCV models (2500-day, 1250-day, 750-day, 500-day, and 250-day), 6 ExpVCV models ($\lambda = 0.93$, $\lambda = 0.94$, $\lambda = 0.95$, $\lambda = 0.96$, $\lambda = 0.97$, $\lambda = 0.98$) and 5 HS models (2500-day, 1250-day, 750-day, 500-day, and 250-day). The capital charges are calculated for 1,137 days from 2 January 1996 to 30 June 2000.
This section illustrates the empirical results of the simulation procedures that were described in the previous section. The aim of these simulations is to find out to what extent two market risk capital approaches and various VaR models produce different capital requirements. First, the results concerning the capital charges for the fixed portfolio are presented. Second, the results concerning the worst-case portfolio are provided.

8.6.1 Capital Charges for the Fixed Portfolio

The required capital amounts for the fixed portfolio are calculated by using the standardised approach and 16 VaR models. The maximum, minimum, mean, median values and the standard deviations of the required capital amounts for the fixed portfolio are given in Table 8.2. In addition, the maximum, minimum and mean values of the required capital amounts are illustrated in Graph 8.4. For the standardised approach and each VaR model, the required capital charges are calculated on a daily basis between 2 January 1996 and 30 June 2000 for a total of 1,137 days.
Table 8.2: Capital Charges for the Fixed Portfolio

<table>
<thead>
<tr>
<th>METHODOLOGY (million USD)</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standardised Approach</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance-Covariance (EqVCV 2500-day)</td>
<td>1.31</td>
<td>1.18</td>
<td>1.23</td>
<td>1.22</td>
<td>0.03</td>
</tr>
<tr>
<td>Variance-Covariance (EqVCV 1250-day)</td>
<td>1.34</td>
<td>0.98</td>
<td>1.09</td>
<td>1.03</td>
<td>0.10</td>
</tr>
<tr>
<td>Variance-Covariance (EqVCV 750-day)</td>
<td>1.14</td>
<td>0.88</td>
<td>0.99</td>
<td>1.00</td>
<td>0.06</td>
</tr>
<tr>
<td>Variance-Covariance (EqVCV 500-day)</td>
<td>1.14</td>
<td>0.83</td>
<td>0.98</td>
<td>1.01</td>
<td>0.08</td>
</tr>
<tr>
<td>Variance-Covariance (EqVCV 250-day)</td>
<td>1.20</td>
<td>0.64</td>
<td>0.94</td>
<td>1.00</td>
<td>0.13</td>
</tr>
<tr>
<td>Variance-Covariance (ExpVCV: $\lambda = 0.93$)</td>
<td>1.24</td>
<td>0.56</td>
<td>0.94</td>
<td>0.98</td>
<td>0.18</td>
</tr>
<tr>
<td>Variance-Covariance (ExpVCV: $\lambda = 0.94$)</td>
<td>1.23</td>
<td>0.56</td>
<td>0.94</td>
<td>0.98</td>
<td>0.18</td>
</tr>
<tr>
<td>Variance-Covariance (ExpVCV: $\lambda = 0.95$)</td>
<td>1.22</td>
<td>0.57</td>
<td>0.94</td>
<td>0.98</td>
<td>0.18</td>
</tr>
<tr>
<td>Variance-Covariance (ExpVCV: $\lambda = 0.96$)</td>
<td>1.20</td>
<td>0.58</td>
<td>0.94</td>
<td>0.98</td>
<td>0.17</td>
</tr>
<tr>
<td>Variance-Covariance (ExpVCV: $\lambda = 0.97$)</td>
<td>1.17</td>
<td>0.59</td>
<td>0.94</td>
<td>0.99</td>
<td>0.17</td>
</tr>
<tr>
<td>Variance-Covariance (ExpVCV: $\lambda = 0.98$)</td>
<td>1.16</td>
<td>0.61</td>
<td>0.94</td>
<td>0.98</td>
<td>0.16</td>
</tr>
<tr>
<td>Historical Simulation (2500-day)</td>
<td>1.52</td>
<td>1.31</td>
<td>1.42</td>
<td>1.41</td>
<td>0.07</td>
</tr>
<tr>
<td>Historical Simulation (1250-day)</td>
<td>1.71</td>
<td>1.02</td>
<td>1.25</td>
<td>1.18</td>
<td>0.18</td>
</tr>
<tr>
<td>Historical Simulation (750-day)</td>
<td>1.31</td>
<td>0.93</td>
<td>1.10</td>
<td>1.07</td>
<td>0.13</td>
</tr>
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<td>1.06</td>
<td>1.00</td>
<td>0.14</td>
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<td>0.73</td>
<td>1.08</td>
<td>1.02</td>
<td>0.24</td>
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The empirical results concerning the fixed portfolio demonstrate the following observations:
1) As the investment amount is held constant in the case of the fixed portfolio, the required capital amounts that are produced by the standardised approach are permanently USD 800,000.

2) The EqVCV models produce average required capital amounts that vary from USD 940,000 to USD 1,230,000 and the standard deviations vary from 0.03 to 0.13. The average capital amounts that the EqVCV models produce increases in accordance with the length of the observation periods.

3) The ‘EqVCV 2500-day’ model that produces the highest average amount (USD 1,230,000) has the lowest standard deviation (0.03) and the ‘EqVCV 250-day’ model that produces the lowest average amount (USD 940,000) has the highest standard deviation (0.13). Compared with the ExpVCV and HS models, the EqVCV models produce lower standard deviations.

4) The EqVCV models produce maximum capital levels ranging from USD 1,140,000 to USD 1,340,000 and minimum capital levels ranging from USD 640,000 to USD 1,180,000. Compared with the ExpVCV models, the EqVCV models produce lower minimum amounts.

5) When the required capital is calculated by using different ExpVCV models, the means do not change and the changes in the standard deviations and the maximum and minimum amounts are negligible. The average required capital amount of each ExpVCV model is USD 940,000. The maximum required capital amounts of the ExpVCV models vary from USD 1,160,000 to USD 1,240,000 and the minimum amounts vary from USD 560,000 to USD 610,000.

6) When the required capital amount is calculated by using the ExpVCV models, the maximum required capital amount decreases and the minimum required capital amount increases as reliance on recent data increases.

7) The standard deviations of the capital amounts that the ExpVCV models produce vary from 0.16 to 0.18 and the ‘ExpVCV 0.98’ model has the
lowest standard deviation. The standard deviations of the capital amounts decrease in accordance with the increase of the decay factors.

8) Compared with the EqVCV and HS models, the ExpVCV models produce the lowest averages but the highest standard deviations.

9) The maximum required capital amounts that the HS models produce vary from USD 1,310,000 to USD 1,960,000 and the minimum capital amounts vary from USD 730,000 to USD 1,310,000. Compared with the EqVCV and ExpVCV models, the HS models produce higher maximum and minimum required capital amounts.

10) Among all the HS models, the ‘HS 750-day’ and ‘HS 500-day’ models produce the lowest maximum capital (USD 1,310,000). The ‘HS 250-day’ model produces the highest maximum capital amount (USD 1,960,000) and the highest standard deviation among all the VaR models.

11) The average required capital amounts that the HS models produce vary from USD 1,060,000 to USD 1,420,000. While the ‘HS 500-day’ model produces the lowest mean among all the HS models, the ‘HS 2500-day’ model produces the highest mean among all the VaR models.

12) The major observations for this simulation are that: (i) the standardised approach is found to produce the lowest required capital amount, (ii) together with the ‘EqVCV 250-day’ model, the ExpVCV models produce the lowest average required capital amounts among all the VaR models, (iii) the ‘HS 2500-day’ model produces the highest average required capital amount, (iv) together with the ExpVCV models, the ‘HS 2500-day’ model also produces higher standard deviations.

The empirical results concerning the fixed portfolio indicate that, the VaR estimates are dependent upon the VaR methodology. An example of how the required capital amounts differ from each other is illustrated in Graphs 8.5. These graphs demonstrate the required capital amounts for the fixed portfolio derived from the standardised approach and three VaR models. These VaR models are; the historical simulation (one-year observation period), the equally weighted variance-covariance (one-year observation period) and the exponentially weighted variance-covariance ($\lambda = 0.94$).
These visual indicators also demonstrate that the required capital differs substantially depending on the model that is applied.

**Graphs 8.5: Required Market Risk Capital Amounts for the Fixed Portfolio**

8.6.2 Capital Charges for the Worst-Case Portfolio

The required capital amounts for the worst-case portfolio are calculated by using the standardised approach and 16 VaR models. The maximum, minimum, mean, median values and the standard deviations of the required capital amounts for the worst-case portfolio are given in Table 8.3. In addition, the maximum, minimum and mean values of the required capital amounts are illustrated in Graph 8.6. For the standardised approach and each VaR model, the required capital charges are calculated on a daily basis between 2 January 1996 and 30 June 2000 for a total of 1,137 days.
The empirical results concerning the worst-case portfolio demonstrate the following observations:
1) When the required capital for market risk is calculated by using the standardised approach, the maximum capital amount is USD 800,000 and the minimum capital amount is USD 400,000. The average capital amount that this approach produces is USD 640,000 and the standard deviation of the capital amounts is 0.11. Compared with the VaR models, the standardised approach produces the lowest required capital amount.

2) Compared with the ExpVCV and HS models, the EqVCV models produce lower maximum amounts. The EqVCV models produce maximum capital levels ranging from USD 880,000 to USD 1,020,000 and minimum capital levels ranging from USD 460,000 to USD 770,000.

3) The average capital amounts that the EqVCV models produce vary from USD 740,000 to USD 910,000 and the means increase in accordance with the length of the observation periods. While the ‘EqVCV 2500-day’ model produces the highest average capital amount (USD 910,000) among all the EqVCV models, the ‘EqVCV 250-day’ model produces the lowest (USD 740,000).

4) On the other hand, although the ‘EqVCV 250-day’ model produces the lowest mean, this model produces the highest standard deviation among all the EqVCV models.

5) The standard deviations of the EqVCV models vary from 0.04 to 0.13. Compared with the ExpVCV and HS models, the EqVCV models produce lower standard deviations in general.

6) When the required capital is calculated by using different ExpVCV models, the means do not change and the changes in the standard deviations and the maximum and minimum amounts are negligible. The average required capital amount of each ExpVCV model is USD 740,000. The maximum required capital amounts of the ExpVCV models vary from USD 1,010,000 to USD 1,050,000 and the minimum amounts vary from USD 400,000 to USD 440,000.

7) The standard deviations of the capital amounts that the ExpVCV models produce vary from 0.16 to 0.18 and the ‘ExpVCV 0.98’ model has the
lowest standard deviation. The standard deviations of the capital amounts decrease in accordance with the increase of the decay factors.

8) Compared with the EqVCV and HS models, the ExpVCV models produce the lowest averages but the highest standard deviations.

9) The maximum required capital amounts that the HS models produce vary from USD 1,020,000 to USD 1,290,000 and the minimum capital amounts vary from USD 530,000 to USD 900,000. Among all the HS models, the 'HS 750-day' model produces the lowest maximum capital (USD 1,020,000). While the 'HS 250-day' model produces the highest maximum capital amount (USD 1,230,000), this model also produces the lowest minimum capital amount (USD 530,000). However, the 'HS 250-day' model has the highest standard deviation among all the HS models.

10) The average required capital amounts that the HS models produce vary from USD 890,000 to USD 1,060,000. While the 'HS 500-day' model produces the lowest mean among all the HS models, the 'HS 2500-day' model produces the highest mean.

11) The major observations for this simulation are that; (i) the standardised approach produces the lowest average required capital amount, (ii) together with the 'EqVCV 250-day' model, the ExpVCV models produce the lowest average required capital amounts among all the VaR models, (iii) the 'HS 2500-day' model produces the highest average required capital amount, (iv) together with the ExpVCV models, the 'HS 2500-day' model also produces higher standard deviations.

12) Compared with the case of the fixed portfolio, the models produce relatively lower required capital amounts due to the diversification impact of investment.

The empirical results concerning the worst-case portfolio indicate that, similar to the results of the fixed portfolio, the VaR estimates are dependent upon the VaR methodology. An example of how the required capital amounts differ from each other is illustrated in Graphs 8.7. These graphs demonstrate the required capital amounts for the worst-case portfolio derived from the standardised approach and three VaR models. These VaR models are; the historical simulation (one-year
observation period), the equally weighted variance-covariance (one-year observation period) and the exponentially weighted variance-covariance ($\lambda = 0.94$). These visual indicators also demonstrate that the required capital differs substantially depending on the model that is applied.

**Graphs 8.7: Required Market Risk Capital Amounts for the Worst-Case Portfolio**

The empirical results that are provided in this section demonstrate that different approaches produce different required market risk capital levels. These results imply that banks with the same risk could have different capital amounts depending only on the selected methodology for calculating the required market risk capital. This is a weakness of the market risk capital regulations, as these regulations cannot ensure a 'level playing field' for financial institutions in order to eliminate the competitive inequalities. Therefore, giving an option to banks to determine the VaR methodology could create a moral hazard problem as banks may choose an inaccurate model that provides less required capital amounts. As an example, the simulation of the worst-case portfolio illustrates that if a financial institution that uses a 'HS 2500-day'
model switches over to the standardised approach to calculate the required market risk capital, that institution could provide 66 percent capital savings on average.

Although the objective of implementing the market risk capital regulations is to secure the stability and solvency of the financial system, such a moral hazard problem might lead banks to use a model that produces lower levels of capital amounts and not choose the one that provides more accurate risk estimates. In addition, as the use of alternative models might yield different capital charges, an outsider such as a shareholder or a regulator may not make reliable comparisons based on these numbers. Therefore, bank regulators should be very cautious when approving the use of different approaches for banks that have similar portfolios.

In addition, supervisors should allow models that provide accurate risk estimates. The methodologies that produce inaccurate estimates would not provide capital charges that reflect individual banks’ true risk exposures and accordingly would not provide a sufficient cushion to cover possible losses due to market risk. Furthermore, market participants, which attempt to assess individual banks’ risk taking, might be misled when these models produce inaccurate estimates. Therefore, the assessment of the accuracy of the VaR models is a key concern for risk practitioners and regulators. The accuracy of 16 VaR models that are applied to the fixed and worst-case portfolios is examined in the next section.
8.7 The Backtesting Process of the VaR Models

In the previous section, it was demonstrated that applying different methodologies to a particular portfolio could yield significantly different assessments of risk. In this section, the models that provided the VaR estimates are validated by backtesting. As financial institutions use the VaR models to measure their market risk, the accuracy of the VaR estimates is of concern to risk practitioners and regulators. Therefore, risk practitioners use backtesting to verify the accuracy of their VaR models and regulators require a regular backtesting from banks that use internal VaR models for calculating the required market risk capital.

The aim of this section is to provide an assessment of whether different VaR models that are applied to the fixed and worst-case portfolios measure market risk efficiently. Therefore, the VaR estimates are compared with their respective portfolio profit and loss for 1,136 days using the sample period from 2 January 1996 to 29 June 2000. If the daily loss on the trading activities is less than the ex ante VaR estimate, this situation is defined as 'an exception'.

As backtesting is a process that compares the realised returns with the model generated risk measures, the primary steps of this process are to provide the portfolio profit and loss and to calculate the VaR estimates. The calculation of the VaR estimates by using the variance-covariance (EqVCV and ExpVCV) and historical simulation approaches was explained in the previous sections. In this section, in order to test the validity of 16 VaR models that are used to calculate the VaR estimates, backtesting is applied. While the VaR estimates that are calculated for the capital purposes are based on a ten-day holding period, the Basle Committee requires banks to apply backtesting to the VaR estimates that are based on a one-day holding period. In addition, the Basle Committee amendment requires that the VaR estimates should be based on a 99 percent confidence level. Therefore, backtests are applied to the VaR estimates that are based on a one-day holding period and at a 99 percent confidence level.
The most straightforward way to backtest is to plot the daily profit and loss against the ex ante VaR estimate and to demonstrate the exceptions. The graphs that are presented in Appendix 8.1 plot the observed returns divided by the VaR estimates. In each graph, the points that are below the horizontal line demonstrate the exceptions. These graphs indicate how VaR models behaved over time and provide a good visual indication of the behaviour of the exceptions.

As demonstrated by these graphs, the exceptions are relatively high when VaR is calculated for the worst-case portfolio. This visual indication might imply that the risk measures of the VaR models are probably too low or these models are not adequate to calculate the VaR estimates. On the other hand, the exceptions are relatively small when VaR is calculated for the fixed portfolio. This might imply that the VaR models provide overestimated risk measures.

Although plotting the observed returns divided by the VaR estimates provides a good visual indication, verifying the accuracy of a model by plotting the exceptions is a very simple method. Therefore, the performances of the VaR models are backtested by applying the more formal methodologies that were explained in the sixth chapter of this thesis. These methodologies are; the Basle Committee approach, statistical backtests and ranking tests. The results that are obtained by applying these three methodologies are presented below.

8.7.1 The Basle Committee's 'Traffic Light' Approach

The first method that is used to backtest the accuracy of VaR models is the methodology required by the market risk regulation of the Basle Committee. This method is based on the binomial assumption and it is the simplest backtesting method. This approach only counts the number of days on which portfolio loss is greater than the VaR estimate. Such days are defined as the VaR exceptions and the proportion of the VaR exceptions should be consistent with the stated confidence level.
In the regulatory backtesting, banks are required to count the number of days over the prior year (250 trading days) on which the portfolio loss exceeded the 99 percent VaR forecast. If a bank’s VaR model has generated zero to four exceptions over a 250-day period, it is said to be in the green zone. If it has generated five to nine exceptions, it is in the yellow zone and if there are more than ten exceptions, it is in the red zone. Therefore, this approach is also called the ‘traffic light approach’.

Table 8.4 shows the number of exceptions and Table 8.5 shows the realized percentages of exceptions for the fixed and worst-case portfolios. If the VaR models perform well, it is expected that at the 99 percent confidence level, the exception ratio should be 1 percent. If the exception ratio is greater than 1 percent, then the VaR model underestimates market risk. (The percentage should correspond to approximately 100 percent minus the VaR confidence level that is selected. For a 99 percent confidence level, it is expected to have losses that exceed the VaR number 1 percent of the time.)

According to the Basle Committee requirements, as long as the VaR estimate does not exceed four times or less in the previous 250-day period (or 2 percent of the time), the multiplication factor remains at its minimal value of three. If there are more than four exceptions, the bank is required to apply a multiplication factor that is more than three.

In this study, the VaR estimates are calculated using the variance-covariance (EqVCV and ExpVCV) and historical simulation approaches at the 99 percent confidence level and therefore it is expected to have losses that do not exceed the VaR number only 1 percent of the time. As it is shown in Table 8.5, the VaR calculations for the fixed portfolio do not produce exceptions of more than 2 percent. However, for the worst-case portfolio, the number of exceptions exceeds the 1 percent value considerably, indicating that the required market risk capital generated for this portfolio is not sufficient to cover losses.
Table 8.4: Backtesting Results—Number of Exceptions

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* Year 2000 estimates are based on 6 months.
Table 8.5: Backtesting Results—Percentage of Exceptions (%)

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<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Historical Simulation (1250-day)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Historical Simulation (750-day)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Historical Simulation (500-day)</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Historical Simulation (250-day)</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variance-Covariance (EqVCV: 2500-day)</td>
<td>6</td>
<td>13</td>
<td>12</td>
<td>8</td>
<td>15</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Variance-Covariance (EqVCV: 1250-day)</td>
<td>6</td>
<td>16</td>
<td>16</td>
<td>12</td>
<td>18</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>Variance-Covariance (EqVCV: 750-day)</td>
<td>8</td>
<td>18</td>
<td>20</td>
<td>13</td>
<td>16</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Variance-Covariance (EqVCV: 500-day)</td>
<td>7</td>
<td>23</td>
<td>17</td>
<td>11</td>
<td>16</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Variance-Covariance (EqVCV: 250-day)</td>
<td>1</td>
<td>25</td>
<td>16</td>
<td>11</td>
<td>14</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Variance-Covariance (ExpVCV: A= 0.93)</td>
<td>20</td>
<td>16</td>
<td>17</td>
<td>10</td>
<td>13</td>
<td>16</td>
</tr>
<tr>
<td></td>
<td>Variance-Covariance (ExpVCV: A= 0.94)</td>
<td>20</td>
<td>16</td>
<td>17</td>
<td>10</td>
<td>12</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Variance-Covariance (ExpVCV: A= 0.95)</td>
<td>20</td>
<td>17</td>
<td>16</td>
<td>10</td>
<td>12</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Variance-Covariance (ExpVCV: A= 0.96)</td>
<td>19</td>
<td>17</td>
<td>15</td>
<td>10</td>
<td>13</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Variance-Covariance (ExpVCV: A= 0.97)</td>
<td>18</td>
<td>18</td>
<td>16</td>
<td>11</td>
<td>13</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Variance-Covariance (ExpVCV: A= 0.98)</td>
<td>16</td>
<td>19</td>
<td>16</td>
<td>10</td>
<td>13</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Historical Simulation (2500-day)</td>
<td>4</td>
<td>10</td>
<td>10</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Historical Simulation (1250-day)</td>
<td>4</td>
<td>10</td>
<td>12</td>
<td>9</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>Historical Simulation (750-day)</td>
<td>4</td>
<td>12</td>
<td>14</td>
<td>9</td>
<td>8</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Historical Simulation (500-day)</td>
<td>4</td>
<td>17</td>
<td>15</td>
<td>10</td>
<td>7</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>Historical Simulation (250-day)</td>
<td>9</td>
<td>18</td>
<td>12</td>
<td>6</td>
<td>6</td>
<td>10</td>
</tr>
</tbody>
</table>
On the other hand, the results indicate that the historical simulation methodology with 2,500 days of data appears to work better than the other methodologies.

The evaluation of the VaR models through backtesting is important because in order to measure and manage market risk, it is crucial to have an accurate model. However, counting the number of days that losses exceeded the VaR number is a simple backtest procedure and does not measure the accuracy of the models. Therefore, the accuracy of models is also backtested by applying statistical backtests and ranking tests. These tests are provided below.

8.7.2 The Statistical Backtests

Backtests based on the statistical frequency tests are also used to validate VaR models and the frequencies of exceptions are tested by using both binomial tests proposed by Kupiec (1995) and the conditional frequency test proposed by Christoffersen (1998).

Backtesting is a process that validates the VaR models by comparing the VaR estimates to their respective realised portfolio profit and loss. After constructing the portfolio profit and loss over a daily time interval, the number of exceptions was determined by the following hit function:

$$I_{ts} = \begin{cases} 1 & \text{if } x_{t,t+1} \leq -VaR_{t(a)} \\ 0 & \text{if } x_{t,t+1} > -VaR_{t(a)} \end{cases} \quad t \in \{1,2,\ldots,n\} \quad (8.5)$$

where $x_{t,t+1}$ represents the profit or loss between the end of date $t$ and date $t+1$; and $VaR_{t(a)}$ represents the reported VaR. If an institution's loss on the trading activities between the end of date $t$ and date $t+1$ is less than or equals its negative VaR calculated on date $t$, this situation is defined as an exception (1). If an institution's loss on the trading activities between the end of date $t$ and date $t+1$ exceeds the negative VaR calculated on date $t$, this situation is defined as a failure (0).
In order to construct the hit function sequence (e.g.; 0,1,0,0,1,1,0,...,0) for all observations, this process is rolled forward by comparing the VaR estimates to their respective realised portfolio profit and loss for 1,136 days using the sample period from 2 January 1996 to 29 June 2000.

After constructing the hit function sequence, the performances of the VaR models are backtested by applying three statistical tests. These are; the one-sided binomial test, the two-sided binomial test and the Christoffersen test.

The statistical backtests are based on a standard hypothesis-testing paradigm. First, the null hypothesis is specified and then a significance level is selected and the probability associated with the null hypothesis being true is estimated. If the estimated value of the probability exceeds the significance level, the null hypothesis is accepted. If the estimated value of the probability does not exceed the significance level, the null hypothesis is rejected.

For the statistical backtests, the null hypothesis is that the VaR estimates exhibit a specified property characteristic of accurate VaR estimates. If the null hypothesis is rejected, the VaR estimates do not exhibit the specified property and the underlying VaR model could be said to be inaccurate. If the null hypothesis is accepted, then the model could be said to be accurate.

As VaRs are calculated at the 99 percent confidence level, the significance level is selected as 1 percent. A small significance level indicates that it is less likely to accept the null hypothesis and more likely to incorrectly reject an accurate model. However, choosing a small significance level also indicates that it is less likely to incorrectly accept a false model.\(^56\)

The first statistical test that is used to validate the VaR models is the one-sided binomial test based on the frequency of tail losses. This approach tests whether the

\(^{56}\) Incorrectly rejecting an accurate model is called as Type I error. A Type II error is the probability of accepting a false null hypothesis.
observed frequency of losses that exceed VaR is consistent with the frequency of tail losses that is predicted by the model.

At the 1 percent significance level, the model predicts that $p = 1 - \alpha = 0.01$, which indicates that the null hypothesis is $H_0 : p = 0.01$. As there are 1,136 observations in the sample, the model predicts 11 exceptions ($n \times p = 1136 \times 0.01 = 11$). If the observed frequency rate ($\hat{p}$) exceeds $p$ (0.01), a one-sided alternative hypothesis is specified ($H_1 : p > 0.01$). The probability value of the test is then the probability under the null that $x \geq \text{observed frequency}$ and this could be calculated as $1 - \Pr[x < \text{observed frequency}]$. If this probability value is higher than $p$ (0.01), then the model is acceptable.

In order to implement a one-sided binomial test, the number of observations ($n$), the number of exceptions ($x$) and the significance level ($p$) are used (the test statistics were calculated by using the 'binomdist' function in Excel). Table 8.6 demonstrates the total number of exceptions and probability values of the VaR models.
Table 8.6: Backtesting Results for the One-Sided Binomial Test

<table>
<thead>
<tr>
<th>VaR Models</th>
<th>Fixed Portfolio</th>
<th>Worst-Case Portfolio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of Exceptions</td>
<td>Probability Value</td>
</tr>
<tr>
<td>Variance-Covariance (EqVCV)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1) 2500-day</td>
<td>3</td>
<td>0.9964*</td>
</tr>
<tr>
<td>2) 1250-day</td>
<td>8</td>
<td>0.7998*</td>
</tr>
<tr>
<td>3) 750-day</td>
<td>10</td>
<td>0.5831*</td>
</tr>
<tr>
<td>4) 500-day</td>
<td>12</td>
<td>0.3509*</td>
</tr>
<tr>
<td>5) 250-day</td>
<td>17</td>
<td>0.0408*</td>
</tr>
<tr>
<td>Variance-Covariance (ExpVCV)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6) $\lambda = 0.93$</td>
<td>19</td>
<td>0.0123*</td>
</tr>
<tr>
<td>7) $\lambda = 0.94$</td>
<td>19</td>
<td>0.0123*</td>
</tr>
<tr>
<td>8) $\lambda = 0.95$</td>
<td>18</td>
<td>0.0229*</td>
</tr>
<tr>
<td>9) $\lambda = 0.96$</td>
<td>16</td>
<td>0.0692*</td>
</tr>
<tr>
<td>10) $\lambda = 0.97$</td>
<td>12</td>
<td>0.3509*</td>
</tr>
<tr>
<td>11) $\lambda = 0.98$</td>
<td>11</td>
<td>0.4638*</td>
</tr>
<tr>
<td>Historical Simulation (HS)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12) 2500-day</td>
<td>1</td>
<td>0.9999*</td>
</tr>
<tr>
<td>13) 1250-day</td>
<td>3</td>
<td>0.9964*</td>
</tr>
<tr>
<td>14) 750-day</td>
<td>7</td>
<td>0.8798*</td>
</tr>
<tr>
<td>15) 500-day</td>
<td>11</td>
<td>0.4638*</td>
</tr>
<tr>
<td>16) 250-day</td>
<td>11</td>
<td>0.4638*</td>
</tr>
</tbody>
</table>

* indicates that the null hypothesis is accepted at the 1 percent significance level.

The results of the binomial test are presented below by considering first the fixed portfolio and then the worst-case portfolio.

The Fixed Portfolio: The probability values of all models that calculate VaR estimates are higher than the 1 percent probability level. Therefore, all models are acceptable. The ‘HS 2500-day’ model has the highest probability value and the ‘ExpVCV-0.93’ and ‘ExpVCV-0.94’ models have the lowest probability value.

The Worst-Case Portfolio: The probability values of all models that calculate VaR estimates for the worst-case portfolio are lower than the 1 percent probability level ($p$). Therefore, all models are rejected. When the 10 percent significance level is chosen, all historical simulation models and the ‘EqVCV 2500-day’ model are accepted.
Table 8.7 presents the non-rejection levels for different probability levels when the number of observations is equal to 1,136 ($n=1,136$). The second column of the table demonstrates the number of exceptions ($x$) that could be observed in a sample size of 1,136 days without rejecting the indicated null hypothesis that $p$ is the correct probability.

<table>
<thead>
<tr>
<th>Null Hypothesis Probability Level ($p$)</th>
<th>Non-Rejection for $x$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.010</td>
<td>$x \leq 19$</td>
</tr>
<tr>
<td>0.025</td>
<td>$x \leq 38$</td>
</tr>
<tr>
<td>0.050</td>
<td>$x \leq 68$</td>
</tr>
<tr>
<td>0.075</td>
<td>$x \leq 97$</td>
</tr>
<tr>
<td>0.100</td>
<td>$x \leq 126$</td>
</tr>
</tbody>
</table>

Table 8.7 demonstrates that when $p=0.10$ and $n=1,136$, then the model will not be rejected as long as $x \leq 126$. However, values of $x$ greater than 126 indicate that the VaR model is not acceptable as the null hypothesis is rejected. The number of exceptions for the variance-covariance models that calculate VaR for the worst-case portfolio (excluding the ‘EqVCV 2500-day’ model) are higher than 126. As a result, even at the 10 percent significance level, the null hypothesis is rejected for the EqVCV and ExpVCV models excluding the ‘EqVCV 2500-day’ model, which has an exception number of 117. On the other hand, all the historical simulation models are accepted when the coverage rate is 0.10.

The one-sided binomial test results indicate that when the fixed portfolio is considered, the models provide accurate VaR estimates at the 1 percent significance level. However, when the worst-case portfolio is considered, at the 1 percent significance level all VaR models are rejected and only 6 VaR models out of 16 provide accurate VaR estimates at the 10 percent significance level.

The one-sided binomial test provides a single cut-off point. On the other hand, the two-sided binomial test can be used to test whether the observed number of exceptions lies within a confidence interval. This test, which is based on the binomial distribution, shows when a systematic underestimation or overestimation of the VaR model seems to be taking place.
This approach tests the hypothesis that $E[I_i] = p$ against the alternative $E[I_i] \neq p$. Kupiec (1995) presents the use of the likelihood ratio (LR) test statistic in order to test the null hypothesis and therefore this test is known as the Kupiec test.

The null hypothesis for the Kupiec test is that the empirically determined probability matches the given probability. When the VaR coverage rate, $p$, is chosen to be 1 percent, the following null hypothesis is tested;

$$H_0: p = \hat{p} = x/n = 0.01 \quad (8.6)$$

where $x$ represents the number of exceptions and $n$ represents the number of backtesting points. Under the null hypothesis that $p$ is the true probability, the LR test statistic has an asymptotic $\chi^2$ distribution with one degree of freedom (the LR test statistics were calculated by following the steps that were described in the sixth chapter of this thesis and using the Excel software).

Table 8.8 demonstrates the LR test statistics for the models that calculate the VaR estimates for the fixed and worst-case portfolios. If the test statistic does not exceed the relevant critical $\chi^2$ value, the null hypothesis is accepted. If the test statistic exceeds the relevant critical $\chi^2$ value, the null hypothesis is rejected. The relevant critical $\chi^2$ value for one degree of freedom is 6.6349; therefore the model is rejected if $LR > 6.6349$.

Table 8.8 also presents the probability values for each model, which is the probability of the $\chi^2$ distribution of the LR test statistic with one degree of freedom (the probability values were calculated by using the ‘chidist’ function in Excel). If the estimated value of the probability exceeds the significance level, the null hypothesis is accepted. If the estimated value of the probability does not exceed the significance level, the null hypothesis is rejected.
Table 8.8: Backtesting Results for the Kupiec Test (Two-Sided Binomial Test)

<table>
<thead>
<tr>
<th>VaR Models</th>
<th>Fixed Portfolio</th>
<th>Worst-Case Portfolio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of LR</td>
<td>Probability Value</td>
</tr>
<tr>
<td></td>
<td>Failures</td>
<td>Statistic</td>
</tr>
<tr>
<td>Variance-Covariance (EqVCV)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1) 2500-day</td>
<td>3</td>
<td>8.8</td>
</tr>
<tr>
<td>2) 1250-day</td>
<td>8</td>
<td>1.1*</td>
</tr>
<tr>
<td>3) 750-day</td>
<td>10</td>
<td>0.2*</td>
</tr>
<tr>
<td>4) 500-day</td>
<td>12</td>
<td>0.0*</td>
</tr>
<tr>
<td>5) 250-day</td>
<td>17</td>
<td>2.5*</td>
</tr>
<tr>
<td>Variance-Covariance (ExpVCV)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6) $\lambda = 0.93$</td>
<td>19</td>
<td>4.3*</td>
</tr>
<tr>
<td>7) $\lambda = 0.94$</td>
<td>19</td>
<td>4.3*</td>
</tr>
<tr>
<td>8) $\lambda = 0.95$</td>
<td>18</td>
<td>3.3*</td>
</tr>
<tr>
<td>9) $\lambda = 0.96$</td>
<td>16</td>
<td>1.7*</td>
</tr>
<tr>
<td>10) $\lambda = 0.97$</td>
<td>12</td>
<td>0.0*</td>
</tr>
<tr>
<td>11) $\lambda = 0.98$</td>
<td>11</td>
<td>0.0*</td>
</tr>
<tr>
<td>Historical Simulation (HS)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12) 2500-day</td>
<td>1</td>
<td>16.0</td>
</tr>
<tr>
<td>13) 1250-day</td>
<td>3</td>
<td>8.8</td>
</tr>
<tr>
<td>14) 750-day</td>
<td>7</td>
<td>2.0*</td>
</tr>
<tr>
<td>15) 500-day</td>
<td>11</td>
<td>0.0*</td>
</tr>
<tr>
<td>16) 250-day</td>
<td>11</td>
<td>0.0*</td>
</tr>
</tbody>
</table>

* indicates that the null hypothesis is accepted at the 1 percent significance level.

The results of the two-sided binomial test are presented below by considering first the fixed portfolio and then the worst-case portfolio.

**The Fixed Portfolio:** The likelihood ratio test statistics of the ‘EqVCV 2500-day’, ‘HS 2500-day’ and ‘HS 1250-day’ models are higher than the relevant critical $\chi^2$ value for one degree of freedom. Although these models have the lowest exception numbers, they are rejected. The results of the two-sided binomial test indicate that models other than the ‘EqVCV 2500-day’, ‘HS 2500-day’ and ‘HS 1250-day’ models calculate accurate VaR estimates for the fixed portfolio.

**The Worst-Case Portfolio:** The likelihood ratio test statistics of all models that calculate VaR estimates for the worst-case portfolio are higher than the relevant critical $\chi^2$ value for one degree of freedom. Therefore, all models are rejected at the one percent significance level. However, when the 10 percent significance level is selected, it is found that the ‘EqVCV 2500-day’, ‘HS 1250-day’, ‘HS 750-day’,
'HS 500-day' and 'HS 250-day' models are accepted. In addition, the 'IIS 2500-day' model is also found to be accurate when \( p = 0.075 \).

Table 8.9 presents the confidence intervals for different probability levels when the number of observations is equal to 1,136 (\( n = 1,136 \)).

<table>
<thead>
<tr>
<th>Probability Level (( p ))</th>
<th>Non-Rejection Region for ( x )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.010</td>
<td>( 4 \leq x \leq 21 )</td>
</tr>
<tr>
<td>0.025</td>
<td>( 18 \leq x \leq 40 )</td>
</tr>
<tr>
<td>0.050</td>
<td>( 43 \leq x \leq 71 )</td>
</tr>
<tr>
<td>0.075</td>
<td>( 70 \leq x \leq 101 )</td>
</tr>
<tr>
<td>0.100</td>
<td>( 98 \leq x \leq 130 )</td>
</tr>
</tbody>
</table>

The above table indicates that, when \( p \) equals 0.01, the null hypothesis is accepted as long as the number of exceptions is in the \([3(x)22]\) confidence interval. The number of failures less than 4 indicates that the VaR model is overly conservative and overestimates the probability of large losses. If the number of failures is more than 22, then the VaR model underestimates the probability of large losses. For the fixed portfolio, the number of exceptions ranges from 1 to 11 and there are only three models that have less than 4 exceptions. These are; the 'HS 2500-day', 'HS 1250-day' and 'EqVCV 2500-day' models which have 1, 3 and 3 exceptions, respectively. These models are rejected as they are overly conservative and overestimate the probability of large losses.

When \( p \) equals 0.10, then the null hypothesis is accepted as long as the number of exceptions is in the \([97(x)131]\) confidence interval. The number of failures less than 97 indicates that the VaR model is overly conservative and overestimates the probability of large losses. If the number of failures is more than 131, then the VaR model underestimates the probability of large losses. For the worst-case portfolio, the number of exceptions ranges from 81 to 176 and at the 10 percent significance level, there are five models (EqVCV 2500-day, HS 1250-day, HS 750-day, HS 500-day and HS 250-day) that the confidence interval includes the number predicted by the model. The 'HS 2500-day' model has 81 exceptions and overestimates the risk measure at the 10 percent significance level. However, the \([70(x)101]\) confidence
interval includes the number predicted by the 'HS 2500-day' model, which indicates that the model is acceptable at the 7.5 percent level. The ExpVCV and EqVCV models other than the 'EqVCV 2500-day' model are found to be inaccurate and therefore it could be concluded that these models underestimate the risk measures.

The two-sided binomial approach provides better results than the one-sided binomial test as the latter only provides a cut-off point and does not provide any information whether a risk model overestimates the risk measure or not. However, the drawback of both approaches is that they implicitly assume that the exceptions are independent of each other and therefore they do not take into account any information about the temporal pattern of exceptions. In order to deal with this problem, Christoffersen (1998) suggests the conditional backtesting procedure.

The Christoffersen approach separates out the particular null hypothesis that the model has the correct frequency of independently distributed exceptions into two components. These are the coverage and independence hypotheses. Then, these two hypotheses and a joint conditional coverage hypothesis are tested separately.

The coverage hypothesis, which implies that the model generates the correct frequency of exceptions, is the same hypothesis that is provided by the two-sided binomial test. Therefore, under the null hypothesis that $p$ is the true probability, the $LR_{wc}$ test statistic has an asymptotic $\chi^2$ distribution with one degree of freedom.

The independence hypothesis implies that the exceptions are independent. In order to calculate the likelihood ratio test statistic ($LR_{nd}$) of the independence hypothesis, after transforming the hit function sequence into a duration series, the number of days for the following processes is determined.

$n_{00}$ : The number of days that date $t$ and date $t+1$ are not exceptions.

$n_{01}$ : The number of days that date $t$ is not an exception and date $t+1$ is an exception.

$n_{10}$ : The number of days that date $t$ is an exception and date $t+1$ is not an exception.

$n_{11}$ : The number of days that date $t$ and date $t+1$ are exceptions.
The $LR_{ind}$ test statistic has also an asymptotic $\chi^2$ distribution with one degree of freedom.

The final step of the Christoffersen approach is to combine the above tests for unconditional coverage and independence to form a combined test of conditional coverage. The test statistic of the combined hypothesis is;

$$LR_{cc} = LR_{uc} + LR_{ind}$$

which has an asymptotic $\chi^2$ distribution with two degrees of freedom.

The results for the conditional coverage test are shown in Tables 8.10 and 8.11 (the likelihood ratios presented in these tables were calculated by following the steps that were described in the sixth chapter of this thesis and using the Excel software).

Table 8.10: Backtesting Results for the Conditional Coverage Test (The Fixed Portfolio)

<table>
<thead>
<tr>
<th>Var(R) Models</th>
<th>(LR_{uc}) Statistic</th>
<th>(n_{00})</th>
<th>(n_{01})</th>
<th>(n_{10})</th>
<th>(n_{11})</th>
<th>(LR_{ind}) Statistic</th>
<th>Probability Value</th>
<th>(LR_{cc}) Statistic</th>
<th>Probability Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance-Covariance (EqVCV)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1) 2500-day</td>
<td>8.8</td>
<td>1129</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>0.0*</td>
<td>0.8997*</td>
<td>8.8*</td>
<td>0.0122*</td>
</tr>
<tr>
<td>2) 1250-day</td>
<td>1.1*</td>
<td>1119</td>
<td>8</td>
<td>8</td>
<td>0</td>
<td>0.1*</td>
<td>0.7361*</td>
<td>1.2*</td>
<td>0.5398*</td>
</tr>
<tr>
<td>3) 750-day</td>
<td>0.2*</td>
<td>1115</td>
<td>10</td>
<td>10</td>
<td>0</td>
<td>0.2*</td>
<td>0.6733*</td>
<td>0.3*</td>
<td>0.8398*</td>
</tr>
<tr>
<td>4) 500-day</td>
<td>0.0*</td>
<td>1111</td>
<td>12</td>
<td>12</td>
<td>0</td>
<td>0.3*</td>
<td>0.6126*</td>
<td>0.3*</td>
<td>0.8641*</td>
</tr>
<tr>
<td>5) 250-day</td>
<td>2.5*</td>
<td>1101</td>
<td>17</td>
<td>17</td>
<td>0</td>
<td>0.5*</td>
<td>0.4721*</td>
<td>3.0*</td>
<td>0.2264*</td>
</tr>
<tr>
<td>Variance-Covariance (ExpVCV)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6) (\lambda = 0.93)</td>
<td>4.3*</td>
<td>1097</td>
<td>19</td>
<td>19</td>
<td>0</td>
<td>0.6*</td>
<td>0.4212*</td>
<td>5.0*</td>
<td>0.0836*</td>
</tr>
<tr>
<td>7) (\lambda = 0.94)</td>
<td>4.3*</td>
<td>1097</td>
<td>19</td>
<td>19</td>
<td>0</td>
<td>0.6*</td>
<td>0.4212*</td>
<td>5.0*</td>
<td>0.0836*</td>
</tr>
<tr>
<td>8) (\lambda = 0.95)</td>
<td>3.3*</td>
<td>1099</td>
<td>18</td>
<td>18</td>
<td>0</td>
<td>0.6*</td>
<td>0.4463*</td>
<td>3.9*</td>
<td>0.1416*</td>
</tr>
<tr>
<td>9) (\lambda = 0.96)</td>
<td>1.7*</td>
<td>1103</td>
<td>16</td>
<td>16</td>
<td>0</td>
<td>0.5*</td>
<td>0.4988*</td>
<td>2.2*</td>
<td>0.3402*</td>
</tr>
<tr>
<td>10) (\lambda = 0.97)</td>
<td>0.0*</td>
<td>1111</td>
<td>12</td>
<td>12</td>
<td>0</td>
<td>0.3*</td>
<td>0.6126*</td>
<td>0.3*</td>
<td>0.8641*</td>
</tr>
<tr>
<td>11) (\lambda = 0.98)</td>
<td>0.0*</td>
<td>1113</td>
<td>11</td>
<td>11</td>
<td>0</td>
<td>0.2*</td>
<td>0.6426*</td>
<td>0.2*</td>
<td>0.8927*</td>
</tr>
<tr>
<td>Historical Simulation (HS)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12) 2500-day</td>
<td>16.0</td>
<td>1133</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0.0*</td>
<td>0.9665*</td>
<td>16.0</td>
</tr>
<tr>
<td>13) 1250-day</td>
<td>8.8</td>
<td>1129</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>0.0*</td>
<td>0.8997*</td>
<td>8.8*</td>
<td>0.0122*</td>
</tr>
<tr>
<td>14) 750-day</td>
<td>2.0*</td>
<td>1121</td>
<td>7</td>
<td>7</td>
<td>0</td>
<td>0.1*</td>
<td>0.7682*</td>
<td>2.0*</td>
<td>0.3597*</td>
</tr>
<tr>
<td>15) 500-day</td>
<td>0.0*</td>
<td>1113</td>
<td>11</td>
<td>11</td>
<td>0</td>
<td>0.2*</td>
<td>0.6426*</td>
<td>0.2*</td>
<td>0.8927*</td>
</tr>
<tr>
<td>16) 250-day</td>
<td>0.0*</td>
<td>1113</td>
<td>11</td>
<td>11</td>
<td>0</td>
<td>0.2*</td>
<td>0.6426*</td>
<td>0.2*</td>
<td>0.8927*</td>
</tr>
</tbody>
</table>

* indicates that the null hypothesis is accepted at the 1 percent significance level.
If the likelihood ratio test statistics do not exceed the relevant critical $\chi^2$ value, the null hypothesis is accepted. If the likelihood ratio test statistics exceed the relevant critical $\chi^2$ value, the null hypothesis is rejected. The critical values for the likelihood ratio statistics are shown in Table 8.12. The relevant critical $\chi^2$ value for one degree of freedom is 6.6349; therefore the model is rejected if $LR_{\text{ind}} > 6.6349$. The relevant critical $\chi^2$ value for two degrees of freedom is 9.2104; therefore the model is rejected if $LR_{\text{cc}} > 9.2104$.  

Table 8.12: The Critical Values for the $LR_{\text{nc}}$, $LR_{\text{ind}}$ and $LR_{\text{cc}}$ Statistics

<table>
<thead>
<tr>
<th>Confidence Level (c)</th>
<th>$99 %$</th>
<th>$95 %$</th>
<th>$90 %$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asymptotic $\chi^2(1)$ ($LR_{\text{nc}}$ and $LR_{\text{ind}}$)</td>
<td>6.6349</td>
<td>3.8415</td>
<td>2.7055</td>
</tr>
<tr>
<td>Asymptotic $\chi^2(2)$ ($LR_{\text{cc}}$)</td>
<td>9.2104</td>
<td>5.9915</td>
<td>4.6052</td>
</tr>
</tbody>
</table>

57 Tables 8.10 and 8.11 also present the probability values of the $LR_{\text{ind}}$ and $LR_{\text{cc}}$ test statistics.
The results of the conditional coverage test are presented below by considering first the fixed portfolio and then the worst-case portfolio.

**The Fixed Portfolio:** For the independence test, the likelihood ratio test statistics of the VaR models are lower than the relevant critical $\chi^2$ value for one degree of freedom. Therefore, the null hypothesis is accepted at the 1 percent significance level, which indicates that the exceptions are independent. For the conditional coverage test, the likelihood ratio test statistics of the VaR models are also lower than the relevant critical $\chi^2$ value for two degrees of freedom, except for the 'HS 250-day' model, which has only one exception. The results of the conditional coverage test indicate that models other than the 'HS 2500-day' model provide accurate VaR estimates for the fixed portfolio. On the other hand, the results of the coverage hypothesis demonstrate that the 'HS 2500-day' model overestimates risk measures.

**The Worst-Case Portfolio:** For the independence test, the likelihood ratio test statistics of the VaR models are lower than the relevant critical $\chi^2$ value for one degree of freedom. Therefore, the null hypothesis is accepted at the 1 percent significance level, which indicates that the exceptions are independent. For the conditional coverage test, the likelihood ratio test statistics of the VaR models are higher than the relevant critical $\chi^2$ value for two degrees of freedom, which indicates that the models are rejected. Therefore, it could be concluded that when VaRs are calculated for the worst-case portfolio, all VaR methodologies provide inaccurate estimates.

The results suggest that concerning the independence hypothesis, the null hypothesis is accepted for each model that calculates VaR either for the fixed portfolio or for the worst-case portfolio. This indicates that exceptions are independent. On the other hand, the results concerning the joint hypothesis, i.e. the conditional coverage hypothesis, provide confusing conclusions. While in general VaR models are found to provide accurate estimates for the fixed portfolio, the same VaR models provide
inaccurate estimates when VaR is calculated for the worst-case portfolio that generates a loss on each trading day.

8.7.3 The Ranking Tests

As the statistical backtests do not allow the users to rank the VaR models, the tests applied in the previous section are supplemented by the ranking tests proposed by Lopez (1998) and Blanco and Ihle (1999). Table 8.13 demonstrates the ranking test values of the Lopez and the Blanco-Ihle approaches.

The first column of the table demonstrates the VaR models. The second and fifth columns demonstrate the number of exceptions. The test results of the Lopez binomial approach for the fixed and worst-case portfolios are shown in the third and sixth columns, respectively. The results are derived from the loss function implied by the binominal method which uses the same information that is used in the Kupiec test; i.e. the number of exceptions. After setting up the loss function, a score function (quadratic probability function), that takes the loss function and benchmark as its inputs, is established to rank the VaR models. Similar to the tests that are carried out in the statistical backtests, a 1 percent significance level is selected as the benchmark for the loss function. Then, for each VaR model the quadratic probability function is calculated, which takes a value in the range [0,2] and a lower QPS value indicates a better model.

The fourth and seventh columns demonstrate the test results of the Blanco-Ihle approach for the fixed and worst-case portfolios, respectively. The loss function proposed by Blanco and Ihle gives each exception a weight equal to the difference between the tail loss and the VaR estimate, divided by the VaR estimate. Then, a weighted average indicator that incorporates both the size and the frequency of the exceptions is established. This indicator reflects the size loss function of the Blanco and Ihle approach and the frequency loss function of the Lopez approach. In this backtesting, equal weights are given to each function ($\lambda = 0.50$). Finally, different VaR models are evaluated by comparing the indicators and the indicator that shows a lower score demonstrates a more accurate model.
In Table 8.13, the lower scores indicate a better model. As the historical simulation models are found to provide lower test values in general, it could be concluded that these models are better than the variance-covariance methodologies. On the other hand, the ExpVCV methodologies are found to be the worst models as their ranking test values are higher in general.

By using the ranking test values of the Lopez and the Blanco-Ihle approaches, alternative models are compared and ranked from the best to the worst. The ranking of the VaR models are shown in Table 8.14.
Table 8.14: Ranking of the VaR Models

<table>
<thead>
<tr>
<th>Rank</th>
<th>Fixed Portfolio</th>
<th>Worst-Case Portfolio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lopez</td>
<td>Lopez</td>
</tr>
<tr>
<td>1</td>
<td>HS 2500-day</td>
<td>HS 2500-day</td>
</tr>
<tr>
<td>2</td>
<td>EqVCV 2500-day</td>
<td>HS 1250-day</td>
</tr>
<tr>
<td>3</td>
<td>HS 1250-day</td>
<td>EqVCV 2500-day</td>
</tr>
<tr>
<td>4</td>
<td>HS 750-day</td>
<td>EqVCV 1250-day</td>
</tr>
<tr>
<td>5</td>
<td>EqVCV 1250-day</td>
<td>HS 500-day</td>
</tr>
<tr>
<td>6</td>
<td>EqVCV 750-day</td>
<td>HS 500-day</td>
</tr>
<tr>
<td>7</td>
<td>ExpVCV $\lambda = 0.98$</td>
<td>HS 500-day</td>
</tr>
<tr>
<td>8</td>
<td>HS 250-day</td>
<td>EqVCV 750-day</td>
</tr>
<tr>
<td>9</td>
<td>ExpVCV $\lambda = 0.98$</td>
<td>EqVCV 500-day</td>
</tr>
<tr>
<td>10</td>
<td>ExpVCV $\lambda = 0.98$</td>
<td>ExpVCV $\lambda = 0.98$</td>
</tr>
<tr>
<td>11</td>
<td>ExpVCV $\lambda = 0.97$</td>
<td>ExpVCV $\lambda = 0.97$</td>
</tr>
<tr>
<td>12</td>
<td>ExpVCV $\lambda = 0.96$</td>
<td>ExpVCV $\lambda = 0.96$</td>
</tr>
<tr>
<td>13</td>
<td>ExpVCV $\lambda = 0.95$</td>
<td>ExpVCV $\lambda = 0.95$</td>
</tr>
<tr>
<td>14</td>
<td>ExpVCV $\lambda = 0.93$</td>
<td>ExpVCV $\lambda = 0.93$</td>
</tr>
<tr>
<td>15</td>
<td>ExpVCV $\lambda = 0.94$</td>
<td>ExpVCV $\lambda = 0.94$</td>
</tr>
<tr>
<td>16</td>
<td>ExpVCV $\lambda = 0.94$</td>
<td>ExpVCV $\lambda = 0.93$</td>
</tr>
</tbody>
</table>

The ranking tests indicate that the VaR estimates that are calculated by the historical simulation approach based on 10 years of data provides the best VaR estimates for both portfolios. These results make the historical simulation methodology that uses longer datasets an attractive and appropriate choice for the market risk measurement of the foreign exchange portfolios.

On the other hand, the results of the comparison of VaR models point out that a VaR model that relies upon the ExpVCV methodology is highly inappropriate for the foreign exchange portfolios.

As a conclusion, the backtesting results indicate that in order to obtain accurate VaR estimates, the characteristics and risk nature of the portfolio are important issues that should be considered while determining the VaR methodology. Risk practitioners and regulators, who attempt to evaluate a model through backtesting, should backtest the model by carrying out alternative portfolios. Otherwise, they should not rely on the accuracy of the models.
8.8 Conclusions

As the VaR estimates are dependent upon the VaR methodology, the most difficult decision that risk managers make with regard to VaR is to choose an appropriate model. Despite the variation of the outcomes, under the market risk capital regulations, banks could either choose the standardised approach or employ a VaR model to calculate the required capital. The market risk capital regulations do not prescribe any specific methodology of VaR but sets some quantitative standards, such as a 99 percent confidence level, a ten-day holding period, and at least 250 days of historical data. However, the reliance on allowing financial institutions' to determine the VaR methodology on which they base their required capital to cover market risk could create an incentive for them to choose a methodology that provides less required capital amounts. Furthermore, given the use of VaR in the financial institutions' risk management and in the regulatory framework, it is a critical issue to assess the accuracy of VaR models.

In this chapter, the impact of choosing different approaches to calculate the required capital was analysed. In addition, the accuracy of VaR models was evaluated by applying backtesting methodologies. These methodologies test how well the VaR forecasts would have performed in the past by comparing the VaR estimates with realised trading results. In this final section, the empirical results are explained. First, the results concerning the comparison of the required capital amounts, second, the results of the backtests are presented.

In this study, simulations were carried out to calculate the required market risk capitals for a 'fixed' and a 'worst-case' portfolio. The simulations cover the period from January 1996 to June 2000. The required capital charges were calculated by applying the standardised and 16 VaR models. These VaR models are; 5 equally weighted variance-covariance models (2500-day, 1250-day, 750-day, 500-day, and 250-day), 6 exponentially weighted variance-covariance models ($\lambda = 0.93$, $\lambda = 0.94$, $\lambda = 0.95$, $\lambda = 0.96$, $\lambda = 0.97$, $\lambda = 0.98$) and 5 historical simulation models (2500-day, 1250-day, 750-day, 500-day, and 250-day). The capital charges
were calculated for 1,137 days from 2 January 1996 to 30 June 2000. The results of these simulations are explained below.

1) The analysis of risk factors, which are currencies in this study, indicates that the returns are not normally distributed, as they display the kurtosis, which is a common feature of the financial data. The Jarque-Bera tests of each distribution also reject the null hypothesis that variables are normally distributed. However, a variance-covariance methodology that assumes normality is widely used among financial institutions although this approach is not suitable for financial assets because of fat-tailness.

2) The findings of this study raise some questions concerning the variability of the capital requirement across banks as the comparison of different techniques for calculating VaR provides that each methodology produces different measures. Therefore, relying on these models might mislead regulators, as the market risk capital regulations do not provide a ‘level playing field’.

3) The major observations for this simulation are; (i) while the standardised approaches provide smaller capital charges, the historical simulation methodologies provide higher capital charges, (ii) in particular, the ‘IHS 2500-day’ model produces the highest average required capital amount, (iii) together with the ‘EqVCV 250-day’ model, the ExpVCV models produce the lowest average required capital amounts among all the VaR models, (iv) together with the ExpVCV models, the ‘IHS 2500-day’ model also produces higher standard deviations (v) compared with the case of the fixed portfolio, the models produce relatively lower required capital amounts in the case of the worst-case portfolio, due to the diversification impact of investment.

The VaR models are currently in use in the industrialised countries. In addition, the emerging countries have plans to implement these types of models in their risk-based capital regulations frameworks. However, the findings of this study present a warning to those who use or intend to use them. The empirical findings demand a crucial attention as the capital charges for the market risk computations indicate that
the market risk capital regulations could provide capital savings for some banks. The disadvantage of the market risk capital regulations is that these regulations cannot ensure a 'level playing field' for financial institutions in order to eliminate the competitive inequalities. Therefore, giving an option to banks to determine the VaR methodology could create a moral hazard problem as banks may choose an inaccurate model that provides less required capital amounts.

The empirical results concerning these simulations indicate that banks with the same risk could have different capital amounts depending only on the selected methodology for calculating the required market risk capital. Regulators should also take into consideration this crucial issue while allowing banks to use a specific model. As a result, when accepting a bank's application concerning the methodology to calculate the market risk capital requirement, bank regulators should compare the structure of a bank's portfolio with the structure of the peer banks' portfolios and only permit the use of the same methodologies for similar portfolios. Furthermore, because the returns of exchange rates are not normally distributed, applying the variance-covariance methodology that assumes a normal distribution could result in biased estimates of VaR. Therefore, regulators should be cautious while allowing banks to use their own internal VaR models.

This chapter also provides the results of backtesting concerning the performances of 16 VaR models. These are, the regulatory backtesting required by the Basle Committee amendment, the statistical tests, and the ranking tests. The results of the backtesting analysis are presented below.

1) The first method to measure the model performance is the regulatory backtesting. This is a simple 'count the number of exceptions' method and a 99 percent confidence level is considered, which implies that there is a 1 percent chance that the VaR estimates underestimate respective portfolio losses. The results of the regulatory backtesting indicate that in general the VaR models perform reasonably well when VaR is calculated for the fixed portfolio.
2) However, the regulatory backtesting results indicate that when VaR is calculated for the worst-case portfolio, the models do not provide accurate results. For the equally weighted variance-covariance methodology, the regulatory backtesting indicates that the percentage of exceptions is between 10 and 15. For the exponentially weighted variance-covariance methodology, the regulatory backtesting indicates that the percentage of exceptions is between 15 and 16. Although the historical simulation methodology performs better than the parametric models, the percentage of exceptions for the historical simulation models is still high compared with the results of the fixed portfolio (the percentage of exceptions for the historical simulation models is between 7 and 10).

3) In particular, the turmoil years, such as 1997 when the Southeast Asia crisis occurred and 1998 when the Russian crisis occurred, are found to provide a relatively higher number of exceptions in the regulatory backtesting analysis.

4) The statistical tests that were applied include the one-sided binomial test, the two-sided binomial test, and the Christoffersen test. These tests are based on a hypothetical testing framework and were used to test the null hypothesis that the VaR estimates are accurate at the 1 percent significance level. The results of these tests indicate that, in general models that calculate VaR for the fixed portfolio provide accurate risk measures. However, when VaR is calculated for the worst-case portfolio, the statistical backtests offer disappointing results as these models are found to provide inaccurate VaR estimates. As a result, it could be concluded that while some VaR models overestimate the risk measure and accordingly the required capital amount for a particular portfolio, the same VaR models might underestimate the risk measure when VaR is calculated for another portfolio. Therefore, risk practitioners and in particular regulators should be very cautious when evaluating backtesting results.

5) Finally, the VaR models were compared with each other by using two ranking tests, namely the Lopez test and the Blanco-Ihle test. These tests
are forecast evaluation methods that give each model a score in terms of the frequency and size loss functions. The advantage of these approaches is that they are not statistical tests of model accuracy and therefore they do not suffer from the low power of statistical tests. In addition, these tests could be applied for the relatively small datasets. These ranking tests provide additional information on the accuracy of models and the results indicate that the 'HS 2500-day' model is superior compared with other models. However, because the ranking tests are not statistical tests, this result does not indicate whether the performances of other models are significantly worse or not.

The results of this study indicate that a VaR model that provides accurate estimates for a specific portfolio could fail when the portfolio changes. Therefore, the users of VaR and regulators should carefully consider the characteristics and risk nature of a portfolio before applying a model to obtain accurate VaR estimates. Risk practitioners or regulators should backtest a VaR model with alternative portfolios, as additional backtesting gives more information on model accuracy than would otherwise be available.
CHAPTER NINE

CONCLUSION

9.1 Introduction

Banks have a unique role in the well-being of an economy. This role makes them one of the most heavily regulated and supervised industries. Among bank prudential regulations, capital adequacy is a major supervisory concern. In order to strengthen the soundness and stability of banking systems, regulators require banks to hold adequate capital. In 1988, the Basle Committee recommended member countries to implement the risk-based capital regulations. The risk-based capital regulations require banks to hold a certain amount of capital depending on the riskiness of their portfolios. While credit risk was the only risk that was covered by the original Basle Accord, since 1998 banks have also been required to assign capital for their market risk.

In this study, the impact of the market risk capital regulations on bank capital levels and derivative activities was investigated. In addition, this study also analysed the impact of using different approaches in calculating the required market risk capital, as well as the accuracy of VaR models that are allowed to be used within the framework of the market risk capital regulations. The objective of this final chapter is to explain the strategic conclusions of the research. In the second section, the key findings of the research are emphasised. The third section provides the policy implications of the research. The last section provides directions for further research.
9.2 Key Findings of the Research

Among the financial safety nets that policy-makers rely on to ensure the stability of a banking system, deposit insurance and capital adequacy have always played a prominent role. Although policy-makers generally consider that deposit insurance is necessary to protect small depositors and to prevent bank runs, it could also cause a moral hazard problem. Therefore, it is generally accepted that policy-makers implement capital adequacy regulations to overcome the moral hazard problems created by deposit insurance. As a result, bank regulators place an emphasis on the capital adequacy of banks and influence bank capital by setting capital adequacy regulations to ensure that banks hold sufficient capital to absorb unexpected losses. However, the impact of these regulations is not clear.

On the other hand, the second half of the 1990s will be remembered in the finance history as the period that Value at Risk (VaR) has been developed. Indeed, VaR has become the common standard for the measurement of market risk in a very short time period. This development attracted the attention of not only practitioners, but also regulators and academics as well. Following the developments in banks' risk management practices, VaR was implemented in the risk-based capital regulatory framework. Since 1998, banks have been required to set aside capital to cover their market risk, either by employing a standardised approach or by using the internal VaR models.

Due to the ongoing debate concerning the effects of capital adequacy regulations, a key question is to find out the impact of the market risk capital regulations. In order to analyse the impact of these capital regulations on bank activities, an econometric analysis was carried out in this thesis.

The aim of this analysis is to empirically analyse the impact of the market risk capital regulations on bank capital levels and derivative activities. The implementation of these regulations can influence banks either by increasing their capital or by decreasing their
trading activities and in particular trading derivatives. Therefore, the analysis provided in this chapter investigated the impact of the market risk capital regulations on the changes of bank capital levels and derivative activities.

The changes in capital and derivatives usage ratios were modelled by using a partial adjustment framework. The study focused on the large US BHCs as they are more involved in trading activities and therefore subject to the market risk capital regulations. Using quarterly data from the fourth quarter of 1995 to the fourth quarter of 1999 (17 observations), the estimates were obtained by the panel data analysis. There are two reasons that lie behind the choice of US banks for our analysis. First, the US banks are leading financial institutions dominating derivative markets, and second, it is possible to obtain detailed information on them.

Four different capital indicators were used to calculate the changes in bank capital levels. As well as the three capital ratios that are used by the US regulators to measure bank capital adequacy (the total risk-based capital ratio, the tier-1 risk-based capital ratio and the leverage ratio), the equity capital ratio, which is extensively employed in the banking and finance literature, was also used as a dependent variable in the analysis. In order to proxy bank derivative activities, two dependent variables were used; first, the ratio of total of positive and negative fair value of trading derivatives to total assets, and second, the ratio of notional gross amount of trading derivatives to total assets.

In the empirical analysis, six hypotheses were tested. The regulatory cost hypothesis implies that in order to be effective, capital regulations should increase the capital levels of banks, as the regulatory view considers capital as a cushion that absorbs unexpected losses. The second hypothesis that was tested in the study is the capital avoidance hypothesis, which indicates that bank derivative activities increase because of the lack of capital standards. The main results concerning the regulatory cost and capital avoidance hypotheses indicate that while the implementation of the market risk capital regulations has a significant and positive impact on the US BHCs’ risk-based capital ratios, there is no significant impact on derivative activities.
The study also investigated whether there is a relationship between i) bank capital and asset size, ii) derivative activities and asset size. These questions were included in the analysis to test the economies of scale hypothesis. The economies of scale hypothesis suggests that large banks prefer to have lower capital ratios due to the 'too-big-to-fail' doctrine and large banks are involved more in derivative activities due to the specialisation that these instruments require. The fourth hypothesis that was tested in the study is the moral hazard hypothesis. According to the moral hazard hypothesis, banks with low capital invest more in risky portfolios and are involved more in derivative activities. The regulatory discipline hypothesis is the fifth hypothesis that was tested in the study. This hypothesis implies that, because of the bank capital regulations in place, banks with a greater level of capital are more likely to participate in derivative markets. The final hypothesis that was tested in the empirical study is the market discipline hypothesis, which implies that external monitoring and pricing prevent banks from riskier activities. This hypothesis suggests a positive relationship between the indicators of credibility and derivative activities.

Empirical results failed to support the moral hazard, regulatory discipline, and market discipline hypotheses. However, the results support the economies of scale hypothesis, as large banks were found to be more involved in derivative activities. Therefore, it can be concluded that large banks participate actively in derivative markets as they have the specialised management skills.

The second analysis that was investigated in this study is the evaluation of the standardised and the internal models approaches of the market risk capital regulations. Although bank regulators integrated the VaR models in the framework of capital adequacy regulations, these models have limitations and pitfalls. In addition, there is still no industry consensus on the methodology for calculating VaR.
In order to evaluate these approaches, firstly, a documentary analysis was conducted to demonstrate the variations on bank VaR models. Secondly, simulations were carried out to compare the different approaches and to evaluate the accuracy of VaR models.

Although the market risk capital regulations prescribe some quantitative standards, such as a 99 percent confidence level, a ten-day holding period and at least one-year of historical data, these regulations do not set any specific type of VaR model. However, even when the same parameters are used, applying different methodologies could create different outcomes. In order to demonstrate the variations among VaR methodologies of banks, a documentary analysis was conducted. In this analysis, the disclosure practices of 25 international banks were compared. The sample was chosen from a search of banks that report market risk information in their annual reports.

The results of this analysis indicate that in recent years financial institutions were tending to give out more detailed VaR information in their annual reports. On the other hand, the VaR systems that financial institutions use differ widely across institutions. According to the survey results, there are two major VaR methodologies that are in use by banks in their market risk management systems. These are; the variance-covariance and historical simulation methodologies. In addition, there are differences in the underlying assumptions, such as the holding period, confidence interval, or historical observation period.

These results of the documentary analysis indicate that, there is no industry consensus on the methodology for calculating VaR and the assumptions that are used to calculate VaR estimates vary considerably among financial institutions. Therefore, it is very difficult for financial market participants to make comparisons across institutions and to evaluate the risk-taking of individual banks by looking at single VaR values.

After demonstrating the variations of VaR models on banks, the impact of using different approaches while calculating the required market risk capital and the accuracy of VaR models that are allowed to be used within the framework of the market risk
capital regulations were evaluated. In order to calculate the required capital amount, simulations were conducted and different VaR models were evaluated by applying backtesting methodologies.

In these simulations, the required market risk capitals were calculated for a 'fixed' and a 'worst-case' portfolio. The simulations cover the period from January 1996 to June 2000. The required capital charges were calculated by applying the standardised and 16 VaR models. These VaR models are; 5 equally weighted variance-covariance models (2500-day, 1250-day, 750-day, 500-day, and 250-day), 6 exponentially weighted variance-covariance models ($\lambda = 0.93$, $\lambda = 0.94$, $\lambda = 0.95$, $\lambda = 0.96$, $\lambda = 0.97$, $\lambda = 0.98$) and 5 historical simulation models (2500-day, 1250-day, 750-day, 500-day, and 250-day). The capital charges were calculated for 1,137 days from 2 January 1996 to 30 June 2000.

The major observations for these simulations are:

1) While the standardised approaches provide smaller capital charges, the historical simulation methodologies provide higher capital charges,

2) The 'historical simulation model that uses 2,500 days of historical data produces the highest required capital amount,

3) Together with the equally weighted variance-covariance model that uses 250 days of historical data, the exponentially weighted variance-covariance models produce the lowest average required capital amounts,

4) Compared with the case of the fixed portfolio, the models produce relatively lower required capital amounts in the case of the worst-case portfolio, due to the diversification impact of investment.

This analysis also provides the results of backtesting concerning the performances of 16 VaR models. The backtesting methodologies that were applied are; the regulatory backtesting required by the Basle Committee amendment, the statistical tests, and the ranking tests. The major observations for backtesting are:
1) The results of the regulatory backtesting indicate that in general the VaR models perform reasonably well when VaR is calculated for the fixed portfolio. However, when VaR is calculated for the worst-case portfolio, the models do not provide accurate results. Although the historical simulation methodology performs better than the parametric models, the percentages of exceptions for the historical simulation models are still high compared with the results of the fixed portfolio.

2) In particular, the turmoil years, such as 1997, when the Southeast Asia crisis occurred and 1998, when the Russian crisis occurred, were found to provide a relatively higher number of exceptions in the regulatory backtesting analysis.

3) The results of the statistical tests (the one-sided binomial test, the two-sided binomial test, and the Christoffersen test) indicate that, in general models that calculate VaR estimates for the fixed portfolio provide accurate risk measures. However, when VaR is calculated for the worst-case portfolio, the statistical backtests offer disappointing results as these models were found to provide inaccurate VaR estimates. It could be concluded that while some VaR models overestimate the risk measure and accordingly the required capital amount for a particular portfolio, the same VaR models might underestimate the risk measure when VaR is calculated for another portfolio.

4) The VaR models were compared by using two ranking tests (the Lopez test and the Blanco-Ihle test). These ranking tests provide additional information on the accuracy of models and the results indicate that the historical simulation model that uses 2,500 days of historical data is superior compared with other models. These results indicate that the historical simulation model that uses 2,500 days of historical data not only produces the highest average required capital amount but also provides accurate VaR estimates.
9.3 The Implications of the Research

This thesis provides a substantial contribution to knowledge and understanding in the area of financial regulation as it answers the question of "What impact do capital requirements have?" By providing an answer to this vital question, this research extends the knowledge on bank capital regulation.

Understanding the impact of the market risk capital regulations on bank activities is not only important to bank regulators who have already implemented these regulations but also important to those who are planning to implement them. One of the most important tasks of this study is to determine whether the market risk capital regulations have caused banks to change their decisions concerning capital levels and derivative activities. The results suggest that banks that are subject to the market risk capital regulations should be prepared to increase their capital levels as it was found that there is a significant positive relationship between capital regulations and bank capital levels. If banks do not have any intention to increase their capital, they should consider revising their financial risk-taking. Furthermore, regulators should also consider the potential impact of implementing bank regulations on bank capital levels.

On the other hand, implementing a modern risk measurement technique such as VaR into the regulatory framework is a crucial improvement. However, regulators and users should fully understand the limitations of VaR. The main problem concerning the use of VaR models is that there is no best VaR estimation method and the VaR estimates are dependent upon the VaR methodology, parameters, and data assumptions. On the other hand, the use of these models differs widely across financial institutions. Therefore, one of the most difficult decisions that risk practitioners face with regard to VaR is to choose an appropriate model.

The empirical results concerning the simulations indicate that banks with the same risk could have different required capital amounts depending only on the selected
methodology. Regulators should also take into consideration this crucial issue while allowing banks to use a specific model. As a result, when accepting a bank's application concerning the methodology to calculate the market risk capital requirements, bank regulators should compare the structure of the bank's portfolio with the structure of the peer banks' portfolios, and permit the use of the same methodologies for similar portfolios.

On the other hand, the reliance on allowing financial institutions to choose the VaR methodology could generate an incentive for them to prefer a methodology that calculates the minimum capital requirement. As the results of this research indicate, the VaR estimates are dependent upon the VaR methodology. In addition, the models that provide accurate VaR estimates also provide higher required capital amounts. Therefore;

- The market risk capital regulations do not provide a 'level playing field' for banks that are subject to these regulations.
- Giving an option to banks to determine the VaR methodology could create a moral hazard problem as banks may choose an inaccurate model that provides less required capital amounts.

The practical application of this research is that, bank regulators should be very careful in allowing banks to use either a standardised or internal models approach in calculating the required capital amount to cover their market risk. Bank regulators should consider bank portfolios carefully and allow similar methodologies for banks that have similar portfolios. Otherwise, using different approaches could provide capital savings for some banks. As each methodology produces different estimates of VaR, regulators should take the necessary measures to ensure that they provide a 'level playing field' for banks. An alternative is implementing more detailed rules concerning the usage of VaR. This issue is crucial as it is necessary to reduce competitive imbalances, which are caused by the differences in regulatory rules.
In addition, the results of this study indicate that a VaR model that provides accurate estimates for a specific portfolio could fail when the portfolio composition changes. Therefore, the users of VaR and regulators should carefully consider the characteristics and risk nature of a portfolio before applying a model to obtain accurate VaR estimates. In order not to cause a moral hazard problem, regulators should carefully backtest the VaR models with alternative portfolios, as additional backtesting gives much more information on model accuracy that would not be evident otherwise.

9.4 Limitations and Suggestions for Future Research

An interesting issue left for future study is whether the market risk capital regulations have any impact exclusively on banks' speculative derivative activities. Banks are involved in derivatives trading not only for speculative purposes but also for hedging and dealing purposes. This indicates that an increase in derivative activities does not necessarily imply an increase in bank risk-taking when banks are involved in derivatives for hedging purposes. However, unavailability of detailed data that separates the nature of derivative activities is a major limitation of this study. With more detailed data, analysing the impact of capital adequacy regulations on banks' speculative derivative transactions is left to the future research.

In addition, the future work should determine the impact of the market risk capital regulations on bank capital levels and derivative activities on countries other than the US. Further empirical evidence on bank behaviour outside the US would be very useful in assessing other countries' experiences.

Another limitation of the study is that 15 banks were included in the panel data analysis. The reason for employing only 15 banks in the sample is the limited number of banks that are subject to the market risk capital regulations in the US. Therefore, with more observations from the US, depending on the availability of data, repeating the study is another issue that is left to future research.
The data set that was used in the simulations only cover currencies from developed countries. Therefore, employing data from other countries, especially from emerging countries, would be an interesting study, which is also left for the future research.

Finally, starting from 2007, Basel II will be implemented in the capital regulation framework. Analysing the impact of these regulations would extend our knowledge of the impact of capital adequacy regulations on bank behaviour.
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[www.fsa.gov.uk](http://www.fsa.gov.uk) (Financial Services Authority of the UK web site)

### Appendix 2.1: Derivative Instruments

Derivative instruments are off-balance sheet items whose value depends on the value of an underlying asset, which could be a financial asset or commodity. There are four major types of derivatives, namely forwards, futures, options and swaps. These are briefly explained below:

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Forwards</strong></td>
<td>Contracts that oblige the holder to buy or sell a specific underlying to a specified price, quantity and date in the future. These contracts are usually not standardised as the terms of each contract are negotiated individually between buyers and sellers. Forwards are over-the-counter (OTC) instruments and there are no organised exchanges for trading forward contracts, i.e. there is no interposition of clearing house that guarantees the parties of contracts will satisfy their obligations.</td>
</tr>
<tr>
<td><strong>Futures</strong></td>
<td>A futures contract is a form of forward in that it conveys the right to buy or sell a specified commodity or a financial instrument at a fixed price on a future date. The essential feature of futures contracts is that they standardise the quantity of underlying asset to be delivered per contract, the underlying commodity or financial instrument, the minimum price movement and the period of the contract. Unlike forwards, futures are exchange-traded instruments.</td>
</tr>
<tr>
<td><strong>Options</strong></td>
<td>An option is a contract between two parties, conveying the right to buy or sell a certain amount of a specified financial instrument or commodity at a fixed price and at a specified future date or during a specified period of time. An option contract is essentially a forward or futures transaction with the important difference that the buyer of the option acquires the right, but not the obligation, to exercise the contract at his/her own discretion. For enjoying this right, or option, the buyer pays a price or premium to the seller when the contract is made. Options may be purchased and traded either on the organised exchanges or in the OTC markets.</td>
</tr>
<tr>
<td><strong>Swaps</strong></td>
<td>A swap is a contract between two parties. While in the currency swaps parties exchange principal and interest payments in different currencies over a stated time period, interest rate swap parties exchange interest obligations in the same currency on an agreed amount of notional principal for an agreed period of time. Swaps are OTC instruments.</td>
</tr>
</tbody>
</table>
Appendix 2.2: FINANCIAL RISKS OF BANKS

The financial risks that the banks face in their activities are as follows:

<table>
<thead>
<tr>
<th>Risk Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market Risk</td>
<td>Market risk is the risk to an institution’s financial condition resulting from adverse changes in the value of its holdings arising from movements in interest rates, foreign exchange rates, equity prices, or commodity prices. These risks are explained in Appendix 2.4.</td>
</tr>
<tr>
<td>Credit Risk</td>
<td>Broadly defined, credit risk is the risk that a borrower, an issuer, or counterparty will fail to perform on an obligation to the institution. In managing credit risk, institutions should consider settlement and pre-settlement credit risk. These risks are the possibility that a counterparty will fail to honour its obligation at or before the time of settlement.</td>
</tr>
<tr>
<td>Liquidity Risk</td>
<td>Liquidity risk is the risk that an institution will be unable to meet its obligations as they come due because of an inability to liquidate assets or obtain adequate funding, or that it can not easily sell, unwind or offset a particular position at a fair price because of inadequate market dept.</td>
</tr>
<tr>
<td>Country Risk</td>
<td>Country risk is the risk that encompasses the entire spectrum of risks arising from the economic, social, and political environments of a foreign country that may have potential consequences for foreigner’s dept and equity investments in that country.</td>
</tr>
<tr>
<td>Operational Risk</td>
<td>Operational risk (which is also defined as transaction risk) is the risk that deficiencies in information systems or internal controls will result in unexpected loss. Sources of operating risk include inadequate information systems, breaches in internal controls, human error, system failure, or fraud.</td>
</tr>
<tr>
<td>Legal Risk</td>
<td>Legal Risk is the risk that unenforceable contracts (contracts are not legally enforceable or documented correctly), lawsuits, or adverse judgements can disrupt or otherwise negatively affect the operations or condition of the institution.</td>
</tr>
<tr>
<td>Reputational Risk</td>
<td>Reputational risk is the risk that negative publicity about the institution will cause a decline in the customer base or revenue reductions (make this related to the investment portfolio)</td>
</tr>
</tbody>
</table>

### Appendix 2.3: TYPES OF MARKET RISKS

<table>
<thead>
<tr>
<th>Type of Risk</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Interest-Rate Risk</strong></td>
<td>Interest-rate risk is the potential that changes in interest rates may adversely affect the value of a financial instrument or portfolio, or the condition of the institution as a whole. Risk in trading activities arises from open or unhedged positions and from imperfect correlations between offsetting positions. With regard to the interest rate risk, open positions arise most often from differences in the maturities or repricing dates of positions, and cash flows that are asset like (i.e. longs) and those that are liability like (i.e. shorts).</td>
</tr>
<tr>
<td><strong>Foreign-Exchange Risk</strong></td>
<td>Foreign-Exchange risk is the potential that movements in exchange rates may adversely affect the value of an institution's holdings and thus, its financial position. As with all market risks, foreign exchange risk arises from both open or imperfectly offset or hedged positions.</td>
</tr>
<tr>
<td><strong>Equity-Price Risk</strong></td>
<td>Equity-price risk is the potential for adverse changes in the value of an institution’s equity related holdings. Price risks associated with equities are often classified into two categories: general (or undiversifiable) and specific (or diversifiable). General equity price risk refers to the sensitivity of an instrument’s or portfolio’s value to changes in the overall level of equity prices. As such, general risk cannot be reduced by diversifying one’s holdings of equity instruments. Specific equity price risk refers to that portion of an individual equity instrument’s price volatility that is determined by the firm specific characteristics. This risk is distinct from market wide price fluctuations and can be reduced by diversification across other equity instruments.</td>
</tr>
<tr>
<td><strong>Commodity-Price Risk</strong></td>
<td>Commodity price risk is the potential for adverse changes in the value of an institution’s commodity related holdings. Most commodities are traded in markets in which the concentration of supply can magnify price volatility. Moreover, fluctuations in market liquidity often accompany high price volatility. Therefore, commodity prices generally have higher volatilities and larger price discontinuities than most commonly traded financial assets.</td>
</tr>
</tbody>
</table>

## Appendix 2.4: Regulatory Measures and Regulatory Objectives

<table>
<thead>
<tr>
<th>Regulatory Measures</th>
<th>Systemic Risk</th>
<th>Investor Protection</th>
<th>Efficiency Enhancement</th>
<th>Broader Social Objectives</th>
</tr>
</thead>
<tbody>
<tr>
<td>Antitrust enforcement/ competition policy</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Asset restrictions</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capital adequacy standards</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conduct of business rules</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Conflict of interest rules</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Customer suitability requirements</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fit and proper entry tests</td>
<td>✓</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Interest rate ceilings on deposits</td>
<td></td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interest rate ceilings on loans</td>
<td></td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Investment requirements</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liquidity requirements</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reporting requirements for large transactions</td>
<td></td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reserve requirements</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Restrictions on geographic reach</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Restrictions on services and product lines</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Adopted from Allen and Herring, 2001*
## Appendix 4.1: Comparison of Value at Risk Methodologies

<table>
<thead>
<tr>
<th></th>
<th>Variance-Covariance</th>
<th>Historical Simulation</th>
<th>Monte Carlo Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Able to capture the risks of</td>
<td>No, except when computed using a short holding period for</td>
<td>Yes, regardless of the options content of the portfolio.</td>
<td>Yes, regardless of the options content of the portfolio</td>
</tr>
<tr>
<td>portfolios which include</td>
<td>holding period for portfolios with limited or moderate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>options</td>
<td>options content</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Easy to implement</td>
<td>Yes, for portfolios restricted to instruments and</td>
<td>Yes, for portfolios for which data on the past values of</td>
<td>Yes, for portfolios restricted to instruments and</td>
</tr>
<tr>
<td></td>
<td>currencies covered by available &quot;off-the-shelf&quot; software.</td>
<td>the market factors are available.</td>
<td>currencies covered by available &quot;off-the-shelf&quot; software.</td>
</tr>
<tr>
<td></td>
<td>Otherwise reasonably easy to moderately difficult to</td>
<td></td>
<td>Otherwise moderately to extremely difficult to implement.</td>
</tr>
<tr>
<td></td>
<td>implement, depending upon the complexity of the</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>instruments and availability of the data.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Computations performed quickly</td>
<td>Yes</td>
<td>Yes</td>
<td>No, except for relatively small portfolios</td>
</tr>
<tr>
<td>Easy to explain to senior</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>management</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Produces misleading value at</td>
<td>Yes, except that alternative correlations / standard</td>
<td>Yes</td>
<td>Yes, except that alternative estimates of</td>
</tr>
<tr>
<td>risk estimates when recent past</td>
<td>deviations may be used.</td>
<td></td>
<td>parameters may be used.</td>
</tr>
<tr>
<td>is atypical.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Easy to perform “what if”</td>
<td>Easily able to examine alternative assumptions about</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>analyses to examine effect of</td>
<td>correlations / standard deviations. Unable to examine</td>
<td></td>
<td></td>
</tr>
<tr>
<td>alternative assumptions</td>
<td>alternative assumptions about the distribution of the</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>market factors, i.e. distributions other than the normal</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Adopted from Linsmeier & Pearson (1996)
Appendix 7.1: Disclosure Recommendations for Market Risk

Market Risk - Qualitative Disclosures
- Discuss the methods used to measure and manage market risk
- Discuss how performance in managing market risk is assessed
- Describe the major assumptions and parameters used by internal models necessary to understand an institution's market risk disclosures
  - Type of model used
  - Portfolios covered by the model
  - Holding period
  - Confidence level
  - Observation period
- Discuss the method of aggregating risk exposures
- Discuss the method used to recognise correlations between market factors (e.g. correlation assumptions)
- Provide an overview of policies and procedures for validating internal models
- Provide an overview of policies and procedures for back testing internal models
- Provide an overview of policies and procedures for stress testing market risk
- Discuss changes in market risk exposure and risk management strategies from previous year

Market Risk - Quantitative Disclosures
- Provide summary quantitative information on market risk exposure based on internal methods used for measurement, with information on performance in managing those risks
- Provide daily information on profit and losses on trading activities, combined with daily value at risk numbers
- Provide summary VaR results on a weekly or monthly basis
- For those disclosing VaR data, provide high / low VaR
- For those disclosing VaR data, provide average VaR
- Discuss the results of scenario analysis or impact of rate shocks for traded portfolios
- Discuss the number of times (days) actual portfolio loss exceeded VaR
- For non-traded portfolio: provide summary VaR or EaR
- For non-traded portfolios: provide summary results of scenario analysis of impact of rate shocks
Appendix 8.1: Backtesting Graphs of Different Models (1)
Appendix 8.1: Backtesting Graphs of Different Models (2)
Appendix 8.1: Backtesting Graphs of Different Models (3)