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**An Examination of Large Commercial Banks within G-10:  
Risk, Efficiency, and the 1996 Market Risk Amendment**

**Submitted by**

**Michael Forsyth**

**Presented to the Faculty of the Aberdeen Business School, The Robert Gordon  
University in fulfilment of the requirements for the degree of Doctor of  
Philosophy**

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Please note that any errors in this thesis are mine.

## **Abstract**

### **An Examination of Large Commercial Banks within G-10: Risk, Efficiency, and the 1996 Market Risk Amendment**

**Author: Michael Forsyth, in fulfilment of the requirements  
for the degree of Doctor of Philosophy**

The financial industry changed significantly through the 1990s as commercial banks pursued additional profits through non-traditional and off-balance sheet (OBS) activity. The regulatory bodies had to accept the changing risk nature of the industry and the response was the introduction of the 1996 Market Risk Amendment (MRA) by the Basle Committee. The MRA, through a series of 4 key announcements, was reached in January 1996 and fully implemented from January 1997, whereby banks were required to hold incremental capital to cover unexpected losses from market risk. In this study a multivariate regression model is used to investigate the effect of the MRA announcements on the returns to shareholders of commercial banks within G-10 countries (Belgium, Canada, France, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States). The empirical results suggest that bank shareholders in Italy, Sweden, and especially Japan benefited from the introduction of the MRA, while bank shareholders in the United Kingdom, Canada, and especially US experienced significant losses from 4 announcements that led to the final proposal of the 1996 MRA.

The significant growth in income generated through OBS activities, such as trading and fee-based income, changed the risk profile financial institutions. This study employs four VaR methodologies (parametric, historical simulation, Monte Carlo simulation, and Extreme Value Theory) to calculate bank risk in a period of high

financial market volatility: 1992 through to 1998. The results show a strong increase in VaR for the years 1997 and 1998, with Japan showing the largest risk ranking over the period, while the US and Sweden were at the low end of the risk range. The VaR results indicate it may be misleading to compare risk scores across financial institutions if the reported numbers are based on different VaR methodologies. The results from the Monte Carlo (MC) and Extreme Value Theory (EVT) approaches result in the highest VaR estimates, while the parametric results were consistently lower.

This thesis also employed Data Envelopment Analysis (DEA) to compute bank-level technical efficiency under Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) between 1992 and 1998. The results for the entire bank sample across the period of study show inefficiency levels of 39% and 33%, under CRS and VRS respectively. The inclusion of off-balance sheet (OBS) activity in the DEA score is found to be significant, and indicate that the exclusion of this variable as an output leads to a misspecification and underestimation of bank efficiency. A Tobit regression approach was used to examine the relationship between bank efficiency and various bank and environmental variables. The second stage findings show that inflation is detrimental to bank efficiency, while a negative relationship is found between VaR and efficiency, indicating inefficient banks appear to take on less risk. A positive relationship is found between the MRA dummy variable and bank efficiency.

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# *Chapter 1*

## *INTRODUCTION*

### **I Background**

The nature of bank risk changed significantly throughout the 1990s as commercial banks focused more on non-traditional activities such as trading income and off-balance-sheet activity (OBS) in order to generate additional revenues. Avery and Berger (1991) and Koppenhaver and Stover (1991) noted that banks are able to increase risk, and therefore expected return, through greater derivative exposure. DeYoung and Roland (2001) found that non-interest income has accounted for a growing share of bank revenue.

The main sources of non-interest income are fee and commission revenues, with net trading income a dominant factor. The dramatic rise in non-interest revenues has arisen from investment banking, trading, and brokering. Culp and Mackay (1994) emphasise that the innovation and growth in OBSA has yielded substantial gains to the US economy by enabling firms to lower the cost of funding and diversify their funding sources, whilst improving their competitive position.

However, evidence has shown that by expanding the scope of non-traditional activities, overall risk levels within the banking industry have increased. For example, Peek and Rosengren (1997) found that banks active in the derivatives market have lower capital levels and inherently more risk. Wall, Reichel, and Mohanty (1993) found that expansion into non-traditional banking activities impedes bank efficiency, and the level of profitability gained from taking additional risk is not worthwhile. Sinkey and Carter (2000) also found that banks engaging in derivative activities tend

to be larger in size, and have weaker capital levels, smaller maturity gaps, and reduced net interest margins.

The changing nature of commercial banking into non-traditional activities, in particular OBSA, challenged regulators to adopt a more innovative approach to bank capital regulation. The Basle Committee on Banking Supervision is a regulatory body created by the central bank Governors of the Group of Ten nations. The Group of Ten is made up of eleven industrial countries (Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States). The purpose of the Basle Committee is to encourage convergence toward common approaches and standards, and to recommend statements of best practice in banking supervision. The Basle Committee does not have legislative authority, but member countries are implicitly bound to put into practice its recommendations. The committee does allow for some flexibility in how national authorities implement these recommendations.

In 1988, the Basle Committee proposed a set of minimal capital requirements for banks. These requirements came into effect in 1992; with Japanese banks being permitted an extended transition period because of their capital deficiency. The requirements addressed credit risk and the risk of a counterparty defaulting on its obligations, and have come to be known as the 1988 Basle Accord. The aim of the Accord was to ensure that financial institutions retain enough capital to protect themselves against unexpected losses from default risk. The main strength of the Basle Accord was its simplicity in requiring a minimum 8% capital holding level.

However, this simplicity enabled banks to take advantage of loopholes and faults, resulting in an additional burden to the financial system.

In the early 1990s, the Basle Committee decided to update the 1988 Accord to include bank capital requirements for market risk, which is the risk to an institution's financial condition resulting from adverse movements in the level or volatility of interest rate instruments, equities, commodities, and currencies. It is fundamentally different from credit risk, the traditional basis for banking regulation, which requires a relatively straightforward judgment about the likelihood of a borrower defaulting. The Basle Committee released a series of proposed amendments to the 1988 Accord, whereby banks were required to separate and identify a banking book and a trading book and hold capital specifically for trading book market risks. The Amendment prescribed that banks use a Value-at-Risk (VaR) methodology to determine the percentage of capital needed to cover trading book risk. VaR is a risk measurement tool used to calculate the worst possible loss to a portfolio within a certain confidence limit.

## **II Objectives and contributions**

The thesis has three main objectives: first, to evaluate the reaction of commercial banks to the Basle Committee's 1996 Market Risk Amendment; second, to examine and measure bank risk, by calculating each bank's VaR using four different methodologies over the time-frame 1992 to 1998; and third, to evaluate bank efficiency throughout the six-year period, while including an examination of OBS activity. The study also takes into account the determinants of bank efficiency.

The first objective of this thesis is to evaluate the reaction of commercial banks to the Basle Committee's 1996 Market Risk Amendment. This Amendment was the first to allow banks to use their own methodology and risk models to manage capital and risk. The reaction to the Amendment is examined with the primary aim of measuring the impact this regulation had on bank stock market returns. This study differs from existing capital regulation literature in several ways: First, it considers a sample of large commercial banks in eleven developed countries as opposed to being limited to one specific country; Second, it examines the shareholder reactions over a period of time, specifically from the initial market risk proposal in April 1993 through to the finalisation of the Amendment in January 1996; Third, it examines the financial impact of a change in bank capital regulation, which should enhance our understanding of the impact of regulatory changes in the future, for example the impact of Basle II; Fourth, little is known about how banks have reacted to the MRA, therefore, this study should be of interest to regulators, governments, and the investment community.

The second key objective of this thesis is the examination and measurement of bank risk in relation to their pursuit of non-traditional activities. Theoretically, the ideal of risk measurement is clear, however, in practice it is difficult to formalize and quantify. Financial institutions are subject to many sources of risk, including credit risk, operational risk, liquidity risk, and market risk. The most prominent of these risks in trading is market risk, as it reflects the potential losses caused by the change in value of interest rates, equity markets, or foreign exchange rates. Throughout the 1990s the growth of trading activity in financial markets, in addition to periods of economic instability, and a number of widely publicized trading losses resulted in a

re-analysis by academics and investors of the risks financial institutions face, and how they are measured. Edwards and Mishkin (1995) argue that banks must take on greater levels of risk due to declines in traditional banking and associated reductions in profit levels. The changes that are taking place within the banking system may provide incentives for, or impose the need for, assuming a higher risk profile. Simmons (1995), and Chaudhry and Reichert (1999) argue that derivative instruments and non-traditional activity leads to higher bank risk. In contrast, numerous studies have found that the use of derivatives and OBSA have reduced the interest-rate and currency exposure of banks (Shanker, 1996; Venkatachalam, 1996; Choi and Elyasiani, 1997).

There is a lack of empirical evidence in relation to how the risk levels of banks has changed as these institutions have moved away from the more traditional aspects of banking. Furthermore, existing commercial bank risk literature is predominantly limited to U.S. banks. This study utilises VaR methodology to investigate the riskiness of commercial banks within G-10 countries. The VaR method is now tagged as a modern and robust methodology for measuring financial risk and is used to calculate how much a financial institution can lose with a probability  $p$  over a given time-horizon. This method is popular due to its conceptual simplicity and its ability to reduce the financial risk associated with a given position or portfolio down to just one number. Furthermore, the Basle Committee endorsed the VaR approach for measuring market risk, thus increasing its credibility.

VaR can be calculated in numerous ways and its value depends on the assumptions made and models used. The most common classification of VaR methods found in the

literature is that of parametric VaR estimates, historical simulation (non-parametric), and Monte Carlo simulation (non-parametric). The three methods are complementary, but each offers a different view of risk and much debate has focused on which method is more robust. Ideally, an institution would calculate all three methods in order to obtain the most accurate picture of their risk exposure. In addition, Dowd (1999), and Ho (2000) proposed a third non-parametric approach to calculate VaR: Extreme Value Theory (EVT). The thesis employs all four VaR approaches in order to obtain an accurate and valid measure of how bank risk changed during the period 1992 to 1998.

A number of conclusions will come from the analysis of VaR. First, to examine the changing nature of bank risk throughout the 1990s; Second, to determine which country has the riskiest banks; Third, to assess which year was the most volatile in terms of bank risk; Fourth, which VaR method produces the highest risk score, and whether there are important differences in VaR results when these alternative methodological approaches are utilised.

This thesis measures the changing nature of bank risk based on each bank's exposure to interest rate risk, equity risk and foreign exchange risk. Bank risk is measured for a sample of international commercial banks, and direct comparisons can be made for each bank's VaR. The period studied, 1992 to 1998, represents a time when banks were changing the nature of their business and ultimately their risk profile. Therefore, comparisons can be made of each bank's VaR over time. In addition, this study is one of the first to explicitly consider the risk profile of large commercial banks within G-10, using both parametric and non-parametric VaR techniques. Each of the four VaR

methodologies is employed to estimate each bank's weekly VaR based on the impact on equity value of changes in interest rates, equity market volatility, and foreign exchange rate movements.

In addition to studying how the risk profile of banks has changed, the third key objective of this thesis is to examine bank efficiency levels. This thesis applies Data Envelopment Analysis (DEA) to evaluate the efficiency of large commercial banks in G-10 countries for the period 1992 to 1998. DEA is a relatively new technique that measures the relative efficiency of each bank by comparing it to an efficient frontier based on an optimal set of input/output variables taken from the bank sample studied. Given the fact that banks are changing rapidly, it is of considerable interest to measure the efficiency of evolving institutions, and to explain measured variation in the efficiency of institutions.

The research on efficiency in financial institutions is extensive. While multiple studies have examined efficiency levels of various types of banks, and across many countries, very few have focused on commercial banks specifically within G-10. The majority of studies have focused on commercial banks in the U.S. or in Europe, whereas this study considers Canadian and Japanese institutions in addition to U.S. and European banks.

A key contribution of this thesis is the inclusion of non-traditional activities in the efficiency analysis. Most efficiency studies measure bank output via traditional activities, such as loan generation and deposit investment. Commercial banks now focus more on non-traditional business such as derivatives activity, wealth



management, and trading. The exclusion of these OBSA results in an inaccurate efficient frontier. Clark and Siems (2002) measured the impact of off-balance-sheet activities on the efficiency measure of banks and found that such activities are important determinants in explaining bank efficiency.

Financial institutions around the world have experienced substantial changes. Technological progress, reduced information costs, stronger competition and significant deregulation all led to substantial changes. Typically, commercial banks have expanded into non-traditional banking activity. It is accepted in the literature (Berger and Humphrey, 1997) that efficiency measures for both parametric and non-parametric approaches have significant advantages over accounting ratios for measuring performance. To assess banks' ability to increase profitability and risk while conforming to new regulation and global competition is very important. Both regulators and practitioners rely increasingly on efficiency analysis to measure bank performance and compare institutions. This study uses DEA, a non-parametric technique, to measure efficiency levels of G-10 commercial banks. Furthermore, second stage analysis examines the relationship between bank efficiency, risk and regulation.

DEA is a data-driven approach and the location and shape of the efficient frontier is determined by the data sample. The construction of the frontier is based on a 'best observed practice' and is therefore only an approximation to the true, unobserved efficient frontier. The reason being that the frontier is made up of data observations of ratios of output to input and the efficient frontier is defined by these ratios. Being a non-parametric technique, DEA has the advantage of requiring no assumptions about

the functional form and that it needs no assumptions regarding the probability distribution of the error terms, which avoids potential estimation bias.

However, this does not avoid the problem of how to assess the quality of the DEA model and how the results reflect reality. The implications from using a non-parametric approach is: 1) As DEA is deterministic, this method does not take into account statistical error, random shocks or noise; 2) Results are sensitive to model specification, particularly in small samples; 3) It is critical to be clear about what variables should be classified and included as inputs and similarly so for outputs; 4) Not only the choice of but also the number of banks will affect efficiency evaluations. The central concern when judging the quality of a DEA model is that it should be formulated based on the purpose for which the results will be used.

In sum, the third objective of this thesis is to investigate bank efficiency levels, including OBSA in the analysis. This study contributes to the existing literature: First, by employing a non-parametric DEA approach to compare the efficiency scores across G-10 banks, and to determine the rank scores of bank efficiency by country; Second, by examining the change in efficiency of G-10 banks during the period 1992 to 1998; Third, by establishing if differences in efficiency between G-10 countries are the result of their respective economic environments. Dietsch and Lozano-Vivas (2000) have shown that country-specific environmental variables may explain efficiency gaps between countries; Fourth, by investigating the impact of OBSA on bank efficiency using a DEA input-oriented model across all G-10 countries; Fifth, by using a tobit regression approach, this study attempts to determine whether a bank's

efficiency level is dependent on its VaR. Sixth, a dummy variable is included to assess the impact of the 1996 MRA on bank efficiency.

To summarise, the three main objectives of this thesis are:

- To evaluate the reaction of commercial banks to the Basle Committee's 1996 Market Risk Amendment.
- To examine and measure bank risk, including the risks associated with OBSA, by calculating each bank's VaR using four different approaches over the time frame 1992 to 1998.
- To determine the change and determinants of commercial bank efficiency levels throughout the six-year study period.

The outline of the thesis is as follows: This first chapter has presented the research problem and clarified the objectives of this thesis; Chapter 2 provides a literature review and hypotheses surrounding each key objective of the thesis; Chapter 3 presents the methodologies used in this study and the main concepts of event study, Value-at-Risk (VaR), and Data Envelopment Analysis (DEA) are explained; Chapter 4 presents the empirical results and a discussion of the findings; Chapter 5 presents conclusions and directions for future research.

## *Chapter 2*

### ***LITERATURE REVIEW***

#### ***2.1 The 1996 Market Risk Amendment (MRA) and Bank Capital Regulation***

##### **I Introduction**

The changing nature of commercial banking into non-traditional activities, in particular off-balance sheet activities (OBS), challenged regulators to adopt a more innovative approach to bank capital regulation. The Basle Committee on Banking Supervision is a regulatory body created by the central bank Governors of the Group of Ten nations. The Group of Ten is made up of eleven industrial countries (Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States). The purpose of the Basle Committee is to encourage convergence toward common approaches and standards, and to recommend statements of best practice in banking supervision. The Basle Committee does not have legislative authority, but member countries are implicitly bound to put into practice its recommendations that are designed to ensure that banks operate in a safe and secure manner. The Basle Committee's proposals aim for international convergence in terms of regulatory standards, but the committee does allow for some flexibility in how national authorities implement these recommendations.

In 1988, the Basle Committee proposed a set of minimal capital requirements for banks. These requirements came into effect in 1992 with Japanese banks being permitted an extended transition period because of their capital deficiency. The requirements addressed credit risk and the risk of a counterparty defaulting on its obligations, and have come to be known as the 1988 Basle Accord. The aim of the Accord was to ensure that financial institutions retain enough capital to protect

themselves against unexpected losses from default risk. The main strength of the Basle Accord was its simplicity in requiring a minimum 8% capital holding level. However, this simplicity enabled banks to take advantage of loopholes and faults, resulting in an additional burden to the financial system. The Accord was voluntary, specified four tiers of capital, and was applied to international banks.

In the early 1990s, the Basle Committee decided to update the 1988 Accord to include bank capital requirements for market risk, which is the risk to an institution's financial condition resulting from adverse movements in the level or volatility of interest rate instruments, equities, commodities, and currencies. In this way, market risk is fundamentally different from credit risk, the traditional basis for banking regulation, which requires a relatively straightforward judgment about the likelihood of a borrower defaulting. The Basle Committee released a series of proposed amendments to the 1988 Accord, whereby banks were required to separate and identify a banking book and a trading book and hold capital specifically for the trading book's market risk. The Basle Committee's 1996 Market Risk Amendment prescribed that banks use a Value-at-Risk (VaR) methodology to determine the percentage of capital needed to cover trading book risk. VaR is a risk measurement tool used to calculate the worst possible loss to a portfolio within a certain confidence limit.

Prudential regulation has been strengthened substantially, especially in the area of minimum capital standards. New regulation, namely through Basle II, has offered a tool to strengthen risk disclosures and market discipline. However, the implementation of Basle II remains a problem based on current financial turmoil and the wide variety of risk exposures financial institutions have. Furthermore, regulators

must also rely on market discipline to motivate prudent management by enhancing the degree of transparency in banks' public reporting. This can be achieved by public disclosures that banks must make to lend greater insight into the adequacy of their capitalisation.

One of the key problems, and what supervisors have been working on for sometime, is the lack of convergence in supervisory practices, across different banks and countries. In terms of G-10 countries there is not a uniform reporting structure with respect to all the activities commercial banks are allowed to pursue. On the positive side, this means that common patterns that emerge from an international comparison are informative for a regulatory and efficiency debate. However, it is important to note the influence of each country's environmental factors (economy, lending practices, country-specific regulation) on measures of bank risk, efficiency and overall performance. Differences in regulations, institutions and market structures across countries mean that conclusions drawn from the analysis of one country should be generalised to others only very carefully.

Barth, Caprio, and Levine (2006) conducted a survey on bank regulation and supervision practices across countries. It could be possible to use this survey in future research to assess banks that have been exposed to external audits, degree of transparency within their financial statements, and also the use of external credit ratings and reliance on credit monitoring. It would also be useful to examine whether a country has explicit regulatory requirements for the amount of capital that a bank must maintain relative to common guidelines. Other measures which could be examined are whether a country has laws establishing pre-determined levels of bank

solvency; the extent of each country's government safety net that act as deposit insurance systems. One other interesting point to examine would be the fraction of banks in a country that is government owned, especially to the extent to which a country's ownership structure influences its bank capital ratio and the types of nontraditional activities pursued.

The first objective of this thesis is to evaluate the reaction of commercial banks to the Basle Committee's 1996 Market Risk Amendment. This Amendment was the first to allow banks to use their own methodology and risk models to manage capital and risk. The Amendment is examined with the primary aim of measuring the impact this regulation had on bank stock market returns. This study differs from existing capital regulation literature in several ways: First, it considers a sample of large commercial banks in eleven developed countries as opposed to being limited to one specific country; second, it examines the reactions of banks over a period of time, specifically from the initial market risk proposal in April 1993 through to the finalisation of the Amendment in January 1996; third, it examines the financial impact of a change in bank capital regulation, which should enhance our understanding of the impact of regulatory changes in the future, for example the impact of Basle II, the finalized version of which was released in 2004; fourth, little is known about how banks have reacted to the Amendment, therefore, this study should be of interest to regulators, governments, and the investment community.

## **II The Basle Committee's Amendment to the 1988 Basle Accord**

### *(i) The Standardised Approach (April 1993 Proposal)*

The Basle Committee on Banking Supervision published "The Supervisory Treatment of Market Risk" in April 1993 and proposed a standardized market risk measurement framework. This framework separated market risk into four asset classes; interest rate positions, equity market positions, currency positions, and commodity positions, with separate calculation methods for each asset class. Therefore, capital requirements for interest rate positions are calculated on the basis of interest rate sensitivity with a standard set of assumed volatilities in the yield curve. The capital requirement on equity market risk is calculated on every position from an individual equity basis. The currency risk capital requirement is calculated as a percentage of a bank's net open position in each currency. The commodity risk requirement is calculated as a percentage of a bank's open position in each commodity plus a requirement for maturity mismatch of the contracts.

### *(ii) The Internal Models Approach (April 1995 Proposal)*

In April 1995, the Basle Committee released a revised proposal making a number of changes. An important provision, the internal models approach, allowed banks to use either their own proprietary VaR risk model, as opposed to a standardized approach, for calculating market risk capital requirements. The use of a proprietary VaR measure required regulatory approval where a bank was subject to an independent risk management evaluation to prove it was following acceptable risk management practices. Market risk capital requirements were now set to the greater of the previous day's VaR, or the average VaR over the previous sixty business days, multiplied by a factor of at least three. Proprietary measures would need to support a 10-day 99%



VaR metric and also address the non-linear exposures of options. Diversification effects could be recognized within broad asset classes – fixed income, equity, foreign exchange, and commodities. Regulators also allowed banks to correlate risk across products or asset classes, reducing the capital required.

The capital charge for banks that use in-house models is three times the daily VaR of the preceding 60 days. Multiplying by a factor of three ensures banks set aside considerably more capital. A number of banks unsuccessfully lobbied for a reduction in the multiplier. Factors that could influence the estimation of risk, such as flawed distribution assumptions, the inadequacy of past events as a guide to future events, and extreme market movements may hinder the accuracy of a VaR calculation. However, the multiplication factor of three, which was designed to account for all the potential shortcomings in the modelling process, was arbitrary and weak (Walwyn and Litterman, 1998).

The calculation of VaR is based upon a 10-day holding period for any transaction, however, as the holding period for many trades is less than ten days, this is unrealistic. Furthermore, the proposal does instruct banks which VaR method to use i.e. the parametric, historical simulation, or Monte Carlo methods. The Basle Committee opted for 99 percent confidence intervals, meaning that 99 percent of the time the bank would not lose more money than the calculated VaR. However, the risk is that banks might rely too heavily on the VaR number to represent their maximum possible losses. Perhaps a lower confidence level would have been more realistic and provided better signals to banks regarding the level of reliance that can be placed on the VaR figure.

The 1996 Amendment to the Basle Accord ensures a bank's minimum capital requirement takes into consideration market risk and the current trend for increased trading activity. There is a gap in the research concerning the effect the Amendment has had on the stock prices of commercial banks, which this study seeks to address. The reaction of banks in Japan, Canada, the United States, and Europe will be examined in terms of abnormal returns surrounding the four major announcements leading up to the Basle Committee's final proposal. Analyzing and clarifying the drivers of abnormal returns during these periods should provide a better understanding of the impact bank capital regulation changes have on banks within G-10.

### **III Controversy surrounding the Market Risk Amendment**

Much debate has focused on The Basle Committee's approach for the calculation of VaR, particularly in regard to the pre-commitment approach (PCA) versus the internal models approach. The PCA has a pre-determined time period, where a bank is allowed to represent its VaR within certain parameters over a fixed time period. At the conclusion of each fixed time period, the bank's minimum net capital level must be increased or decreased by an amount equal to the difference between the actualized VaR and the model's projections. Kupiec and O'Brien (1997) were advocates of the pre-commitment approach, whereas Gumerlock (1996) argued that the Basle Committee's regulatory mechanisms for measuring and monitoring market risk are superior to that of the pre-commitment approach.

The 1996 Amendment increased the likelihood that banks might underreport market risk exposure in order to lessen their capital burden. Lucas (2001) found evidence that

banks were indeed underreporting market risk and questioned the effectiveness of the regulatory body's back-testing procedures and penalty system. A more stringent penalty scheme might give banks greater incentive to provide more accurate risk metrics. However, imposing penalties for VaR inaccuracies may deter banks from adhering to the regulatory system. It is also important for regulators to consider the possibility of severe market fluctuations before imposing harsher penalties.

Gizycki and Hereford (1998) note that one advantage of the 1996 Amendment is that it enabled banks to use their own quantitative internal risk model, thus adding flexibility to risk measurement. However, although the Amendment is applicable to the trading book, most banks hold interest rate risk on their banking book. As a result, the requirement for capital to be set aside for a trading book's market risk provides the incentive for banks to allocate more risk to their banking book, resulting in regulatory capital arbitrage. Nevertheless, it can also be argued that the regulatory risk-based capital standards have increased risk awareness overall, and led to the development of more sophisticated risk models.

In sum, there is much disagreement across the literature concerning the Amendment to the Basle Accord. This study moves away from a theoretical standpoint and examines the actual impact on bank returns in the event window surrounding each major proposal leading up to the Amendment. The next section comprises a discussion of previous literature examining the effects of bank capital regulation changes prior to the 1996 Amendment.

#### **IV The Reaction to Bank Capital Regulation**

According to Chiuri, Ferri, and Majnoni (2001) it is widely acknowledged that changes to bank capital regulation have an impact on bank behaviour. Their school of thought is that the introduction of capital will improve the resilience of banks to negative financial shocks. However, the authors go on to mention another aspect concerning bank risk taking behaviour, whereby the capital buffer may encourage banks to take on more risk.

Eyssell and Arshadi (1990) examined the stock price reaction of 27 leading US banks to three of the Basle Committee's major bank capital regulation announcements during the period 1986-88. The authors found significant negative returns surrounding these announcements. Madura and Zarruk (1993) found similar negative returns, more so for larger banks. Cooper, Kolari and Wagster (1991) studied the effects of capital requirements on the share prices of banks in Canada, Japan, the United Kingdom, and the United States for twelve announcements during the period January 1987 to July 1988. Their findings show significant declines in the equity returns of US, Canadian and UK banks, with the US banks showing the strongest reaction. In the case of Japanese banks, the evidence is inconclusive, and the authors put this down to investor uncertainty regarding hidden reserves.

Wagster (1996) examined eighteen news announcements leading up to the 1988 Basle Accord and the reaction of 57 banks from 7 countries. The main impact found was a cumulative wealth gain of 32% in the Japanese bank sample. Wagster (1996) assumed that the market perceived the Accord as confirming the competitive edge Japanese banks had over their counterparts in terms of market share gains: If Japanese banks

needed to raise additional capital as a result of the regulation, it would pose little difficulty due to their strong existing reserves. Lu, Shen, and So (1999) analysed the impact the Basle Accord had on the returns of small banks. They hypothesized that previous regulation inhibited smaller banks, and the new regulation allowed these banks to diversify and expand their asset base. Consistent with the authors' hypothesis, the reactions from smaller banks to the announcements were positive. Lu, Shen, and So (1999) also reported a negative reaction by the larger banks in the sample, supporting previous literature (Madura and Zarruk (1993)).

Other studies have looked at bank equity returns in terms of changes in market conditions, policies, and regulatory schemes. Madura and Schnusenberg (2000) investigate how changes in the federal funds target-rate levels affect commercial banks' stock prices. They found that an inverse relationship exists, dependent on the size of the bank and its present capital levels. Biswass, Fraser, and Hebb (2000) examine the changes in deposit insurance premiums in the early 1990s on bank returns. The authors found that increases (decreases) in the premium resulted in decreases (increases) in the market values of the banks studied. Larger banks were most affected by this due to their tendency to operate with low levels of equity capital. Bhargava & Fraser (1998) study the stock market reaction related to four Federal Reserve decisions allowing Bank Holding Companies (BHC) to engage in investment banking and expand the nature of their business. The reaction to this regulation was significantly negative, owing to the increase in market risk exposure along with the added burden to the federal safety net.

The evidence from these empirical studies, which concentrate mainly on bank capital regulation in place prior to the 1996 Amendment, is predominantly negative overall. To date there has been little literature examining the impact of the announcements leading up to the 1996 Amendment of the Basle Accord; one of the key objectives of this thesis is to address this omission.

Based on the previous literature the following hypotheses are formed in relation to the 1996 Market Risk Amendment and the impact on bank equity values:

*The 1<sup>st</sup> Announcement: The Basle Committee issued a framework for applying capital charges to commercial banks' market risk.*

*Announcement Date: 15<sup>th</sup> April 1993.*

In April 1993 the Basle Committee on Banking Supervision issued its first paper entitled 'The Supervisory Treatment of Market Risks'. The Committee proposed a structure for applying capital charges to market risk. The Committee envisaged the use of a 'standardized methodology', that is to calculate the net position in each financial contract (interest rate, equity, or currency) and multiply by 8%. However, the standardized approach fails to take into account the most accurate risk management techniques and is not sophisticated enough to consider correlations and portfolio effects across instruments and markets. As a result, this regulation reduces any competitive advantage banks have built up in terms of risk management and reporting practices.

*Hypothesis 1a:* Large commercial banks within G-10 will experience significant negative abnormal returns from the first Basle Committee bank capital regulation

announcement in regard to market risk.

*The 2<sup>nd</sup> Announcement: The Basle Committee provides banks with the option to use an internal models approach for allocating capital to market risk.*

*Announcement Date: 28<sup>th</sup> April 1995.*

The internal models approach enables the determination of a bank's capital requirement on the basis of its internal risk measurement systems. Under this framework, financial institutions are required to report a daily Value-at-Risk (VaR) figure at the 99 percent confidence level calculated over a ten trading-day period. The minimum capital requirement on a given day is equal to a multiple of the average reported 10-day VaR in the past 60 trading days. The use of internal models represents a major departure from previous regulatory regimes, allowing for more flexibility by moving away from a uniform supervisory standardized approach. The internal models approach ensures a more transparent reporting system, as all banks must calculate VaR. This allows a direct comparison between the risk levels of various institutions (Gizycki and Hereford, 1998). In addition, some banks may not be as advanced as others and may not have the necessary resources to facilitate an internal models approach. In addition, the 10-day 99 percent confidence level is based predominantly on an assumption of normal returns, and therefore does not consider extreme event risk. In sum, the proposal is innovative and the first to pass risk measurement control over to the industry, however, the internal models can result in banks' under-reporting risk and thereby the amount of capital allocated to market risk.

Hypothesis 2a: The reaction to this proposal is expected to be significantly negative due to the VaR methodology not being sophisticated enough to capture extreme risk, in addition to providing an incentive for banks to underreport their risk.

*The 3<sup>rd</sup> Announcement: The first public disclosure of the trading activities of Commercial Banks and Securities Firms. A joint report published by the Basle Committee and The International Organisation of Securities Commissions (IOSCO).*

*Announcement Date: 28<sup>th</sup> November 1995.*

The Basle Committee and IOSCO surveyed the trading activities of a sample of large commercial banks and securities firms within G-10 and was one of the first to address the issue of derivative trading complexity. The findings showed that the trading activities of these banks had grown rapidly and become much more complex in recent years. The findings stressed the need for banks to provide regulators with more transparent qualitative and quantitative reports of the risks that were being taken. Furthermore, market participants should be able to assess a bank's performance in managing exposures to credit risk and market risk as well as the impact of trading derivatives activities on earnings. The report stressed that meaningful public disclosures play an important role in helping supervisors foster financial market stability.

Hypothesis 3a: The reaction to this report is expected to be positive because it increased the level of transparency for risk within the financial system, while providing solutions for future risk measurement and reporting practices that would benefit both regulators and the investment community.



*The 4<sup>th</sup> Announcement: The final Amendment to the Capital Accord to incorporate Market Risk. A companion paper was also released describing the way in which G-10 supervisory authorities plan to use 'back-testing' (ex-post comparisons between model results and actual performance) in conjunction with banks' internal risk measurement systems as a basis for applying capital charges.*

*Announcement Date: 4<sup>th</sup> January 1996.*

The objective in introducing this significant amendment to the Capital Accord is to provide an explicit capital cushion to bolster banks against the risk exposure associated with trading derivatives. This additional capital requirement is expected to strengthen the soundness and stability of the international banking system. Furthermore, the amendment enforces a set of strict qualitative standards to guide the process by which banks calculate and report their market risk capital requirements.

By allowing banks to calculate their own capital levels through an internal models VaR methodology, the Basle Committee did not recognise that market price movements are not always normally distributed and may display fat tails, where movements have a wider dispersion. In addition, VaR estimates are typically based on end-of-day positions and generally do not take into account intra-day volatility. Furthermore, measuring risk from a historical volatility basis is not always a good approximation for the future. Another major drawback of the internal models approach is the prospect of arbitrage opportunities between the banking book and the trading book due to the lower capital charge that may be given to trading positions under the VaR approach suggested by the Basle Committee.

Furthermore, the Basle Committee deemed that all internal VaR numbers had to

multiplied by a minimum factor of three calculate the capital to be held. If significant discrepancies were found between actual trading and modelled VaR numbers, then a plus factor would be added to the minimum number of three. Furthermore, the multiplier of 3 may not be severe enough when it comes to penalising banks for running inaccurate risk models. Furthermore, there was no statistical rationale behind this multiplication factor: it was arbitrary and attempted to compensate for such issues as model risk, extreme events, and misrepresentation of capital.

*Hypothesis 4a:* The framework announced by Basle, enforcing a uniform ten-day holding period interval and an arbitrary multiplication factor to calculate capital charges for market risk, will result in significant negative returns.

## ***2. 2 Bank Risk and Off-Balance-Sheet (OBS) Activity***

### **I Introduction**

The second key objective of this thesis is the examination and measurement of bank risk, through a volatile timeframe of 1992 to 1998, where banks significantly increased their pursuit of non-traditional activities. One of the major developments since the 1992 full implementation of the Basle agreements is the increase in bank's off-balance-sheet (OBS) activity. OBS activity can be defined as transactions that do not appear on the balance sheet. Banks transfer assets off the balance sheet in order to reduce capital requirements and improve capital adequacy. In moving to OBS activity, banks no longer rely on clients to earn interest income, but use their size and reputation to offer a variety of fee-based services and reduce a bank's reliance on interest income. Banks have also developed expertise in risk management, thereby offering hedging solutions to companies through derivative contracts. Major sources

of non-interest income for banks include service charges on deposits, trust-activity income, and trading profits.

Throughout the 1990s the growth of trading activity in financial markets, in addition to periods of economic instability, and a number of widely publicized trading losses resulted in a re-analysis by academics and investors of the risks faced by financial institutions, and how they are measured. Edwards and Mishkin (1995) argue that banks must take on greater levels of risk due to declines in traditional banking and associated reductions in profit levels. The changes that are taking place within the banking system may provide incentives for, or impose the need for, assuming a higher risk profile. Simons (1995), and Chaudhry and Reichert (1999) argue that derivative instruments and non-traditional activity lead to higher bank risk. In contrast, numerous studies have found that the use of derivatives and OBS activity have reduced the interest-rate and currency exposure of banks (Shanker, 1996; Venkatachalam, 1996; Choi and Elyasiani, 1997).

## **II Bank Risk, Capital Regulation, and OBS activity**

Regulators may have achieved their primary goal of improved capitalisation, however, the issue of overall bank risk may not be resolved through this requirement alone. Park (1997) models how regulators screen banks and the asset choice of banks. The results indicate that banks tend towards a riskier asset portfolio as they become subject to higher capital requirements. Similarly, Blum (1999) argues that the positive relationship between risk and expected returns means that higher capital requirements increase the opportunity costs of equity, thus encouraging riskier investments. Hovakimian and Kane (2000) examine risk-shifting incentives in US banks during the

period from 1985 to 1994 and conclude that low capitalised banks engaged in more risk-shifting activities than others. Aggarwal and Jacques (2001) study US banks for the period 1989 to 1991 and examine the impact of the 1991 FDICIA legislation on bank risk. This legislation enforced penalties for banks when their capital levels went below certain predefined levels. The findings of Aggarwal and Jacques (2001) showed that under-capitalised banks increased their capital levels by between 200 and 800 basis points per annum more than well-capitalised banks. Correspondingly, Rime (2001) finds that Swiss banks reacted to regulatory pressure by increasing capital levels without increasing risk. Bichsel and Blum (2001) also examine Swiss data and find a positive correlation between changes in capital and changes in risk. However, Beatty and Gron (2001) found no significant difference in pre and post-regulation conduct of US banks.

The empirical literature on the monitoring of banks by their regulators provides a number of insights, but leaves open other issues that need to be addressed. The necessary information the market requires to assess banks is difficult to come by due to the opacity of banks and the lack of liquidity of bank loans. The revenues stemming from banks' traditional lending base are likely to remain relatively stable as switching and information costs make it financially difficult to break the lending relationship banks benefit from, whereas the revenue streams from non-traditional activities are less predictable. Boyd and Graham (1986) find larger banks' expansion into non-traditional activities increases the risk of failure. Berger, Demetz, and Strahan (1999) find that as banks become larger and more diversified, they tend to hold riskier assets and less equity. Theoretically, diversification can reduce bank risk but Berger, Demetz and Strahan (1999) have shown that banks as pursuers of new activities have

resorted to lower capital levels, increased loan portfolios and the use of more derivatives. The study by DeYoung and Roland (1999) finds that as banks move towards non-traditional earning activities, earnings volatility increases as well as total leverage. Kwan (1997) examined the returns on the securities activities of banks and found that these institutions were riskier and not necessarily more profitable than other affiliates not engaging in securities activity.

Studies have found that fee-based income does stabilise profits. Supporters of this view generally report their findings in terms of potential. Mester (1992) finds diversifying non-traditional and traditional banking leads to diseconomies of scope and some economies of scale. Davis and Salo (1998) find in OECD (Organisation for Economic Co-operation and Development) countries that as non-interest income increases, overall profitability falls. The authors also find non-income growth to be much slower in the US when compared to Europe, and also more volatile. Another finding reported by this study is that larger banks are now much more dependent on this form of income. Aggeler and Feldman (1998) study the income pattern of US banks and find net interest income increased by over 12% in the period 1992 to 1997, yet the largest earning gains stemmed from non-interest income which increased by 34% over the period.

Hughes, Mester and Moon (2001) argue that most research finds no economies of scale because it ignores differences in banks' capital structure, lending practices and risk taking. Results indicate bank size has a negative impact on bank capital ratios and a positive impact on the credit risk ratio. Loan activity allows a bank to hold less capital, invest less in low-yield, high-liquidity assets and increase holdings of higher

risk and return assets. Possibly due to changes in regulation and the fact that larger banks have greater access to capital markets, these banks tend to operate with lower amounts of capital or feel they have less pressure to increase capital due to the ‘too-big-to-fail’ effect and the existence of a government safety net. There also appears to be evidence that off-balance sheet activity and loan sales help banks lower their capital levels to avoid regulatory taxes and improve their risk tolerance (Demetz, 2000).

Overall, the empirical evidence does not conclusively determine whether diversifying through non-traditional activities reduces risk. Evidently, many questions and hypotheses have arisen concerning whether bank performance is significantly altered by banks pursuing and engaging in new profit-pursuing activities. There is a significant gap in the current literature in terms of studies evaluating bank risk on a quantifiable basis, whilst taking into account the significant growth in off-balance sheet assets and non-interest income. Furthermore, existing commercial bank risk literature is predominantly limited to US banks. This study employs Value-at-Risk (VaR) methodology to investigate the riskiness of commercial banks within G-10 countries. This study does not account for the different lending practices within each country of G-10. One possible avenue for future research is to examine the relationship between risk and loan activity (net loans as a percentage of total assets) in the context of VaR and efficiency. If the data was available it would be very interesting to study the different lending practices of the major financial institutions within country. This would provide a detailed analysis of each country’s exposure to different asset classes and risk buckets.

### **III Value-at-Risk (VaR) Methods**

The VaR method is now tagged as a modern and robust methodology for measuring financial risk and is used to calculate how much a financial institution can lose with a probability  $p$  over a given time-horizon. This method is popular due to its conceptual simplicity and its ability to reduce the financial risk associated with a given position or portfolio down to just one number. Furthermore, the Basle Committee endorsed the VaR approach for measuring market risk, thus increasing its credibility.

VaR can be calculated in numerous ways and its value depends on the assumptions made and models used. The most common classification of VaR methods found in the literature is that of parametric VaR estimates, historical simulation (non-parametric), and Monte Carlo simulation (non-parametric). The three methods are complementary, but each offers a different view of risk and much debate has focused on which method is more robust.

Studying the method and the accuracy of disclosed VaR figures based on proprietary models is important, especially regarding bank capital regulation. In order to reduce the capital charges linked to market risk, banks may try to underestimate their VaR (Lucas, 2001) or even decrease the quality of risk management systems (Danielsson, Jorgensen and de Vries, 2002). However, Cuocco and Liu (2006) conclude that VaR-based capital requirements can be very effective in ensuring calculation and reporting accuracy of market risk. VaR research has typically focused either on the quantification of VaR (Roulstone, 1999, and Basel Committee on Banking Supervision's 1999- 2001 surveys) or the accuracy of VaR disclosure (Perignon, Deng and Wang, 2006). Few empirical studies have examined the accuracy of actual

VaRs figures (Berkowitz and O'Brien, 2002, Jaschke et al. (2003), Berkowitz, Christoffersen and Pelletier, 2006, and Perignon, Deng and Wang, 2006). Berkowitz and O'Brien, (2002) find that over 80% of their bank sample reported higher VaR values, and exceeded the 99<sup>th</sup> percentile by an average of 70%. However, Jaschke et al (2003) found that two-thirds of their sample had higher VaR values, but were on average less than the 99<sup>th</sup> percentile by 4%.

The literature on VaR suggests it is important to both quantify VaR in addition to measuring the accuracy of disclosure. This is inline with one of the three foundations of Basel II agreement in terms of meaningful disclosure. Little is known on the actual accuracy of disclosed VaRs. Future research should try to test whether disclosed VaRs are useful in forecasting the volatility of trading revenues, but this does depend on receiving bank specific data on trading activity and performance. Furthermore, it would be interesting to categorise banks that are and are not well capitalised and if there are any significant differences between their actual and reported VaR.

The most commonly used method for calculated VaR is a parametric approach due to its ease and speed of calculation. This approach assumes a normal distribution, however, it fails to consider that stock returns can be asymmetric and tend to have fatter tails than inferred under a normal distribution. Therefore adopting a parametric approach to calculate VaR may result in the under-estimation of a bank's risk.

Historical simulation is a non-parametric approach that makes no assumptions about the shape of the distribution of asset returns: This is the method's largest advantage. Historical simulation calculates the hypothetical distribution of returns based on how



the asset would have behaved under past scenarios. However, this non-parametric approach works under the assumption that future risks are much like past risks, which is less likely in today's volatile market environment. Another potential risk of this approach occurs where the past timeframe, used in the VaR calculation, is characterised by low volatility and includes no extreme events. Underestimation of a bank's VaR would occur under these circumstances.

A second non-parametric approach is Monte Carlo simulation, which generates random pricing scenarios. Jorion (1997) claims that this approach is the most flexible of all VaR estimation techniques. The hypothetical returns under each scenario are converted into a histogram of expected profits and losses, from which VaR can be calculated. Similar to the historical simulation, an advantage of Monte Carlo simulation is that it does not assume asset returns are distributed normally. However, the methodology is computationally intensive, especially for extensive asset portfolios.

Dowd (1999), and Ho (2000) proposed a third non-parametric approach to calculate VaR; Extreme Value Theory (EVT). Traditional VaR calculation methods tend to ignore extreme events and focus on risk parameters that consider up to 99% of the distribution of returns. This presents a major problem because it is the extreme events that move markets significantly and result in the largest losses. By focusing on the extreme tail of a distribution, VaR can be estimated with a confidence of greater than 99 percent. The difference EVT makes to VaR estimates is that it represents that tail of an extreme value distribution. As a result, a VaR figure calculated using EVT would be higher than a VaR figure calculated using traditional methodologies.

In sum, the parametric approach assumes a normal distribution in returns of the evaluated parameters. Historical simulation assumes the returns will follow a similar level of volatility as in the past. Monte Carlo simulation considers a random generation process of parameter returns. EVT uses past movements in the market to determine extreme levels of risk. This study employs all four VaR approaches in order to obtain an accurate and valid measure of how bank risk changed during the period 1992 to 1998.

This thesis measures the changing nature of bank risk based on each bank's exposure to interest rate risk, equity risk, and foreign exchange risk. Bank risk is measured for a sample of large international commercial banks and direct comparisons can be made for each bank's VaR. The period studied, 1992 to 1998, represents a time when banks were changing the nature of their business and ultimately their risk profile. Therefore, comparisons can be made of each bank's VaR over time. This study is one of the first to explicitly consider the risk profile of large commercial banks within G-10, using both parametric and non-parametric VaR techniques. Each of the four VaR methodologies is employed to estimate each bank's weekly VaR based on the impact of changes in interest rates, equity market volatility, and foreign exchange rate movements. Based on previous literature this study examines the following hypotheses:

*Hypothesis 5a:* As banks have increased their non-traditional activities this should result in an overall increase in bank risk as measured by VaR.

Hypothesis 6a: Banks exposure to currency and foreign exchange risk has diminished through the study period based on a greater exposure to off-balance-sheet activities and less reliance on more traditional forms of business.

Hypothesis 7a: Based on the underlying assumptions, parametric VaR understates the riskiness of banks when compared to the other approaches (historical simulation, Monte Carlo and EVT).

### ***2.3 Bank Efficiency Literature***

#### **I Introduction**

In addition to studying how the risk profile of banks has changed, the third key objective of this thesis is to examine bank efficiency levels. This thesis applies Data Envelopment Analysis (DEA) to evaluate the efficiency of large commercial banks in G-10 countries for the period 1992 to 1998. DEA measures the relative efficiency of each bank by comparing it to an efficient frontier based on an optimal set of input/output variables taken from the bank sample studied. Given the fact that banks are changing rapidly, it is of considerable interest to measure the efficiency of evolving institutions.

The research on efficiency in financial institutions is extensive; Berger and Humphrey (1997) noted that nearly 120 papers were published on this topic between 1992 and 1996. While multiple studies have examined efficiency levels of various types of banks across many countries, few have focused on commercial banks specifically within G-10, while there are a multitude of efficiency analyses on US bank efficiency (for instance, Aly et al (1990); Elyasiani and Mehdiyan (1995) and Miller and Noulas

(1996); Akhavein, Berger and Humphrey (1997); Berger and Mester (1997); and Berger, Hancock and Humphrey (1993)). A key contribution of this thesis is the inclusion of non-traditional activities in the efficiency analysis. Most efficiency studies measure bank output via traditional activities, such as loan generation and deposit investment. Commercial banks now focus more on non-traditional business such as derivatives activity, wealth management, and trading. Lang and Welzel (1996), Drake (2001) acknowledge the increased involvement of banks in non-traditional activities and include non-interest income within the efficiency model. Altunbas et al (2001), Isik and Hassan (2003), and Rao (2005) use off balance sheet items as an output variable. This study estimates the efficiency of the bank sample with and without off-balance sheet activities in order to observe whether it will have an impact on efficiency. Furthermore, regression is used to explain the efficiency of banks.

In sum, the third objective of this thesis is to investigate bank efficiency levels, including OBS activity in the analysis. This study contributes to the existing literature in a number of ways. First, it employs a non-parametric DEA approach to compare the efficiency scores across G-10 banks, and to determine the rank scores of bank efficiency by country; second, it examines the change in efficiency of G-10 banks during the period 1992 to 1998; third, it establishes whether differences in efficiency between G-10 countries are the result of their respective economic environments; fourth, it investigates the impact of OBS activity on bank efficiency using a DEA input-output model across all G-10 countries; and fifth, by using a Tobit regression approach, this study attempts to determine whether a bank's efficiency level is dependent on its VaR.

## **II Efficiency Analysis and Data Envelopment Analysis (DEA)**

The majority of studies of bank efficiency can be categorised into those that use either parametric techniques or non-parametric techniques. Berger and Humphrey (1997) report the mean level of bank cost inefficiency for 60 parametric studies as 15%, and the mean for the 62 non-parametric studies as 28%. DEA has become a popular method for measuring efficiency in different national banking industries as studies by Elyasiani and Medhian (1990), Berg et al (1993), Brockett et al (1997) demonstrate. US commercial banks are by far the most studied from the point of view of efficiency. The literature below discusses at US, non-US and country comparison studies.

### **III U.S. Bank Efficiency**

Aly et al (1990) applied a five output, three input DEA intermediation approach to 322 US banks. They found that efficiency levels were relatively low and technical efficiency dominated scale efficiency. Studies by Elyasiani and Mehdiian (1995) and Miller and Noulas (1996) compared the relative efficiency of small and large banks using DEA. Both studies concluded that larger banks were more efficient during the competitive and less regulated era of the 1980s. Humphrey and Pulley (1997) studied the effect of deregulation on profit efficiency. They found profit efficiency levels between 81% and 85%, far higher than those of other studies, for instance, Akhavein, Berger and Humphrey (1997); Berger and Mester (1997); and Berger, Hancock and Humphrey (1993) find efficiency levels of 24%, 46%, and 65% respectively.

Spong, Sullivan and De Young (1995) try to identify a number of characteristics of the most efficient and least efficient banks. They then use these characteristics to reveal factors that are present only within financial institutions that are run efficiently.

The study examines banks that are deemed efficient by satisfying selection criteria both in terms of cost efficiency and profitability. The final sample resulted in seventy-three efficient banks and seventy low efficiency banks. Their findings suggest that the average bank in the low efficiency sample has a cost efficiency index of 71%, indicating that the most efficient bank could produce the same outputs for 71% of the cost.

Kwan and Eisenbeis (1996) examined the trade-off between risk and capitalisation and measured the inefficiencies of 256 large bank holding companies during the period 1986 to 1991. They used a simultaneous equation approach to draw upon agency theory and highlight the incentives for management in managing risk and how these incentives may be affected by regulatory pressure. The findings of this study suggest that risk; capital and inefficiency are simultaneously determined. They also report that as asset quality decreases, measured inefficiencies under risk neutrality also decrease. These results are consistent with the findings of Hughes, Lang, Mester and Moon (1996). Kwan and Eisenbeis (1996) also found that as capital increases, banks become more efficient; i.e. that well-capitalised banks are run more effectively. They also indicate that rapidly growing institutions tend to be less efficient than institutions with moderate growth patterns and are likely to have higher loan risk.

The impact of bank regulation and capitalisation on bank efficiency has been widely studied, especially the US (Berger and Mester, 2003; Sturma and Williams, 2004). Overall, the effects of these regulatory efforts have been mixed (e.g., Kumbhakar and Sarkar, 2003; Altunbas et al., 2001; Yildirim and Philippatos, 2007). Some studies suggest that financial reform improves efficiency. Das and Ghosh (2006) used DEA

to evaluate the efficiency of Indian commercial banks during the post reform period of 1992-2002. They found that medium-sized public banks performed reasonably well and efficiency improved. In contrast, other studies find that financial reform has no efficiency effect or leads to a decline in operating efficiency. For instance, banking efficiency in the US was relatively unchanged by deregulation (Bauer et al., 1998; Elyasiani and Mehdi, 1995). Similarly, Fukuyama and Weber (2002) found that the efficiency of Japanese banks during 1992-1996 declined. Das and Ghosh (2006) also found a positive relationship between banking efficiency and capital adequacy. This result supports the rationale for capital adequacy requirements and is consistent with the notion that well-capitalized banks are perceived to be relatively safe, lowers their cost of borrowing, and results in enhanced efficiency.

#### **IV Non-U.S. Bank Efficiency**

Studies of efficiency have also focused on banks within various countries such as Japan (Tachibanaki et al, 1991; Fukuyama, 1993; McKillop et al, 1996), Ireland (Glass and McKillop, 1992; Lucey, 1993), and Nordic countries (Berg et al, 1993). Adenso-Diaz and Gascon (1997) provide further evidence on bank efficiency levels by the identification of alternative measures of efficiency and by linking these to the stock returns of Spanish financial institutions. They estimate the measures of partial efficiency as a function of production costs, systematic risk, specific risk and branch network distribution. DEA is used to estimate the efficiency measures assigned to the production costs and branch network distributions of the banks. Daily stock return data are used to calculate the risk measures in the analysis, which are systematic and specific risk measures. The authors assume a statistical relationship exists between some or all of these efficiency functions and market performance. The findings

suggest that specific risk is the most influential when determining bank stock price performance.

Tachibanaki et al (1991) used a two-output translog cost function with a sample of sixty-one banks for the period 1985 to 1987 and found evidence of economies of scale. Fukuyama (1993) used a DEA intermediation approach for 145 commercial banks in the country, finding that these banks should have produced the same level of outputs, consuming 14% less resources when compared to maximum utility. McKillop et al. (1996) analysed cost and efficiency within the five largest Japanese banks and found a range of between 1.08 and 1.28 for economies of scale (a figure greater than one represents economies of scale). Altumbas et al. (2000) employ a parametric model and a fourier flexible stochastic cost frontier model to determine both scale economies and X-efficiencies in Japanese banks. The three outputs they utilize are total loans, total securities, and off-balance-sheet items; the three inputs being labour, capital, and total funds. It is important to note that Japanese banks were known to conceal the extent of their of bad debts throughout the 1990s (Hall, 1999).

Glass and McKillop (1992) use a multi-product translog model to examine efficiency levels within Irish banks for the period 1972 to 1990, incorporating two inputs and two outputs. They found no evidence of economies of scale, whilst significant economies of scope were discovered in the latter years of the 1980s. Lucey (1993) studied seventeen banks to estimate the profit function and report technical efficiency levels averaging 83% over the period between 1988 and 1991.



Berg et al (1993) employ a DEA model to study 126 banks in Sweden, 503 in Finland, and 130 in Norway. The findings show Finnish banks as relatively inefficient and compare the relative efficiency of the three countries using a CRS model and VRS model. The CRS approach determines the efficient frontier from the sample of banks sampled. This approach is appropriate when all banks are operating at an optimal scale. McAllister and McManus (1993) note that factors such as imperfect competition and regulatory requirements may cause banks to operate at a sub-optimal level. The VRS approach ensures an inefficient bank is benchmarked against similar sized banks. As a result, VRS envelops the data more closely than CRS and consequently VRS technical efficiency scores are greater than or equal to CRS technical efficiency scores. Bukh et al (1995) studied banks in Norway, Sweden, Finland, and Denmark and found efficiency levels of 54%, 85%, 52%, and 78% respectively using a DEA framework.

A number of more recent studies (Beccalli et al., 2006, Eisenbeis et al. 1999, Chu and Lim, 1998) have sought to link bank efficiency to stock returns, generally finding a positive relationship. Beccalli et al., (2006) find a positive relationship between bank efficiency and stock returns suggesting a positive relationship between efficiency and shareholder value creation. In terms of returns, the risk-taking propensity of banks is expected to have a significant influence on the ability to generate returns. The number of studies dealing with bank risk is again substantial and deals with a variety of issues including: measurement methodologies (Duffie 2005, Lucas and Klaassen, 2006 and Galluccio and Roncoroni, 2006); the adequacy of new capital requirements to credit risk management practices (Jacobson et al., 2005); relationships with other risks

(Zheng 2006). As a result of Basle II recent studies have focused on operational risk and measurement issues (Scandizzo 2005, De Fontnouvelle et al., 2007).

## **V Cross-Country Efficiency**

The comparison of different country's banking systems and performance is quite problematic as there are many country-specific factors to consider. These elements can distort efficiency results and raise several difficulties in comparing country specific results. Cross-country studies by Yildirim and Phillipatos (2002), and Kosak and Zajc (2004) did not take country-specific variables into account when measuring efficiency. Bikker (2002) and Maggi and Rossi (2003) calculated bank inefficiency by including country dummy variables. Grigorian and Manole (2002) employed a different approach where the authors estimated bank efficiency scores in the first stage, then in the second stage regressed the efficiency results on country-specific macroeconomic variables. Bos and Kool (2006) followed a similar approach.

Allen and Rai (1996) compared cost inefficiency across 15 developed countries. The findings show that large banks exhibit the highest measures of cost inefficiency. The authors also find institutions in Japan, Australia, Austria, Germany, Sweden, and Canada to be the most efficient, while banks in France, Italy, the United Kingdom, and the United States are least efficient. Pastor et al (1997) apply DEA to 427 banks in eight countries where efficiency averaged 86%, ranging between 55% and 95%. This study found the UK to be at the lower end of the scale, while France was the leader. Concurring with past evidence, the US was viewed as relatively inefficient, being second lowest with an 81% efficiency average. However, it is important to note that cross-country studies are difficult to interpret as different regulatory and

economic conditions that exist in each country. On the other hand these studies do provide valuable information for comparing banks within specific countries and determining inefficiencies, which is key for major banks operating in a global marketplace.

Pastor et al (1997) used a DEA technique to define a common frontier for EU countries that incorporated the different environmental variables of each country. Their results indicate that Germany, Denmark, Spain, Luxembourg, and France had the highest efficiency scores. Dietsch and Weill (1998) studied 11 EU countries covering the years 1992 to 1996 using cost and profit frontiers and found a mixed picture of efficiency scores across countries. Bikker (2002) studied 15 EU member states over the years 1990-1997 using stochastic frontier methods and showed a clear trend of increasing efficiency over time with Luxembourg, Germany, the United Kingdom, and Denmark being the most efficient and Belgium, Greece, and Italy at the low end of the spectrum.

Hasan, Lozano-Vivas, and Pastor (2000) examine bank efficiency within ten leading European countries. The authors calculate the technical efficiency of banks within each country using an input-oriented DEA approach based on a variable-returns model. The authors note that the measure only represents basic efficiency and incorporates bank variables only. The authors create a common frontier by taking into account different bank technologies and environmental factors. The outputs used are loans, deposits, and other earning assets. Inputs are labour and physical assets and are represented by personnel expenses and non-interest expenses. The environmental factors used represent the macroeconomic state of the respective countries.

As banks evolve and expand through more OBS activity, traditional bank efficiency and performance measures will not accurately reflect a bank's condition and position within the marketplace. To accurately model bank efficiency, the inputs and outputs should reflect the range of activities that banks engage in. The authors find that excluding a proxy for OBS activity may distort traditional efficiency measures and results. The authors also find that efficiency is not linked to size when a proxy for activities is included in the model. In order to evaluate the effects of including OBS activity, the authors employ two efficiency models; one with and one without the OBS proxy. The authors use three inputs and three outputs to measure the level of efficiency. The average efficiency between the high and low profit frontiers, as categorized by the return-on-equity, is between 53% and 77%. The findings of Siems and Clark (1997) show the inclusion of an OBS proxy helps explain why banks do not become less efficient as they consolidate and grow. The study showed that with the inclusion of OBSA, banks appear to be equally efficient across asset size categories.

Rogers (1998) points out that non-traditional activities have been largely ignored in the estimation of bank efficiency. Siems and Clark (1997), Rogers (1998) and Isik and Hassan (2003) note that models excluding non-traditional outputs may have a negative impact on banks that are heavily involved in such activities. Consequently, some recent studies have addressed this issue of increased importance of non-traditional activities, by including the value of off-balance sheet items or non-interest income in the output vector (Akhigbe and McNulty, 2003; Drake and Hall, 2003; Bos and Kolari, 2005). However, many other studies continue to estimate efficiency frontiers without accounting for non-traditional activities (e.g. Maudos et al., 2002;

Carvallo and Kasman, 2005; Fries and Taci, 2005; Kasman and Yildirim, 2006; Lensink et al., 2008).

While the study of EU cross-country bank efficiency is robust, little has been done to model off-balance sheet activity. This thesis aims to add to the existing literature in this direction and extend the sample to include banks from Canada, Japan, and the United States. The comparability of banks across countries is inhibited due to each country's efficiency estimate being relative only to the efficient frontier for that country. The frontiers for each country are different and therefore only illustrate the dispersion of banks in terms of that country's best-practice standard. Alternatively, bank efficiency can be tested against a global frontier. Bank efficiency comparisons against a global frontier allow for a better comparison across nations as banks are set against one standard benchmark. Following a similar approach to Casu and Molyneux (2003), this study defines the common frontier following the traditional approach, i.e. building up the G-10 frontier by pooling the data set for the banks in all 11 countries in the sample.

In addition to applying DEA to evaluate G-10 bank efficiency performance, this study examines the following hypotheses:

*Hypothesis 8a*: Efficiency scores change significantly with the inclusion of an off-balance-sheet variable as an additional output.

*Hypothesis 9a*: There is a statistical relationship between bank efficiency and equity performance.

*Hypothesis 10a*: Macro-economic variables significantly impact a bank's efficiency score.

Hypothesis 11a: Efficiency scores increase as a bank's VaR increases.

Hypothesis 12a: The 1996 Market Risk Amendment has a significant impact on a bank's efficiency.

The aforementioned literature provides little guidance with respect to the impact of the 1996 Market Risk Amendment; the risk profile of commercial banks through 1992 to 1998, a period of high market volatility; and little has been done to examine the impact of off-balance-sheet activity across G-10 banks. Furthermore, this study attempts to explain the determinants of efficiency by considering macro-economic variables, each bank's VaR, and the impact of the 1996 Market Risk Amendment on efficiency levels. The next chapter discusses the methodologies and data sample used to test the hypotheses stated above.

## ***Chapter 3***

### ***METHODOLOGY***

This chapter discusses the various methodologies used in the analysis. The key elements of each methodology are explained and a critical appraisal is presented. Section II deals with the event study methodology; Section III discusses data envelopment analysis; Section IV discusses value at risk and Section V draws some conclusions.

#### **I Event-Study Methodology**

The efficient market hypothesis (EMH) claims that speculative market prices fully reflect all available relevant information. Event studies are used in tests of EMH to determine if prices incorporate information fully surrounding the announcement of a key event. A capital market is said to be efficient if asset prices fully reflect all available information. If EMH holds, the information about the event should be incorporated into prices before or on the day the information is revealed. As a result, there should be no impact on returns after the event. The efficient market hypothesis is categorized by three forms - the weak form; the semi-strong form; and the strong form. The weak form efficient market hypothesis asserts that current prices fully reflect the information held in the historical price series. Thus, any market participant cannot predict future price changes from analyzing past price patterns. The semi-strong form of market efficiency asserts that the current price of a stock not only reflects all historical information, but is fully responsive to all current public information. The price response to any public information will therefore be quick, accurate and unbiased. The strong form efficient market hypothesis asserts that the

current price fully reflects all historical information, all public and private information, and therefore no market participant can monopolize private information to earn abnormal returns. The distinctive feature of an efficient market is that prices reflect all available information. If prices reflect all information in an accurate and instantaneous manner, then there is no chance to form a trading strategy to earn incremental returns.

The event-study technique provides an estimate of the market's reaction to an announcement. Event-study can provide evidence on the movement of stock prices around the occurrence of specific events, particularly those outside the norm. This methodology is based on the theory that markets are deemed efficient and all publicly available information is incorporated into the share price upon release, thereby removing any arbitrage opportunities or abnormal profit making.

This thesis uses event-study methods based upon residual analysis of the market model (Henderson (1990); Brown and Warner (1985)) to examine the impact of the 1996 Amendment to the Basle Accord announcements. This model has been widely used to examine market reactions to activities that might influence investor decision-making. The inclusion of an interest rate factor adds explanatory power to bank stock movement (Benink and Wolff, 2000). As financial institutions usually function and profit through the interest spread between deposits and loans, the interest rate risk is widely regarded as one of the most important risks faced by banks, as pointed out by Mishkin (1999). Furthermore, Choi and Jen (1990) and Kwan (1991) find interest rates to be a significant factor in explaining bank stock returns and support the two-factor event study methodology that includes interest rates.



The issue of interest rate sensitivity of bank stock returns has been largely explored in banking literature. Empirical studies have provided substantial evidence for bank stock returns exhibiting a statistically significant relationship with interest rate changes. (Flannery and James, 1984; Brewer and Wang, 2000). However, studies by Choi et al. (1996), Allen and Jagtiani, (1997) and Benink and Wolff, (2000) conclude that interest rate sensitivity has decreased in the early 1990s due to the availability of interest rate derivatives and their use for hedging. Most of the studies use a variety of short-term and long-term returns as the interest rate factor without providing any rationale for their use. Yet, there is no consensus on the choice of the interest rate factor that should be used in testing the two-factor model (Adjaoud and Rahman (1996), Flannery, et al. (1997) and Elyasiani and Mansur (1998)). By way of contrast, if long, medium, or short- term rates become more volatile, bank stock returns also become more volatile in the following period (Elyasiani and Mansur, 1998). Faff and Howard (1999) state that bank's may be more exposed to short-term interest rates as a result of the maturities mismatch between the major components of the banks' balance sheet in the form of deposits and loans. More recently, as the importance of the traditional bank product mix has declined and focused on shorter-term securities, the maturity length of the interest rate risk has also declined. It is also possible that long term interest rate sensitivity is low as banks are better placed to hedge this exposure as compared to shorter term interest rate risk. Nevertheless, Lyng and Zumwalt (1980), Unal and Kane (1988), Bae (1990) have shown that bank returns are likely to be more sensitive to longer-term interest rates than either medium or short term. As of now there is no real consensus in the literature regarding the interest rate factor that should be used.

Examples of two-factor models, largely concerned with market and interest rate risk, include Brewer and Lee (1990), Akella and Greenbaum (1992), Madura and Zurruck (1995), and Adjaoud and Rahman (1996). Alternatively, Choi, et al. (1992) and Wetmore and Brick (1994) employed a three-factor approach to model market, interest rate and foreign exchange rate risk simultaneously. In line with the globalization of banking and increased non-traditional activities, banks do have significant foreign currency exposure. However, Gizycki and Lowe (2000) suggest that while exposed to fluctuations in foreign exchange rates banks may have adequately hedged their exchange rate risk. However, Brooks et al (2000) argue that proxies for foreign exchange rate risk do not adequately reflect the true exposure of a bank's exchange rate risk. Nonetheless, this study does suffer from limitations in this regard, all of which suggest future directions for research. Similarly, this study follows Choi and Jen (1990) and Kwan (1991) who used a two-factor approach that utilized short-term interest rates. However, an alternative approach might be a model that includes a foreign exchange rate factor and also long-term interest rates.

Event studies involve estimating the market model to determine what the expected returns for the duration of the event period examined. Abnormal returns associated with an event are calculated by subtracting expected returns of the market model from the actual rates of return from the event. The bank return generating process is described by the following equation:

$$R_{it} = \alpha_i + \beta_i \cdot R_{mt} + \gamma_i \cdot R_{rt} + \varepsilon_{it} \quad (1)$$

where:

- $R_{it}$  = daily rate of return of stock  $i$  in time  $t$
- $\alpha_i$  = intercept
- $\beta_i$  = measure of systematic risk
- $R_{mt}$  = daily rate of return on the market index in time  $t$
- $\gamma_i$  = measure of interest rate sensitivity
- $R_{it}$  = daily rate of return on interest rates in time  $t$
- $\varepsilon_{it}$  = disturbance term over the estimation period

Using the market model approach, it is possible to estimate for each bank coefficients  $\alpha$ ,  $\beta$ , and  $\gamma$  for the period prior to the event window of each announcement. The estimation method commonly used for estimating the coefficients is the Ordinary Least Squares method, where the estimation period generally ranges between 120 and 250 days (Campbell, Lo and MacKinlay, 1997).

Daily returns were calculated for the three parameters  $\alpha$ ,  $\beta$ , and  $\gamma$  for an estimation period from 150 days before each announcement (day -150) until 26 days (day -26) prior to each announcement. Events were defined to occurring on day zero ( $t = 0$ ), after which daily returns were calculated for the event window (days -10 through +5) using the aforementioned equation.

The ‘normal’ return is predicted for the days covered by the event window. The difference between the ‘actual’ and the ‘normal’ return during the event window is termed ‘abnormal’ return and is calculated using the following equation:

$$\underbrace{AR_{it}}_{\text{"Abnormal"}} = \underbrace{R_{it}}_{\text{"Actual"}} - \underbrace{\left[ \hat{\alpha}_i + \hat{\beta}_i \cdot R_{mt} + \gamma_i \cdot R_{jt} \right]}_{\text{"Normal"}} = \hat{\varepsilon}_{it} \quad (2)$$

The abnormal return, or residual, is the difference between the actual return and the return predicted by the market model for each event period. Abnormal returns are expected to be zero under the null hypothesis. If there were no abnormal returns,  $\hat{\varepsilon}_{it}$  would be equal to zero. In order to derive conclusions about the effect of bank capital regulation announcements in a broader sense, the average of the abnormal returns (AAR) is used to estimate the average effect of the event across the number of banks examined,  $N$ , and is represented as:

$$AAR_t = \frac{1}{N} \cdot \sum_{i=1}^N AR_{it} \quad (3)$$

The total effect of the event over time is termed the cumulative average abnormal return (CAAR) and is the simple sum of  $AAR_t$  over various time intervals of the event window.

$$CAAR_{SE} = \sum_{t=S}^{t=E} AAR_t \quad (4)$$

In the analysis  $t_S$  and  $t_E$  are start and end points, respectively, for the time period of interest.

$CAAR_{SE}$  and  $AAR_t$  are tested for their significance using both parametric and non-parametric t-tests. Prior to conducting the t-test, the aggregate of the pre-event standard deviation of abnormal bank returns is computed. The following formula estimates the standard deviation of daily abnormal returns during the estimation or pre-event period (from -150 to -26):

$$\sigma_{i,pre} = \sqrt{\frac{\sum_{t=-150}^{-26} (AR_{it} - AAR_{pre})^2}{n-1}} \quad (5)$$

where:  $\sigma_{i,pre}$  = standard deviation of abnormal returns of bank  $i$  estimated from the pre-event measurement period.  $AAR_{pre}$  = the average of abnormal returns of bank  $i$  estimated from the pre-event measurement period.  $n$  = the number of days in the pre-measurement period.

The standard deviation of abnormal returns for each bank can be aggregated by squaring and summing these values across all banks, dividing by the number of banks in the sample, and then taking the square root of the value. The formula is as follows:

$$\sigma_{N,pre} = \sqrt{\frac{\sum_{i=1}^N \sigma_{i,pre}^2}{N}} \quad (6)$$

where:  $\sigma_{N,pre}$  = the aggregate of pre-event standard deviation of abnormal returns across all banks.  $N$  = the number of banks in the sample.

The t-test for  $AAR_t$  is:

$$AAR_{t-stat} = \frac{AAR_t}{\sigma_{N,pre}} \quad (7)$$

For cumulative abnormal returns, the t-test formula is:

$$CAAR_{t-stat} = \frac{CAAR_t}{\sigma_{N,pre} \sqrt{N_t}} \quad (8)$$

Parametric t-tests rely on the important assumption that a bank's abnormal returns are normally distributed. The issue with this is that the normal distribution depends on homoscedastic errors (constant variance) and clearly this is not the case at the time of the announcement when abnormal returns may occur. Hence the usual t-test is flawed because it assumes a normal distribution as the number of observations increases. Therefore, this study also employs non-parametric testing. To test for the fraction of positive and negative average abnormal returns, the generalized sign test (GST) is used. The sign test is a simple binomial test of whether the frequency of positive abnormal returns equals 50%. The GST is a refined version of the sign test, and allows the null hypothesis to be a value other than 50%. The null hypothesis for the GST is that the fraction of positive returns is the same as in the estimation period. The fraction of positive returns expected is derived from the abnormal returns seen during the estimation period (-150 to -26 days), and set against event period (-10 to +5 days).

$$p = \frac{1}{n} \sum_{i=1}^n \frac{1}{150} \sum_{t=E_1}^{E_{150}} S_{it} \quad \text{where } S_{it} = \begin{cases} 1 & \text{if } AR_{it} > 0, \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

This test statistic uses the normal approximation to the binomial distribution with parameter  $p$ , and defines  $w$  as the number of banks in the event window, where the cumulative abnormal return is positive. The generalized sign test is as follows:

$$Z_G = \frac{w - np}{\sqrt{np(1-p)}} \quad (10)$$

(i) *Event-Study Data Selection*

The Basle Committee's four key announcements during the period January 1992 to December 1997 were collected from *The Bank of International Settlements* and from a news search on *Financial Times CD-ROM News*. The Amendment is complex in its content and the proposals that led up to its formalisation were diverse. As a result, this study focuses only on the four key announcements relating to major changes in bank capital regulation for market risk.

Daily stock prices for large commercial banks in each country were collected from *FT-Prices CD-ROM* and *Bloomberg*. The daily market-closing observations of each country's interest-rates on short-term government debt were also collected, along with each country's respective equity indices from *DataStream International* and *Bloomberg*. The final sample satisfies the following data filters: 1) The announcement of each proposal leading up to the Amendment must be found in the records of The Bank of International Settlements. 2) The countries subject to the Amendment have publicly available interest rate and equity index data for the period from 150 days before to 10 days after each announcement. 3) Each sample bank has not been taken over or failed during the period studied. 4) Share price data was available for each bank from 150 days before the first announcement on the 15<sup>th</sup> of April 1993 and 10

days after the final announcement on the 4<sup>th</sup> of January 1996. This procedure resulted in a sample of 109 banks.

## **II Value-at-Risk (VaR) Methodology**

Analysing commercial banks solely on the basis of the average returns generated for the investor is a straightforward way to make comparisons. However, an analysis of returns alone is not sufficient. Risk is an essential and integral part of making returns for investors. Methods for measuring risk have proliferated, to the point that there is little or no conceptual cohesion between the different approaches. However, all risk measures share the common theme of trying to combine uncertainty with the probability of loss, disappointment or an unsatisfactory outcome.

The following section discusses in turn the major risk measures that are applied in the financial community, starting with the simplest. The goals and essential properties of each are considered, while discussing their advantages and disadvantages.

### *(i) Ranges, Quartiles and Percentiles*

The simplest form of risk is the dispersion of observed returns, usually in equity values. The range is the distance between the highest and lowest observed returns but this method is extremely sensitive to the presence of outliers in the data. Furthermore, it only provides information about the maximum and minimum returns, yet does not show any evidence of the other returns and the movements in between these extreme values. Therefore, percentiles are sometimes used to measure the variability of a distribution. They are often used to describe a data set by dividing the data into four groups, with each group containing a quarter of the observations. The  $p$ th percentile is



a number such that  $p\%$  of the returns of the set fall below and  $(100 - p)\%$  of the returns fall above.

(ii) *Variance and Volatility (Standard Deviation)*

Over a single period, the risk of an investment should be associated with the possible dispersion of returns around the arithmetic mean, denoted  $\bar{R}$ . The larger the dispersion, the greater the potential risk. For instance, take a series of  $T$  returns and measure the dispersion of returns around the mean return. The variance solves the problem of averaging to zero and is calculated as the average squared deviation from the mean return. Squaring the deviation makes each term positive so that values above the mean do not cancel out values below the mean return. Second, squaring adds more weighting to the larger differences. However, the return differences are squared, so that the units of variance are not the same as the units of return. Hence it is necessary to take the square root of the variance to come back to the same units as the returns, the standard deviation. The standard deviation is often referred to as the volatility.

Interpreting an average return or a volatility figure is relatively easy. The normal distribution is the most widely used general-purpose distribution because it has several attractive statistical properties: Firstly, all normal distributions have the same general shape and are characterized by two parameters, the mean and standard deviation. Secondly, in a normal distribution, the mean, median and mode are equal so the distribution is symmetrical. The central limit theorem tells us that the sum of random variables approximates a normal distribution with a large number of observations.

Assuming normally distributed returns is extremely appealing to researchers and practitioners because of the well known mathematical properties that make them easy to process and understand. However, it is worth considering how accurate such an approximation is. Empirical observation of financial markets has often revealed large movements occur more frequently than would be expected if returns were normally distributed. For instance, the 1987 equity crash recorded negative returns that were over twenty standard deviations from the mean, relative to the volatility noted in the period before the crash. Furthermore, most return distributions are skewed, where there is a greater likelihood of yielding higher or lower returns than would be expected under normal distribution conditions.

Skewness is the third central moment of a distribution, after the mean and standard deviation. It measures the symmetry of a return distribution around its mean. Therefore, zero skewness indicates a symmetrical distribution. A positively skewed distribution is the outcome of rather small losses but larger gains, so it has long tail on the right-hand side of the distribution. Mathematically, the skewness is calculated as follows:

$$\frac{T}{(T-1)(T-2)} \sum_{t=1}^T \left( \frac{R_{t-1,t} - \bar{R}}{\sigma} \right)^3 \quad \text{T is the number of observations} \quad (11)$$

As a reference, the standard normal distribution is perfectly symmetrical and has a skewness coefficient equal to zero. Kurtosis is the fourth central moment of a distribution. It measures the degree of peak and heaviness of the tails of a distribution.

A normal distribution has a kurtosis value equal to zero. Formally, the kurtosis is defined as:

$$\frac{T(T+1)}{(T-1)(T-2)(T-3)} \sum_{t=1}^T \left( \frac{R_{t-1,t} - \bar{R}}{\sigma} \right)^4 - \frac{3(T-1)^2}{(T-2)(T-3)} \quad (12)$$

where: T is the number of observations. The measure is always positive regardless of the sign of the deviation of the observation from the mean. The normal distribution has skewness and kurtosis values equal to zero. However, normal distributions are rarely encountered in practice.

(iii) *Volatility to Downside Risk*

Volatility via the standard deviation approach measures the dispersion of returns around the historical average. Since positive and negative deviations from the average are penalized equally in the calculation process, the concept really only makes sense in a symmetrical framework. This creates problems because even though two investments may have the same mean and volatility, they may differ significantly in terms of higher moments of skewness and kurtosis. Secondly, it is questionable how relevant the dispersion of returns around the average is. The next argument against volatility is that investors are more adverse to negative deviations than with positive ones of the same magnitude, called prospect theory and was originally conceptualized by Kahneman and Tversky (1979). This theory calls for heavier weight on negative returns. Even when the distribution is symmetrical, volatility will not be in line with most investors' perceptions. These drawbacks on volatility as a measure of risk explain why the investment community and researchers have developed several

alternative risk measures. Unlike standard deviation, downside risk measures attempt to define risk more in accordance with the investor's perception. Most of the investment community should be interested in minimizing downside risk rather than volatility. Furthermore, distributions may not be normally distributed, and so variance or standard deviation cannot perform well as a risk measure. Therefore a downside risk measure is what most of the investment community would need to make optimal decisions.

Another key measure of risk is the notion of drawdown, which is defined as the decline in the net asset value from the highest historical point. Often expressed again as a percentage loss, it can be interpreted as the 'regret' an investor would have for not selling at the most profitable level. Drawdown statistics can be measured in a variety of ways. An individual drawdown is basically any losing period during an investment cycle. The maximum drawdown is the maximum loss, usually in percentage terms, that an institution or investor could have experienced within a specific time period. By looking at the size and duration of past drawdown's an institution can assess the financial pain, were that situation to recur. Drawdown's have one major advantage over volatility: they refer to a physical reality, and as such they are less abstract. In the United States, the Commodity Futures Trading Commission (CFTC) requires managed futures advisors to disclose their maximum drawdown. However, a large number of hedge fund managers voluntarily disclose this statistic as evidence of the quality of their track record. However, despite their intuitive nature, maximum drawdown statistics should be used with caution. Firstly, all other things being equal, this number will be greater as the frequency of the measurement interval becomes smaller. Investments that are marked to market daily may thus appear at a

disadvantage to less frequently valued investment. Therefore, it is not valid to compare this statistic between time series with different reporting intervals. Secondly, maximum drawdown's will be greater for a longer time series. Hence, it is not possible to make comparisons between time series with different time lengths. In addition, maximum drawdown statistics show a single number derived from a single string of data without any averaging method. Due to the uniqueness of this observation, the result can be highly error-prone and thus not necessarily always useful in building statistical inferences for the future. From a statistical perspective, a better risk measure would be the average of a series of largest maximum loss. Lastly, this method cannot identify the current risk in a portfolio until after losses occur.

(iv) *Beta and market risk*

Another relative risk measure is beta, which measures how risky an institution may be as compared to the overall stock market. A commercial bank that moves in harmony with the market is said to have a beta level of 1. Beta measures the risk of a bank by detailing how much its market price changes compared to changes in the overall market. The general consensus is a beta value of greater than one suggests the stock is riskier than the market, while a stock with a beta of less than one is less risky. However, beta only focuses on the impact of the overall stock market, and does not consider other influences which are considered specific risk. Beta is an incomplete explanation of risk and returns.

The risk measurement methods discussed earlier, volatility, downside risk, maximum drawdown statistics, and beta, but they do not provide any information about the probability of a given adverse risk factor move. Furthermore, the difficulty with these

risk measures lies less in measuring them at the individual level than in aggregating them to estimate the total risk.

Ideally, a risk measure should be able to summarize an institution's exposure to market risk as well as the probability of an adverse move. In the Amendment to the Basle Capital Accord, the Basle Committee on Banking Supervision (1996) recommended the adoption of a Value-at-Risk (VaR) based approach to assess risk and determine minimum capital requirements for financial institutions.

Today, VaR is one of the most widely used quantitative measurement tools for risk management. VaR corresponds to a particular percentile of a return distribution. The major advantage of VaR is the simplicity of its definition. VaR summarises in a single number the worst potential loss an institution or investor risks incurring under normal conditions, whatever the risk sources and their complexity. As a result, decision makers can decide whether or not to increase or decrease the level of risk. In addition, VaR provides investors with standardized risk information and facilitates risk transparency.

(v) *Value-at-Risk (VaR)*

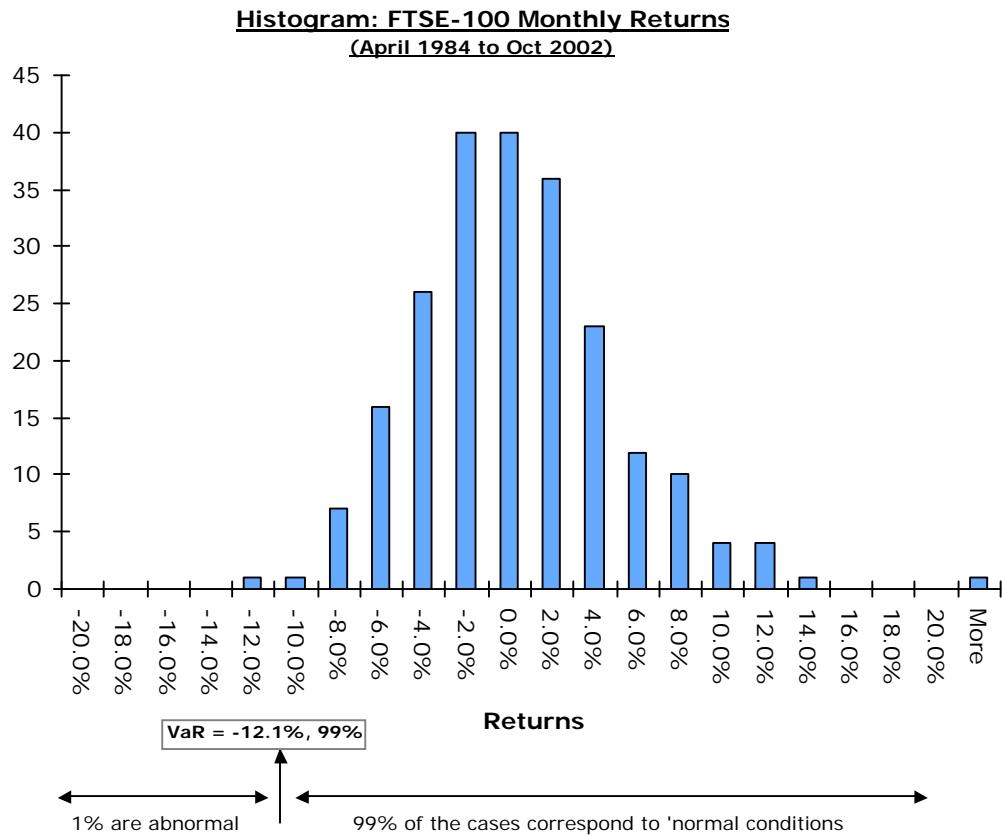
VaR is a relatively recent risk measure in finance, but its equivalent has been used for several years in statistics. The VaR of a position is the maximum amount of capital that the position can expect to lose within a specific holding period (for example, ten days or one month) and with a specified confidence level (for example 95 percent or 99 percent). In terms of probability theory, VaR at the  $p\%$  confidence level is the  $(1 -$

$p$ )% quantile of the profit and loss distribution. Note the VaR is often expressed as a percentage loss rather than as an absolute dollar loss to facilitate comparisons.

For example, to compute the one-month 99 percent VaR of the FTSE-100 from April 1984 to October 2002, using monthly data it is necessary to observe the series of one-month returns for the stock, build up the corresponding return distribution, and exclude 1% of the cases as being ‘abnormal’ market conditions, as shown in Figure 1 below. The worst case remaining return (-12.1%) is the Value-at-Risk of the index, expressed in percentage terms. It corresponds to the 1% percentile of the return distribution, i.e. 1% of the observed values are lower than the VaR and 99% are higher than the VaR. When the distribution of the returns is a normal distribution, VaR is simply equal to the average return minus a multiple of the volatility (for instance, a confidence level of 99%, VaR is equal to the average return minus 2.33 times the standard deviation). In this case, the concept of VaR does not generate any new information; it is just a different, less technical form of risk reporting, in which the term volatility is replaced by the term VaR. It is therefore not surprising that VaR has become a standard tool in risk management for banks and other financial institutions. However, without the assumption of a normal distribution, VaR can be a problematic risk measure. In particular, VaR is not sub-additive (Artzner et al, 1999). That is, the sum of the risks of two separate portfolios (X and Y) may be lower than the risk of the pooled portfolio (X+Y). Mathematically:

$$VaR(X + Y) \leq VaR(X) + VaR(Y) \quad (13)$$

**Figure 1** Histogram of FTSE -100 Returns.



(vi) *VaR Methodology*

This thesis calculates VaR by estimating the effect of a bank's main components of risk on its equity value, which arises from changes in interest rates, foreign exchange rates, and stock index returns. This approach is consistent with recent studies focusing on VaR within banking (Berkowitz and O'Brien, 2002; Frey and McNeil, 2002).

The methodology is based on a two-stage approach. The first stage uses a 3-factor model of the form:

$$R_{it} = \alpha_{it} + \beta_{mt} R_{mjt} + \beta_{rt} R_{rjt} + \beta_{xt} R_{xjt} + u_{it} \quad (14)$$



where:  $R_{it}$  is the return on bank stock  $i$  during time period  $t$ ;  $B_{mt}R_{mjt}$  is the market beta and the return on the market index in country  $j$  at time  $t$ ;  $B_{rt}R_{rjt}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$ ;  $B_{xt}R_{xjt}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$ ;  $\alpha_{it}, u_{it}$  are the bank-specific constant and random error term, respectively.

The stock price data of a bank is used as a proxy to capital market risk similar to the approach used by Chaudry et al (2000), Hirtle (1997), and McAnally (1996). This 3-factor approach analyses the relationship between bank equity value, market, interest, and exchange rate risk by estimating individual betas using weekly stock return data.

In the second stage, the individual betas are used to construct a bank VaR defined as:

$$VaR = c \left[ (\beta_{m,i} \sigma_{mj})^2 + (\beta_{r,i} \sigma_{rj})^2 + (\beta_{x,i} \sigma_{xj})^2 \right]^{1/2} \quad (15)$$

where:  $c$  reflects a given level of statistical confidence, the betas pertain to each individual bank  $i$ , and  $\sigma_{mjt}, \sigma_{rjt}, \sigma_{xjt}$  represent the standard deviations of the market index, interest rate and exchange rate in country  $j$ . These statistics are calculated from historical weekly data.

In the second stage, the VaR is calculated using 4 different methodologies: the parametric approach, historical simulation, Monte Carlo simulation, and an Extreme Value Theory (EVT) approach.

(vii) *The different approaches to VaR*

1. Parametric Approach

The parametric approach assumes the risk factors (interest rates, foreign exchanges rates, stock indices) that determine the value of a bank's equity are normally distributed. Since the normal distribution is fully described in its first two moments, the mean and standard deviation, standard mathematical properties of the normal distribution are used to calculate the loss that will be equalled or exceeded 1 percent of the time i.e. Value-at-Risk. The main advantage of the parametric approach is its simplicity and ease in calculation. Assuming normally distributed returns, the VaR of bank  $i$  is simply estimated as:

$$VaR_i = E(R_i) + z_c \sigma_i \quad (16)$$

where:  $z_c$  depends on the level of confidence, -1.96 with 95 percent probability, -2.33 with 99 percent probability, and  $E(R_i)$  and  $\sigma_i$  are bank  $i$ 's expected return and volatility, respectively. For instance, a portfolio with an expected return of +5% per month and a monthly volatility of 4% has a 95% one-month VaR equal to -2.84%. That is there is a 5% chance that the portfolio will lose more than 2.84% of its net asset value in a one-month interval.

The problem with parametric VaR is that it focuses only on the expected return and the volatility of the banks considered. Favre and Galeano (2002) show that constructing a portfolio using the parametric approach without taking into consideration skewness and kurtosis could underestimate the risk by 12% to 40% p.a. depending on historical returns.

## 2. Historical Simulation

The historical simulation approach calculates the change in the value of bank equity by using actual historical movements of the key market factors. Historical VaR is computed from the empirical cumulative distribution function of the historically simulated interest rate, market, and foreign exchange rate returns. The main advantage of this approach is that it is non-parametric and does not assume anything about the distribution of returns. However, the major drawback is the assumption that future risks are much like the risk environment of the past, which is less likely in today's more volatile environment. To calculate historical VaR, data is required for all risk factors (interest rates, market index, and foreign exchange rates) in the past, and a model that can assess the impact on returns for each risk factor's price scenario. The use of the actual historical changes in the prices of the chosen market factors to compute the hypothetical profits and losses are the distinguishing feature of historical simulation. Once the hypothetical profit and losses for each period have been calculated, the distribution of profit and losses and the VaR can then be determined. The historical simulation process can be described as follows:

The first step is to identify the basic market factors. The market factors were identified in the previous section and are the short-term interest rate of country  $j$ , the

exchange rate index of country  $j$ , and the market index of country  $j$ . The next step is to obtain historical values of the market factors for the period 1992 to 1998. Weekly changes in these rates will be used to construct hypothetical values of the market factors used in the calculation of hypothetical profits and losses. The next step is key whereby the equity value of bank  $i$  is subject to changes in all the market factors experienced in each year of the study period. Thereafter, the bank equity value is evaluated under each of the scenarios and the resulting profits/losses are ranked by size. The resulting empirical distribution of returns is viewed as the probability distribution. The VaR is then determined as the quantile of the profit and loss distribution that is implied by the chosen confidence level. The historical simulation does avoid the problems of not requiring the underlying risk factors to be normally distributed. However, the method is data intensive and the resulting VaR depends heavily on the chosen window length of historical data.

### 3. Monte Carlo Simulation

Finally, the *Monte Carlo approach* estimates VaR by simulating the random behaviour of the three risk factors and estimating the impact of their changes on each institution's equity value. The hypothetical values under each scenario make up a distribution of gains and losses from which VaR can be calculated. The idea underlying Monte Carlo simulation is to approximate the behaviour of a real-world system, for example, a commercial bank, within an artificial simulated environment. The Monte Carlo Simulation is similar to the historical simulation approach. The main difference is that rather than relying on the historical distributions, a simulation using the observed changes in the market factors over the last  $N$  periods generates a distribution of returns. In this study, a random number generator is used to calculate

1,000 hypothetical changes in the three market factors. These are then used to construct hypothetical profits and losses on the equity value of bank  $i$ . Finally, the VaR of bank  $i$  is determined from this distribution of returns. However, criticism has focused on the above approach not being able to consider ‘fat tails’ in the distribution of returns. By definition, VaR focuses only on portfolio losses in ‘normal’ market conditions and is intended for use as a predictor of low probability events. However, as market variables are non-normal VaR does not consider losses during extreme market conditions, such as when risk factors take unprecedented values or values that occurred outside the historical period considered. Fat tails exist due to many more occurrences away from the mean than that predicted by a normal distribution. As a result, this study employs a fourth methodology, Extreme Value Theory (EVT).

#### 4. Extreme Value Theory

Traditional VaR measures seem to ignore extreme events and focus on risk measures that address the entire distribution of returns. This is a major problem, as it is the extreme and unexpected events that cause most of the losses, and distress in financial systems. EVT focuses on the extreme value of the tail of a distribution and the confidence level of EVT-calculated VaRs is much higher than that of traditional VaR methodologies.

EVT is devoted to the development of models and techniques for estimating the behaviour of extreme events. In contrast to classical statistical inference that focuses on central measures of a distribution and where the normal curve is the norm, EVT focuses exclusively on modelling the tails of the distributions. The justification for using EVT techniques is that the distributions of extreme events differ significantly

from normality. In practice, extreme value theory suggests two major related approaches to extreme returns. The first consists of dividing the sample of available returns into consecutive blocks and focusing on the minimum return in each of these blocks. The second approach consists of looking only at those returns in the sample that are below a given threshold, and modelling these separately from the rest of the observations (Embrecht et al (1999)). This study follows the latter approach whereby the worst-case losses are reported.

(i) *VaR-Study Data Selection*

The data for this study includes a cross-country time-series of publicly traded commercial banks in the 11 G-10 countries. All these countries have stock exchanges and the time period covered is 1992 to 1998. The period is sufficiently long to assess the risk factors of each sample bank, and provide a robust set of observations. The sample ranges between 76 and 109 with a total of 511 observations.

The weekly return on the stock of each bank is matched with the country index return, interest and foreign exchange rates. The sources of this market data were *Bloomberg*, *FT Prices* and *DataStream International*.

The steps to conducting the VaR are as follows:

1. Calculate the weekly return on bank stock  $i$ .
2. Calculate the market beta and the return on market index in country  $j$
3. Calculate the interest rate beta and the return on short-term government securities in country  $j$
4. Calculate the foreign exchange beta and the return on a foreign exchange index for country  $j$

5. The stock price data is employed as a proxy to capital market risk similar to the approach employed by Chaudhry et al (1999, 2000).
6. The next stage employs the individual beta's of bank i and is used to construct each bank's VaR, under a given level of statistical confidence
7. The beta's pertain to each individual bank, bank i, in addition to the standard deviations of the market index, interest rate and exchange rate in country j
8. The weekly return on the stock of each bank is matched with the country index return, interest and foreign exchange rates.
9. The VaR is computed from equation (15) using historical volatilities for the rate of change in the market index, interest rates, and foreign exchange. Each VaR represents the fraction of a bank's equity at risk in one week with a 99% degree of confidence.
10. EViews, MATLAB, and Excel were used to aggregate the historical data and calculate VaR.
11. The below details the method behind each VaR approach.

A variety of methods exist for estimating VaR. Each model has its own set of assumptions, but the most common assumption is that historical market data is the best estimator for future changes.

Parametric Approach – the assumption is that the risk factor returns (market, interest rate, foreign exchange) are always jointly normally distributed and that the change in VaR is linearly dependent on all risk factor returns. Since this approach assumes a normal distribution, statistical properties of this distribution are applied for the calculation of VaR. The calculation of parametric VaR is a two-step process. The first is to estimate the distribution of bank equity price changes based on changes in the three market risk factors. From this distribution of price changes, VaR is calculated simply as the average return minus a multiple of the volatility. One major drawback of this approach is the assumption of normality of asset returns, which does not

always hold. Also, correlation between assets may not always be stable, particularly when there is a major event risk.

Historical simulation approach – the assumption is that the returns in the future will have the same distribution as they had in the past. This approach is simple and transparent. It involves running the historical bank returns to the 3 market risk factors to yield a distribution of changes in each bank's equity value. From this distribution a percentile (the VaR) is calculated. The distribution is sorted in ascending order and, if a 95 per cent confidence level is used, then this equates to a return below which five per cent of the observations lie. For example, if N equals 100 historical days, then the VaR number is represented by the 5th worst loss. This shows the maximum possible loss that can be suffered in 95 out of 100 days. The historical simulation approach has the advantage that historical data determine the joint probability distribution of market variables. The main disadvantages of historical simulation are that it is computationally slow and does not easily allow volatility changes to be updated and incorporated very quickly. Alternatively, it is possible to use the technique of what is known as Extreme Value Theory to smooth the numbers in the left tail of the distribution in an attempt to obtain a more accurate estimate of the 1% point of the distribution. The approach used in this thesis is to take the worst-case scenario for each market factor over the previous timeframes and calculate the VaR on this basis i.e. a worst case loss from historical movements. There are conflicting theoretical models of VaR accuracy and what is the optimal method. The popularity of the historical simulation approach at commercial banks has been noted by Pritsker (2001), Berkowitz and O'Brien (2002), Berkowitz, Christoffersen and Pelletier (2006), and Perignon, Deng and Wang (2006). However, the VaR approach needs to consider



conditions such as dataset quality, simplicity, confidence intervals and returns of financial instruments distributions.

Monte Carlo Simulation approach - this methodology has a number of similarities to historical simulation method. The main difference is that, rather than carrying out the simulation using actual historical changes in the three market factors to generate hypothetical portfolio profits or losses, one chooses a statistical distribution that is believed to adequately approximate the possible changes in market factors – this is the key reason why Monte Carlo results can be higher than other methods as the distribution is somewhat discretionary and subjective. Theoretically, any appropriate distribution can be chosen, although most use the normal distribution, as its parameters are easy to compute and comprehend. After estimating the parameters, a random number generator is used to generate thousands of hypothetical changes in the values of each market factor. The number of iterations performed in this study was 1000. For each iteration a random scenario of market movements was used based on the standard deviation of the market risk factor returns. Thereafter, the impact on bank i's equity under the simulated market scenarios was computed. The resulting returns were sorted in order to provide a simulated distribution of returns. The VaR is determined in the same way as was done in the historical simulation method. The advantages of the Monte Carlo approach it is perhaps the most effective of all methods, especially when more complex instruments are involved in the real world. It is also very flexible, as it does not make a definite assumption about asset returns. However, the procedure for Monte Carlo simulation can be quite complex and time consuming. Also, the distribution chosen is subjective and may not turn out to accurately reflect the portfolio returns.

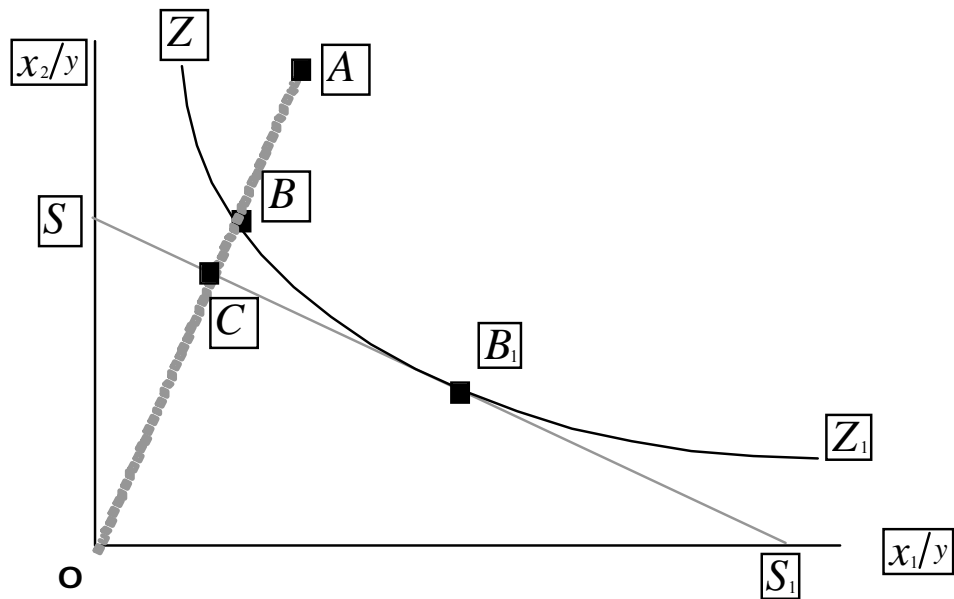
### **III Data Envelopment (DEA) Methodology**

Data envelopment analysis (DEA) has become more dominant in efficiency measurement in many sectors of industry (Banker et al, 1993). The location and shape of the efficiency frontier is determined by the data, with the simple notion that a decision-making unit DMU employs less input than another to produce the same amount of output is considered more efficient. Those observations with the highest ratio of output to input are considered efficient, and the frontier is constructed by joining these observations up within the input-output space, and therefore connects one efficient observation to another. The construction of this frontier is based on the best observed practice within the sample studied and can only act as an approximation to the true, unobserved efficiency frontier. Inefficient DMUs are ‘enveloped’ by the efficiency frontier in DEA, and the inefficiency is calculated relative to this surface (Cooper, Seiford and Tone 2000). DEA literature mainly uses the terminology of a decision-making unit for each organisation being analysed. The section below defines the input-oriented and output-oriented approaches.

(i) *Input-oriented efficiency*

Input-oriented efficiency keeps output levels fixed and explores the proportional reduction in input usage. For instance, assume a DMU uses two inputs ( $x_1, x_2$ ) to produce a single output ( $y$ ) as shown in Figure 2 below, source Coelli et al, (1998).

**Figure 2** *Technical and allocative efficiency under an input orientation*



Here the assumption is that curve  $ZZ_1$  represents the production frontier. If any DMU is efficient, it will lie on the production frontier or above it if they are inefficient. Using the input-orientation, DMUs which lie above the production frontier could proportionally reduce their input usage  $(x_1, x_2)$  for a given level of output  $(y)$ . Therefore, DMU  $A$  could proportionally reduce its input use, and move to a more feasible and technically efficient production point, such as that adopted by DMU  $B$ .  $SS_1$  reflects the ratio of the price inputs  $(x_1, x_2)$ . In technical efficiency, the distance  $BA$  is the amount by which all inputs could be proportionally reduced without a reduction in output. This would be expressed in percentage terms by the ratio  $BA/OA$ . The technical efficiency (input-orientation) ( $TE_{IN}$ ) of DMU  $A$  could be expressed as follows:

$$TE_{IN} = \frac{OB}{OA} \quad \text{which is equal to } 1 - BA/OA. \quad (17)$$

Pure technical efficiency ( $TE$ ) shows the deviation from the production frontier  $ZZ_1$  and this value lies between 0 and 1 with a value of 1 indicating full technical efficiency (if DMU  $A$  produced at a point  $B$ ).

If input prices are used and are known, they can be used to calculate the allocative efficiency ( $AE_{IN}$ ) of the DMU operating at point  $A$  by the following ratio:

$$AE_{IN} = \frac{OC}{OB} \quad (18)$$

where the distance  $CB$  is the reduction in production costs that would occur if production were to take place at the efficient point  $B_1$  instead of at the technically efficient, but allocatively inefficient, point  $B$ .

Therefore, technical efficiency reflects the ability of a DMU to produce the maximum amount of output given a set of inputs, and allocative efficiency, which reflects the ability of a DMU to use inputs in optimal proportion given respective prices. The product of these measures can be combined to give a measure of total economic efficiency ( $EE_{IN}$ ) such that:

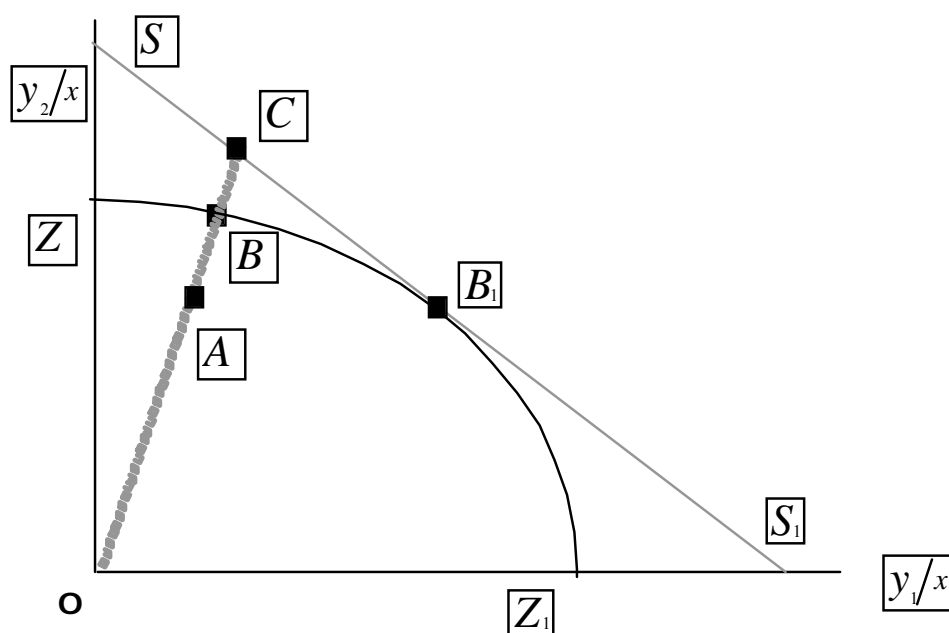
$$EE_{IN} = TE_{IN} \times AE_{IN} \quad (19)$$

$$= \frac{OB}{OA} \times \frac{OC}{OB} = \frac{OC}{OA}$$

(ii) *Output-oriented efficiency*

An alternative to the above exposition would be to examine efficiency measurement under an output orientation. Suppose a DMU produces two outputs,  $(y_1, y_2)$  from a single input ( $x$ ) as shown in Figure 3, source Coelli et al, (1998).

**Figure 3** *Technical and allocative efficiency under an output orientation*



The curve  $ZZ_1$  represents production possibility whereby all efficient DMUs lie on this frontier and below it if they are inefficient, such as point A. If there were available information about the relative value of the two inputs it would be possible to construct  $SS_1$  which reflects the market value of the two outputs  $(y_1, y_2)$ . The efficient point of  $B_1$  where  $ZZ_1$  is a tangent to the  $SS_1$  line.

The technical efficiency ( $TE_{out}$ ) of DMU A could be expressed as follows:

$$TE_{out} = \frac{OA}{OB} \quad (20)$$

while the allocative efficiency ( $AE_{out}$ ) could be expressed as:

$$AE_{out} = \frac{OB}{OC} \quad (21)$$

Total economic efficiency ( $EE_{out}$ ) is given by:

$$EE_{out} = TE_{out} \times AE_{out} \quad (22)$$

$$= \frac{OA}{OB} \times \frac{OB}{OC} = \frac{OA}{OC}$$

In banking, prices for key statistics are not always available, and so many studies restrict the analysis to the calculation of technical efficiency and not total economic efficiency. All of these measures of efficiency, (technical, allocative, and economic), are bounded by 0 and 1.

DEA assesses efficiency in two stages. Firstly, a frontier is identified based on either those DMUs within the sample using the lowest input mix to produce outputs or those achieving the highest output mix given their inputs (i.e. the input or output orientation). Secondly, each DMU is assigned an efficiency score by comparing its

output/input ratio to that of the efficient DMUs that envelope the surface. The efficiency of a DMU is determined by its distance from this surface – and highlights the extent by which it could improve its outputs given its current level of inputs (or reduce its inputs given its current level of outputs). Efficiency in DEA is therefore defined as the ratio of a weighted sum of outputs of a DMU divided by the weighted sum of its inputs. Technical efficiency ( $TE$ ) is computed by solving for each DMU the following:

$$\max = \left( \frac{\sum_{s=1}^S u_s \times y_{s0}}{\sum_{m=1}^M v_m \times x_{m0}} \right) \quad (23)$$

subject to:

$$\frac{\sum_{s=1}^S u_s \times y_{si}}{\sum_{m=1}^M v_m \times x_{mi}} \leq 1 \quad i = 1, \dots, I \quad (24)$$

where:

$y_{s0}$  = quantity of output  $s$  for  $DMU_0$

$u_s$  = weight attached to output  $s$ ,  $u_s > 0$ ,  $s = 1, \dots, S$

$x_{m0}$  = quantity of input  $m$  for  $DMU_0$

$v_m$  = weight attached to input  $m$ ,  $v_m > 0$ ,  $m = 1, \dots, M$

This mathematical form seeks out for  $DMU_0$  the set of output weights and input weights that maximises the efficiency, subject to the constraint that when applied to all other DMUs, none can have an efficiency level greater than 1. The weights are chosen to cast the DMU in the best possible way, in the sense that no other set of weights will yield a higher level of efficiency. In order to select the optimal weights, a linear objective function is maximised subject to a set of linear constraints and selects values for  $u$  and  $v$  that maximise the  $i$ th DMU.

This study employs an input-orientated technical efficiency approach to determine bank efficiency levels through the period 1992 to 1998. DEA has been widely used in efficiency studies, however, it is important to consider other efficiency measurement techniques. The next section will discuss the differences between DEA and a common parametric approach, Stochastic Frontier Approach (SFA) and demonstrate why DEA was the chosen for this study.

### *(iii) Comparing Efficiency Methods*

Several techniques have been proposed in the literature to measure efficiency with frontier approaches (Berger and Humphrey, 1997). Many studies have examined the efficiency of banks using either parametric techniques, for example the Stochastic Frontier Approach (SFA), or non-parametric techniques such as DEA. The main differences are due to the way in which parametric and non-parametric techniques establish and shape the efficient frontier. First, DEA assumes correct model specification and that all data are observed without error. In contrast, SFA allows for the possibility of measurement error. SFA requires assumptions to be made about the



functional form and the error distribution, whereas in DEA there are no standard tests. In SFA, the error itself is the focus of attention.

One of the key strengths of DEA is that it can readily model multiple-output production processes. Both the SFA and DEA methods may be susceptible to the influence of outliers and small sample sizes. DEA is more vulnerable to outliers, because of its inherent process of placing each DMU in the best possible way. SFA estimates are derived from full sample information and the technique is less prone to outsider influence. Nevertheless, it may be that these ‘outliers’ are the very DMUs that are most inefficient, so excluding them on the basis of statistical criteria may undermine the exercise. Small sample sizes do not prevent the application of DEA, but as with all parametric estimation processes, SFA estimates are likely to be more imprecise the smaller the sample size.

The first decision in SFA is whether to estimate a production or a cost function. Where DMUs produce multiple outputs poses problems and most econometric attempts to reduce the estimation to a single output. This is not particularly satisfactory, as the estimates of efficiency tend to be sensitive to which output is chosen to represent  $Y$  (Fernandez, Koop and Steel, 2000). Under SFA, a cost function allows a single dependent variable, cost  $C$ , to be estimated. Information about different outputs can be included as a vector of explanatory variables  $\mathbf{Y}$ , hence:

$$y_i = \alpha + \beta_1 Y_i + \beta_2 x_i + \varepsilon_i \quad (25)$$

Explanatory variables,  $\mathbf{x}$ , are used to explain differences among DMUs in their observed levels of output or cost. In terms of the residual, the requirement for efficiency analysis is some indication of what constitutes ‘best practice’. In standard econometric analysis, the residual would not be accorded special attention as it simply represents the deviation between observed data and the relationship predicted by the model and can be interpreted as a statistical error, caused by measurement error or other variables not considered. However, in efficiency analysis, the residual can be used to describe the extent to which a DMU operates from best practice.

In the case of a cost function, a DMU with a residual of zero is interpreted as showing average efficiency, while a negative (positive) residual highlights above (below) average efficiency. If  $Y$  represents output, the interpretations would be reversed. This method indicates that observations can be ranked according to their average efficiency. The observation lying the greatest distance below the cost function is defined as being most efficient in the sample, as its costs are lower for than that for any other observation studied. This then implies that a cost (or production) frontier can be estimated. For a cost function this would be done by adding  $\min(\varepsilon_i)$  to the intercept and subtracting it from the residuals. The process would be reversed for a production function. The key assumption under a SFA framework is that the inefficiency component and the random component of the residual have different distributions. The random component is assumed to follow a normal distribution. If  $\varepsilon_i$  is normally distributed, all residual variance is assumed to stem from random noise and measurement error. If  $\varepsilon_i$  is skewed, then this is taken as evidence that inefficiency exists in the sample. Subject to  $\varepsilon_i$  being skewed, stochastic frontier analysis decomposes the error term into two parts with zero covariance:

$$\boldsymbol{\varepsilon}_i = \boldsymbol{v}_i + \boldsymbol{u}_i \quad \text{cov}(\boldsymbol{v}_i, \boldsymbol{u}_i) = 0 \quad (26)$$

$\boldsymbol{v}_i$  can be viewed as stochastic (random) events that are not under control of the DMU.  $\boldsymbol{u}_i$  is the term that defines how far the DMU operates above the cost frontier.

In estimating the stochastic frontier for cross-sectional data, it is necessary to specify the distributional characteristics of the two components of the residual. These distributions must be different to distinguish between them econometrically.

The  $\boldsymbol{u}_i$  must be observed indirectly since direct estimates of only  $\boldsymbol{\varepsilon}_i$  are available.

The choice of distribution for  $\boldsymbol{u}_i$  will yield different estimates of inefficiency, both in the sample and for individual DMUs that are tested.

As stated, the measure of efficiency for each DMU  $i$ ,  $eff_i$ , depends on the type of function estimated. In the case of a production frontier,  $eff_i$  will lie between 0 and 1.

For the cost function, the values are usually inverted such that  $0 < \frac{1}{eff_i} < 1$ .

SFA interprets inefficiency by focusing on the residuals. However, results are sensitive to the estimation decisions that are made. If estimates of individual DMUs are little affected by alternative technical choices, then greater confidence can be placed in the results. Given the challenges associated with using SFA, such as specification of functional form and identification and extraction of efficiency estimates, an alternative analysis is used. Data envelopment analysis (DEA) requires

no prior specifications of the functional form, with the efficiency frontier positioned and shaped by the data.

Berger and Humphrey (1997) and Goddard et al (2001) provide a detailed account and comparison of different bank efficiency methods. Nevertheless, there is no clear consensus on which efficiency approach is more robust (Isik and Hassan, 2003). Berger and Humphrey (1997) agree, noting that 69 studies in their survey used a non-parametric approach (DEA), and 61 used parametric methods. Goddard et al (2001) reviewed empirical literature and showed similar results between parametric and non-parametric approaches. Ultimately, there is no conclusive evidence as to the best method for estimating the efficient frontier. Regardless which method is used, the choice of input and output variables is vital.

(iv) *Efficiency variables*

There is ongoing debate regarding the definition of inputs and outputs. Berger and Humphrey (1997) note that two concepts have been adopted: ‘the intermediation approach’ and the ‘production approach’. The first approach considers outputs as earning assets and inputs as deposits. Contrary to the above, according to the ‘production approach’ a bank exists to produce loans, deposits, and other assets (outputs) by using labour and capital (inputs). Among others, Lozano-Vivas et al (2002) modelled bank efficiency under the production approach, whereas Altunbas et al (2001) employed the intermediation approach. Berger and Humphrey (1997) note that neither approach is correct theoretically as they do not fully capture the dual role of banks as transaction providers and as being financial intermediaries. The authors suggest the production approach is more valid for evaluating the efficiencies of

branches of financial institutions and the intermediation approach may be more appropriate for evaluating the efficiency of entire financial institutions.

As a result, this study adopts an input-oriented intermediation approach, using a model with two inputs and two/(three) outputs. The inputs are: deposits and total operating expenses. Ideally a separate input for labour would be included. However, details on employment numbers or expenses were not available for all banks. As a result an operating expense variable was used. Several recent studies that examine the efficiency of banks with DEA or SFA techniques acknowledge the increased involvement of banks in non-traditional activities and include either non-interest (Drake, 2001; Lang and Welzel, 1998) or off-balance-sheet items (Bos and Kolari, 2005; Rao, 2005) as an additional output. Altunbas et al (1999) and Drake and Hall (2003) note that failure to account for risk can significantly distort efficiency scores. Lang and Welzel (1998), Drake (2001), Tortosa-Ausina (2002) use non-interest income as a proxy for off-balance sheet activities. Altunbas et al (2001) use the value of off-balance sheet items rather than non-interest income.

This study estimates the efficiency of the bank sample with and without off-balance-sheet activities to observe the impact on efficiency and tests for differences in the means. As a result one of the outputs in the efficiency analysis of this study is off-balance-sheet activity. Outputs used are: loans, other earning assets, and (off-balance-sheet items). This study also incorporates country-specific variables to account for several aspects such as macroeconomic conditions. As in previous studies (Pastor and Serrano, 2006; Kasman and Yildirim, 2006) this study controls for macroeconomic conditions within each country with the annual growth in GDP, CPI, unemployment,

and industrial production. Incorporating country-specific economic variables is as important as running the correct variables in the DEA model. Yildirim and Philippatos (2007) indicate that favourable economic conditions will improve bank efficiency, while Boyd et al (2001) indicate that countries with high inflation have underdeveloped financial systems and banks.

This study employs an input-orientated DEA technical efficiency model. Per Coelli et al (1998), the input-orientated measure addresses the question: ‘By how much can input quantities be proportionally reduced without changing the output quantities produced?’ DEA can be implemented by assuming either a constant returns to scale (CRS) or variable returns to scale (VRS). There are arguments that CRS is only appropriate when all DMUs are operating at an optimal scale, which might not be the case in the face of competition or regulatory requirements. In a sample where a few large banks are present, the use of a VRS framework raises the possibility that these large banks will appear efficient for the simple reason that there are no truly efficient banks (Berg et al, 1991). Avkiran (1999) states that under a VRS approach each unit is only compared against units of a similar size, instead of against all units. As a result, the assumption of VRS is more suitable for a larger sample of DMUs. In this thesis, as in Drake and Hall (2003), and Das and Ghosh (2006), efficiency estimates are obtained under both CRS and VRS assumptions. The CRS model works under the assumption that no significant relationship exists between the scale of operation and efficiency and delivers results for the overall technical efficiency (OTE) of the DMU. The VRS model splits OTE into a product of two components, and provides a measure for pure technical efficiency (PTE), which is the measure devoid of scale

efficiency, which is the second component. Coeli et al. (1998) suggest scale efficiency can be calculated as a ratio of TE (CRS) to TE (VRS).

It is also of considerable interest to explain the DEA efficiency scores by investigating the determinants of technical efficiency. In such cases, it is common to use a two-stage procedure. In the first stage, technical efficiency is assessed whilst in the second stage, the DEA efficiency scores, are explained by relevant variables not directly included in the DEA analysis, namely risk and country specific variables. As defined, the DEA score falls between the interval 0 and 1 making the dependent variable a limited dependent variable. The Tobit model is suggested as an appropriate multivariate statistical model in the second stage to consider the characteristics of the distribution of efficiency measure (Grosskopf, 1996). It is not possible to carry out standard ordinary least squares (OLS) regression of efficiency scores on the explanatory variables as the efficiency scores of banks go no higher than 1. Due to the fact that the efficiency score, the dependent variable, is censored, the appropriate model to use in the context is a Tobit regression model, which is a limited-dependent variable model (Greene, 2003). As a result this study uses Tobit regression to explain the differences in efficiency scores.

(v) *Tobit Regression (Second Stage Analysis)*

Since DEA efficiency scores are constrained to be between 0 and 1, the distribution of scores is censored. Using the DEA efficiency scores as dependent variables, an ordinary least squares (OLS) regression will result in biased estimates. As a result, following Gillen and Lall (1997) and Chilingirian (1995) a Tobit censored regression model is used to evaluate the censored data.

(vi) *Variables for Tobit Regression*

Independent Variables: GDP, CPI, Unemployment Rate, Industrial production, Value-at-Risk (VaR as measured by the Monte Carlo approach), 1996 Market Risk Amendment : 1 if the time period studied is post 1996 when the market risk regulation was imposed, 0 otherwise. Environmental factors are influences that are not traditional inputs and outputs, and are not under the control of the bank (Coelli et al, 2005). The key environmental influences used in this study are GDP, CPI, Unemployment, and Industrial Production.

Dependent Variable: EFF. The efficiency score EFF was modified to describe the degree of inefficiency by setting  $INEFF = (1/EFF) - 1$ . In this case the inefficiency scores are regressed, i.e. thus, a negative sign on a coefficient indicates a positive association with efficiency, which allows it to be modelled by the following form:

$$INEFF^* = \sum_j \beta_j \cdot x_j + v$$

$$INEFF = 0, \quad IF \quad INEFF^* \leq 0$$

$$INEFF = INEFF^*, \quad IF \quad INEFF^* > 0$$

Greene (2003) suggested that a convenient normalization in Tobit studies is to assume a censoring point at zero. The Tobit model is adequate when it is possible for the dependent variable to assume values beyond the truncation point, zero in the present case. McCarty and Yaisawarng (1993) argue that this is the case in the DEA analysis, where there would be a concentration of variables between zero and unity.



Environmental variables describe factors that could influence the efficiency of a bank, but are not traditional inputs and are assumed outside the control of the institution. Inadequately accounting for the environment may lead to flawed conclusions. However, there remains an active debate about how to incorporate such variables into DEA. As Fries and Taci (2005) mention, most applications in bank efficiency use a two-step procedure, whereby DEA is solved using traditional inputs and outputs, and the efficiency scores from the first stage are then regressed on the environmental variables. The DEA efficiency scores are then used as the dependent variable in a regression analysis. A censored Tobit regression model is often considered appropriate for these data, as both ends of the 0-1 distribution bound them.

One problem with second stage regression is that it involves a generated dependent variable but, more importantly, the estimated efficiency scores could well be serially correlated. Furthermore, the censoring of the dependent variable (the estimated efficiency score) may result in too many values of 1, and standard inference is not appropriate. Coelli et al (2005) mentions that the two-stage estimation procedure is unlikely to provide estimates, which are as efficient as those that could be obtained using a single-stage estimation procedure.

One possible approach is to use a three-stage approach to account for the environmental variables. The two-stage approach is extended by following the second stage Tobit regression with another DEA evaluation. There have been a number of adjustments to these approaches, for instance running a double DEA model (Lozano-Vivas, Pastor and Pastor 2002), or running a second-stage SFA model followed by a third-stage DEA model, to additionally take account of stochastic noise. To add to the

debate, Banker and Natarajan (2008) have provided theoretical justification for the use of the two-stage models in DEA to evaluate contextual variables affecting DEA efficiency scores.

(v) *DEA-Study Data Selection*

The data on US, Canada, Japan and EU commercial banks are derived from BankScope, a database published by Bureau VanDjick. The data are collected for a sample of commercial bank observations operating in Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States. The country-specific macro-economic variables were collected from Bloomberg. The sample for each year ranges between 76 and 109 commercial banks. Before analysing the results of the thesis, it is important to note the key facts about the commercial banking industry in G-10 countries. First, the industry really consists of two markets: retail and wholesale banking. Retail banking is skewed towards small firms and households, while wholesale banking focuses on larger firms and other financial institutions. Many banks provide both services, but this adds to the complexity of analysing commercial banks on an international scale. In general, research has not distinguished explicitly between retail and wholesale banking. Furthermore, in countries with a heavily bank-oriented financial system, the bank industry may evolve differently than in countries where there is more scope for securities activities, in terms of both products offered and risk management. This is a very important point to consider when making comparisons of banks across various countries, especially with respect to economies of scale, lending practices, and how diversified the business is between traditional and non-traditional banking activities.

Furthermore, although Basle tries to provide an international framework for bank capital regulation, there are differences in regulation at the country-specific level. In some countries commercial and investment banks are (or have been in the past) strictly separated (e.g. the US until recently), while in others (such as Germany or Italy) can operate jointly as universal banks and even have cross-shareholdings with industrial companies. These differences do make for varied market structures, risk appetites, and how bank's pursue new opportunities, again hampering international comparisons. For instance, there are divergences in the activities in which EU banks and US banks are able to engage, and this should widen still over time. The US is out of step with the majority of the other countries in terms of providing banks with the opportunity to engage in securities insurance and derivative activity. The limited regulatory intervention in the EU provides flexibility to establish universal banking systems.

Commercial banks are still subject to different regulatory treatment than other financial firms such as investment banks. The traditional role of commercial banks compared to non-depository financial service firms has declined over time, however, they do remain the largest and most important type of depository institution in terms of total assets. The focus of this thesis is on commercial banks. However, it is clear that over time it is becoming ever more difficult to show differences between the various types of financial service firms and institutions. One avenue for future research would be to compare the risk and efficiency differences between investment and commercial banks and if the divide has narrowed as expected through time.

This thesis assumes a global frontier with a series of cross section estimations, split by year. When efficiency analysis is carried out on cross-sectional data in addition to general issues of specifying the estimation model, much attention is drawn to the interpretation placed on the residual and the assumptions required in order to extract estimates of efficiency. Some of the strong assumptions required for efficiency analysis based on cross-sectional data may be relaxed if panel data is employed. Panel data has the advantage of exploiting the additional information that is available when observed at more than a single point in time.

There are also drawbacks regarding time-invariant estimators in terms of the assumption that bank efficiency is constant over time. The assumption of a constant level of efficiency is not particularly appealing in contexts where data are observed over long periods or the impact of external influences that may affect the pattern of efficiency. When panel data are available, one of the most common approaches and advantages in DEA literature is to apply a Malmquist index of the change in productivity. Productivity change can be measured using a Malmquist productivity index and is based on constructing quantity indices as ratios of distance functions. The Malmquist index approach is a powerful technique used in efficiency analysis and is the most robust method when attempting to determine the dynamic changes in efficiency levels. The Malmquist index does not require price information and does not rely on any assumptions about functional form. The approach also splits out technical change and technical efficiency change and can therefore offer valuable insights into productivity change within the banking industry. Furthermore, at a macro level, the approach is able to provide useful insights into overall productivity changes. The Malmquist approach is essentially used in an explanatory form of data analysis,

much can be gained from the analytic insight it provides and should be utilised with panel data.

#### **IV Conclusion**

In sum, this thesis employs an Event-Study methodology to examine the impact of market risk regulation on bank returns. The risk of the bank sample is examined through four robust VaR techniques as detailed above. Data Envelopment Analysis is used to measure commercial bank efficiency. Tobit regression examines the determinant factors of bank efficiency, taking into account country-specific economic variables, risk and dummy variables for the Market Risk Amendment.

## ***Chapter 4***

### ***EMPIRICAL RESULTS***

#### ***4.1 Reaction to the Market Risk Amendment: Analysis of the Results***

##### **I Introduction**

This section details the results of the event-study analysis of the four key announcements leading up to the 1996 Market Risk Amendment. The VaR results are then presented by year and by country under each of the four risk methodologies – the parametric approach, historical simulation, Monte Carlo simulation, and Extreme Value Theory approach. In addition the efficiency results are reported. DEA is employed under an intermediation approach for constant returns to scale (CRS) and variable returns to scale (VRS) and including and excluding an OBS variable for each approach. The determinants of efficiency from the Tobit regression results are then reported.

##### **II Analysis of Reaction to the First Announcement:**

***The Basle Committee issued a framework for applying capital charges to the market risks incurred by banks.***

The event period average abnormal returns (AAR) cumulative abnormal return (CAR) are computed using the two-index market model (Choi and Jen (1990), and Kwan (1991)). The test statistic is constructed following the standard abnormal return method described by Brown and Warner (1985). A non-parametric test is also employed. The interest-rate coefficients are summarised by country shown in Appendix I.

Table 1 reports the Cumulative Abnormal Returns for different time intervals surrounding the first event on 15<sup>th</sup> April 1993. Figure 4, also shown below, displays the -10 to +5 day CAR categorized by country. The first hypothesis (H1a) suggests that the first announcement by the Basle Committee in relation to allocating capital to market risk, has a negative impact the equity value of the bank sample during the event study period. The reasoning behind this hypothesis is that the Committee suggested banks use a standardized approach to measure risk, an approach that was dated and allowed no flexibility, whereas many large successful banks were already utilizing innovative and flexible approaches to calculate risk and capital levels.

The results for the first announcement show that there exists no cross-country pattern of significant negative abnormal returns. As a result, hypothesis H1a is rejected. In terms of the individual countries results, the United States and Germany showed the most statistically significant negative reactions to this initial proposal by the Basle Committee. The U.S. bank sample experienced a significant  $CAR_{-10,+5}$  of -4.31% with a statistically significant t-test score and a GST result significant at the 99 percent confidence level. Furthermore, the U.S. returns were significantly negative for the window -5 to +5 days and also -1 to +1 days. Germany also reacted with significantly negative returns, but only in the -10 to +5 event window with a  $CAR_{-10,+5}$  of -5.10%. However, only the non-parametric test yielded a significant result. For the sample of French commercial banks, all four event windows showed negative cumulative returns, however, only the  $CAR_{0,+5}$  of - 3.92% was statistically significant at a 90 percent confidence interval. The GST statistic for the  $CAR_{0,+5}$  was not significant.

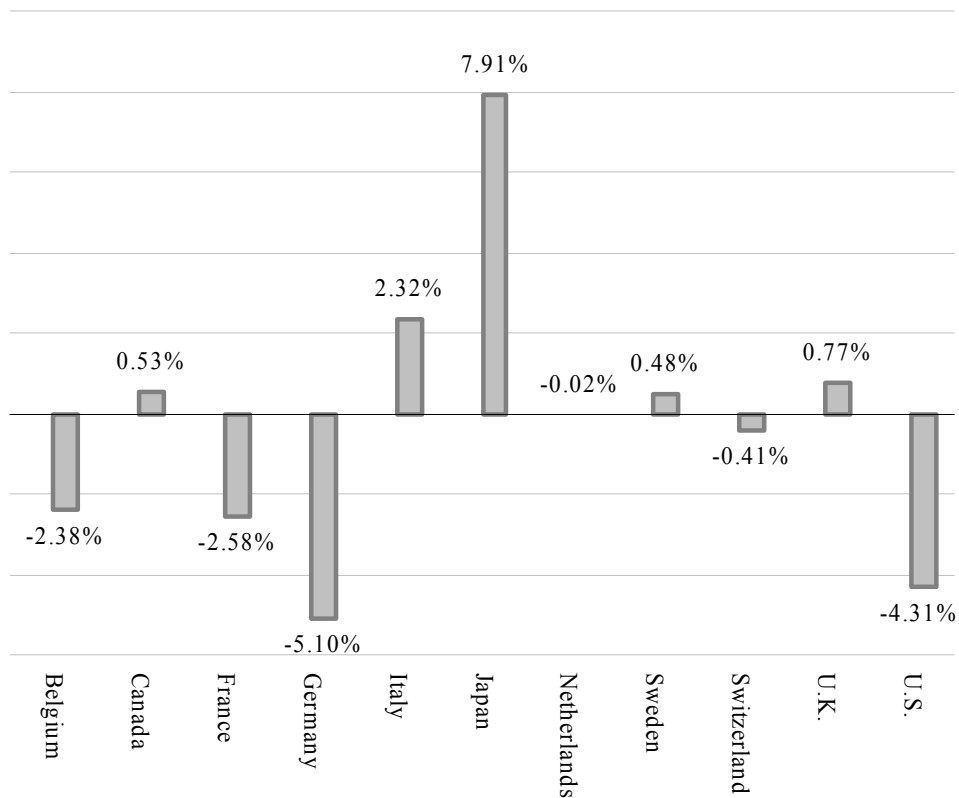
The Japan results showed large positive returns over the -10 to +5 day window, with a  $CAR_{-10,+5}$  of +7.91%. However, the bulk of the upward movement in returns took place prior to the announcement date, that is, between -10 and -5 days. The result for the sample of Japanese banks is consistent with the findings of Wagster (1996) that Japanese banks responded positively to the first piece of bank capital regulation, the Basle 1988 Accord that covered credit risk. Similarly, in this case, the Japanese banks reacted favourably to the imposition of bank capital regulation for market risk.

**Table 1** *Reaction to the First Announcement made by the Basle Committee*

	<u>Belgium</u>	<u>Canada</u>	<u>France</u>	<u>Germany</u>	<u>Italy</u>	<u>Japan</u>	<u>Netherlands</u>	<u>Sweden</u>	<u>Switzerland</u>	<u>U.K.</u>	<u>U.S.</u>
<u>Cumulative CAR (%)</u>											
<b>Days -10 to +5</b>	-2.38%	0.53%	-2.58%	-5.10%	2.32%	7.91%	-0.02%	0.48%	-0.41%	0.77%	-4.31%
<b>t-stat</b>	-0.76	0.08	-0.79	-1.68	0.29	1.49	-0.01	0.03	-0.19	0.15	-1.97 *
<b><u>gen. sign test</u></b>	-2.05	-0.18	-0.41	-3.90 **	-0.07	2.82 **	0.36	0.43	-0.34	0.51	-2.74 ***
<b>Days -5 to +5</b>	-1.58%	-1.19%	-2.29%	-1.61%	0.40%	-4.26%	-0.20%	1.58%	-1.05%	1.02%	-2.83%
<b>t-stat</b>	-0.61	-0.21	-0.84	-0.64	0.06	-0.97	-0.10	0.12	-0.59	0.24	-2.72 **
<b><u>gen. sign test</u></b>	-1.00	-0.74	-0.07	-1.55	-0.44	-0.77	-0.45	0.27	-1.49	0.17	-2.95 ***
<b>Days -1 to +1</b>	-0.41%	2.97%	-0.39%	0.14%	-0.77%	0.15%	0.26%	1.08%	-0.02%	-0.14%	-1.77%
<b>t-stat</b>	-0.30	1.02	-0.28	0.10	-0.22	0.06	0.26	0.16	-0.02	-0.06	-1.32
<b><u>gen. sign test</u></b>	-0.45	2.67 **	-0.48	0.53	-1.03	-0.71	1.15	0.14	0.02	-0.90	-3.77 ***
<b>Days 0 to +5</b>	-0.97%	0.67%	-3.92%	-0.28%	1.03%	-0.27%	-0.19%	0.42%	-1.28%	0.96%	-4.31%
<b>t-stat</b>	-0.51	0.16	-1.96 *	-0.15	0.21	-0.08	-0.13	0.04	-0.97	0.30	-1.32
<b><u>gen. sign test</u></b>	-0.78	0.12	-0.35	-0.74	0.01	0.14	0.65	0.61	-1.52	0.19	-1.45



**Figure 4** Reaction to the First Announcement, CAR -10 to + 5



### III Analysis of the Second Announcement:

*The Basle Committee provides banks with the option to use an internal models approach for allocating capital to market risk. Announcement Date: 28<sup>th</sup> April 1995.*

Table 2 reports the Cumulative Abnormal Returns in reaction to the second Basle Committee announcement on 28<sup>th</sup> April 1995. Figure 5, also shown below, displays the -10 to +5 day CAR categorized by country. The second hypothesis (H2a) expected the reaction to this proposal due to banks being allowed to measure their own market risk and having the incentive to manipulate the allocation of capital. However, the results of the analysis show that banks in the majority of the countries included in the sample reacted positively to this second announcement. The internal models approach

was the first piece of bank capital regulation that allowed banks to calculate risk using their own risk models and this might explain the positive returns surrounding the event period. Furthermore, although the move away from the ‘standardised approach’ provided banks with more flexibility, some would argue that the internal models approach provided banks with incentive and freedom to engage in regulatory arbitrage by transferring risk from the trading book to the banking book. Therefore, H2a is rejected.

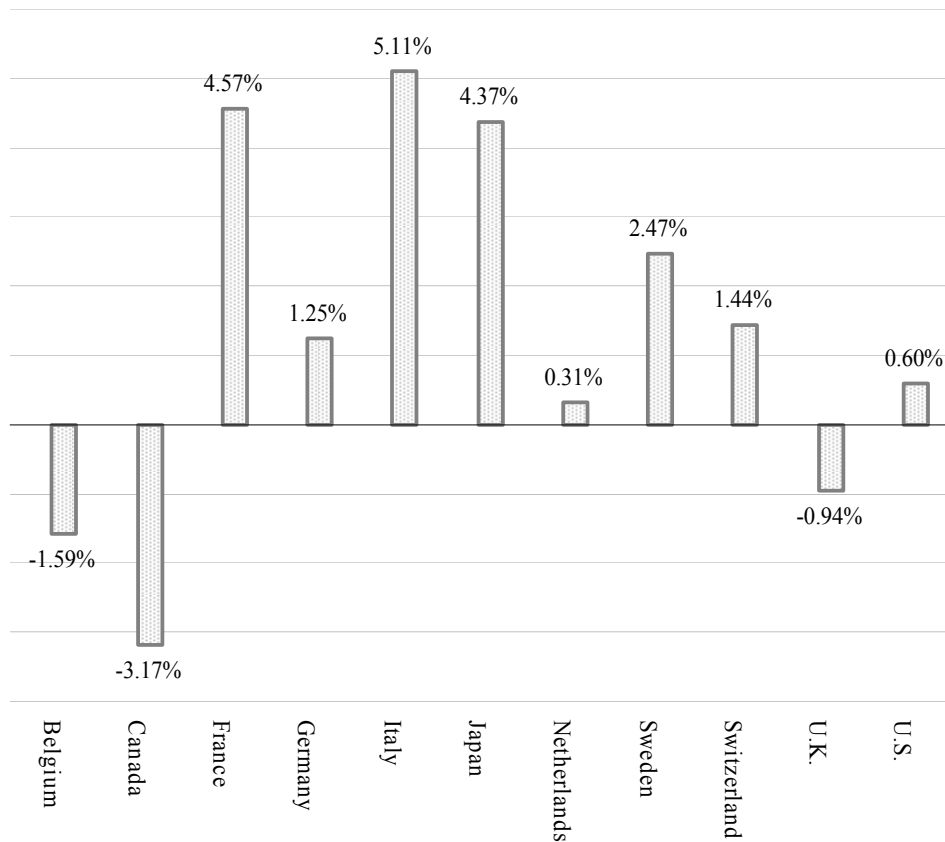
The French banks reacted positively to the internal models approach proposed by the Basle Committee, and results were significant with a  $CAR_{-10,+5}$  of +4.57% and a  $CAR_{-5,+5}$  of +2.62%. The GST result for these periods was statistically significant at a 99 percent confidence level and a 95 percent confidence level, respectively. The result for the German bank sample was also positive, but only for the event period of -5 to +5 days,  $CAR_{-5,+5}$  of +2.17%, and was only statistically significant from a non-parametric level. The Italian bank sample showed positive abnormal returns throughout the event window, with a  $CAR_{-10,+5}$  of +5.11%, and a GST statistic that was significant at the 99 percent level. Switzerland banks showed a positive reaction to the second announcement and had a  $CAR_{-10,+5}$  of +1.44%, with a significant GST statistic. This time around, the United States banks showed a statistically significant positive reaction, whereas the reaction to the first announcement was statistically negative. The  $CAR_{-10,+5}$  for the United States for the second announcement was +0.60% and +1.77% for  $CAR_{-5,+5}$ . Both CAR figures were statistically significant using a non-parametric method.

Only the commercial banks within Belgium, Canada, and the United Kingdom showed negative abnormal returns during the period surrounding the second announcement, and none of these were statistically significant.

**Table 2** *Reaction to the Second Announcement made by the Basle Committee*

	<u>Belgium</u>	<u>Canada</u>	<u>France</u>	<u>Germany</u>	<u>Italy</u>	<u>Japan</u>	<u>Netherlands</u>	<u>Sweden</u>	<u>Switzerland</u>	<u>U.K.</u>	<u>U.S.</u>
Cumulative CAR (%)											
<b>Days -10 to +5</b>	-1.59%	-3.17%	4.57%	1.25%	5.11%	4.37%	0.31%	2.47%	1.44%	-0.94%	0.60%
<b>t-stat</b>	-0.56	-0.69	1.33	0.38	1.29	1.11	0.10	0.39	0.59	-0.21	0.30
<b>gen. sign test</b>	-0.75	-0.81	6.22 ***	1.65	4.53 ***	1.27	0.25	1.33	5.04 ***	-0.46	4.64 ***
<b>Days -5 to +5</b>	-1.20%	-0.90%	2.62%	2.17%	3.84%	2.08%	0.89%	2.80%	0.24%	-0.37%	1.77%
<b>t-stat</b>	-0.51	-0.24	0.92	0.81	0.74	0.64	0.33	0.54	0.12	-0.10	1.08
<b>gen. sign test</b>	-0.47	-0.95	3.70 **	5.09 ***	3.09 **	1.48	0.88	1.99	2.98 **	0.22	5.50 ***
<b>Days -1 to +1</b>	-0.98%	-1.03%	0.02%	-0.89%	2.78%	-0.47%	0.03%	1.44%	-1.24%	-0.30%	0.41%
<b>t-stat</b>	-0.81	-0.52	0.01	-0.64	1.02	-0.28	0.02	0.53	-1.17	-0.15	0.47
<b>gen. sign test</b>	-1.17	-0.35	1.89	-2.01 *	1.47	-0.71	1.19	1.41	-1.39	-0.59	2.56 **
<b>Days 0 to +5</b>	-0.51%	0.27%	0.50%	-0.51%	0.93%	1.88%	0.32%	2.75%	1.63%	-0.25%	1.30%
<b>t-stat</b>	-0.29	0.10	0.24	-0.26	0.24	0.78	0.16	0.72	1.09	-0.09	1.08
<b>gen. sign test</b>	-0.74	-0.87	1.90	-0.09	1.71	2.46 **	0.76	1.58	3.67 **	-0.47	3.89 ***

**Figure 5** Reaction to the Second Announcement, CAR -10 to + 5



**IV Analysis of the Third Announcement:**

*The first public disclosure of the trading activities of Commercial Banks and Securities Firms. A joint report published by the Basle Committee and The International Organisation of Securities Commissions (IOSCO). Announcement Date: 28<sup>th</sup> November 1995.*

Table 3 reports the Cumulative Abnormal Returns for the event period surrounding the third significant Basle Committee announcement on 28<sup>th</sup> of November, 1995. Figure 6, also shown below, depicts the -10 to +5 day CAR categorized by country. The third hypothesis (H3a) anticipated a positive reaction from the banking community to this third announcement by the Basle Committee and IOSCO. The reaction was expected to be positive because this proposal increased the level of transparency for risk within the financial system and provided solution for risk

measurement and reporting. The results are somewhat conflicting with mixed reactions to the third announcement. As a result, H3a is also rejected.

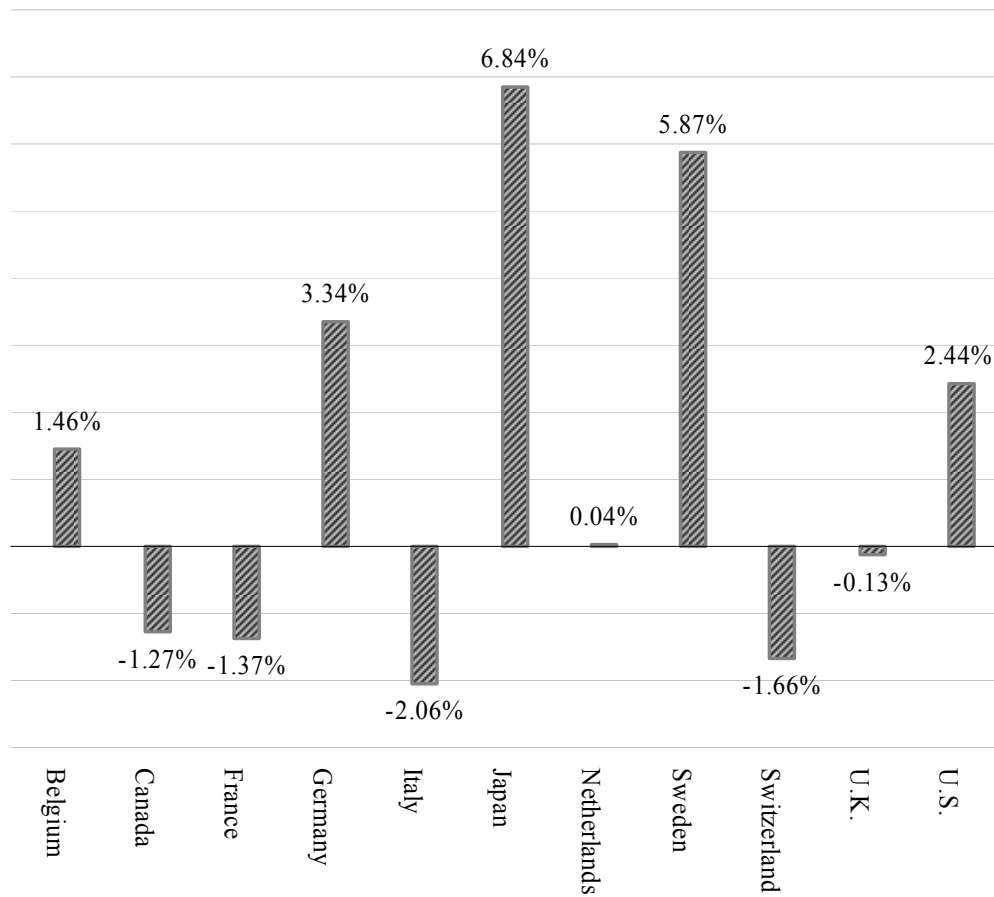
Germany, Japan, Sweden, and the United States all showed a significantly positive reaction to the issue of the joint report. Germany had a  $CAR_{-10,+5}$  of +3.34% and a  $CAR_{-5,+5}$  of +4.99%. The Japanese bank sample showed a  $CAR_{-10,+5}$  of +6.84% and a  $CAR_{-5,+5}$  of +5.14%, and the reaction was also positive in event windows -1 to +1 days, and 0 to +5 days. The Swedish reaction was +5.87% in the period -10 to +5, but was not statistically significant, yet  $CAR_{-1,+1}$  was statistically significant with a return of +3.57%. The reaction from U.S. banks was positive with a  $CAR_{-10,+5}$  of +2.44%, with the ten-day period surrounding the event also showing a statistically significant positive return of 2.96%.

Significantly negative reactions were seen in the sample of banks from Canada, France, and Italy. The reaction from Canadian banks was significant at  $CAR_{-5,+5}$  and  $CAR_{0,+5}$  windows, with returns of -1.34% and -1.28% respectively. French banks experienced significantly negative returns with a  $CAR_{-5,+5}$  of -4.99% and a  $CAR_{0,+5}$  of -4.07%. The Italian bank sample showed negative returns across all the event windows, but only  $CAR_{-5,+5}$  was significant with returns of -3.12%.

**Table 3** Reaction to the Third Announcement made by the Basle Committee

	<u>Belgium</u>	<u>Canada</u>	<u>France</u>	<u>Germany</u>	<u>Italy</u>	<u>Japan</u>	<u>Netherlands</u>	<u>Sweden</u>	<u>Switzerland</u>	<u>U.K.</u>	<u>U.S.</u>
<u>Cumulative CAR (%)</u>											
<b>Days -10 to +5</b>	1.46%	-1.27%	-1.37%	3.34%	-2.06%	6.84%	0.04%	5.87%	-1.66%	-0.13%	2.44%
<b>t-stat</b>	0.77	-0.29	-0.39	1.14	-0.43	1.99 *	0.01	1.21	-0.80	-0.03	1.22
<b><u>gen. sign test</u></b>	1.01	-2.18 *	-2.91 **	3.28 **	-0.80	5.98 ***	1.09	1.18	-0.73	-0.69	3.94 ***
<b>Days -5 to +5</b>	0.52%	-1.34%	-4.99%	2.76%	-3.12%	5.14%	-0.35%	4.28%	-0.74%	0.43%	2.96%
<b>t-stat</b>	2.39 *	-2.99 **	-3.46 **	2.28 *	-3.81 **	2.29 **	-1.38	2.14 *	-1.35	0.77	3.47 ***
<b><u>gen. sign test</u></b>	1.73	-2.78 **	-0.78	6.89 **	-0.45	5.73 ***	-0.50	0.94	-1.18	0.24	4.10 ***
<b>Days -1 to +1</b>	0.11%	0.11%	-2.07%	1.37%	-0.59%	2.81%	0.00%	3.57%	-0.98%	-0.55%	0.47%
<b>t-stat</b>	2.05	0.20	-2.57 *	5.72 ***	-0.55	3.47 ***	0.02	3.75 **	-2.48 *	-1.09	1.62
<b><u>gen. sign test</u></b>	0.97	1.27	-1.00	2.89 **	-1.11	6.23 ***	1.07	2.17 *	-1.28	-1.20	0.18
<b>Days 0 to +5</b>	-0.07%	-1.28%	-4.07%	1.51%	-1.41%	4.35%	-0.59%	2.09%	-0.19%	1.22%	1.32%
<b>t-stat</b>	-0.74	-4.08 ***	-3.00 **	2.43 *	-1.99	3.10 ***	-2.01	3.82 **	-0.45	2.09 *	2.49 **
<b><u>gen. sign test</u></b>	-0.89	-2.16 *	-0.71	2.61 **	-0.07	7.26 ***	-0.55	0.62	-1.05	0.12	3.44 ***

**Figure 6** Reaction to the Third Announcement, CAR -10 to + 5



**V Analysis of the Fourth Announcement:**

*The final Amendment to the Capital Accord to incorporate Market Risk. A companion paper was also released describing the way in which G-10 supervisory authorities plan to use ‘back-testing’ (ex-post comparisons between model results and actual performance) in conjunction with banks’ internal risk measurement systems as a basis for applying capital charges. Announcement Date: 4<sup>th</sup> January 1996.*

Table 4 below, reports the Cumulative Abnormal Returns for the event period surrounding the fourth and final significant Basle Committee announcement relating to market risk, made on the 4<sup>th</sup> of January, 1996. Figure 7, also shown below, shows the -10 to +5 day CAR categorized by country. The fourth hypothesis (H4a) expected a negative reaction from the sample of banks that were studied. This was due to the

fact that the methodology suggested by the Basle Committee was not robust enough when applying a uniform ten-day holding period and a 99 percent confidence interval to calculate VaR. Furthermore, the Committee applied an arbitrary multiplication factor of 3 or more to account for any unforeseen event risk, model inaccuracies, and for misrepresentations of risk in the banking book, instead of the trading book. Although the Amendment to the Basle Accord provided a new market risk framework for the financial industry, the methodology it employed was not robust or flexible enough to counter the changing risk profile of banks and the environment they operated within.

The results from the reaction to the fourth announcement by the Basle Committee are conflicting, with Canada, Sweden, the United Kingdom, and the United States displaying a negative reaction, whereas the sample of banks studied within Germany, France, and Japan showed a positive reaction to the final announcement. Therefore, H4a is rejected.

The reaction by the six largest commercial banks in Canada was negative,  $CAR_{-10,+5}$  -1.24%, but was only statistically significant at the non-parametric 90 percent confidence level. A negative reaction was also seen from the sample of Swedish banks, with a  $CAR_{0,+5}$  statistic of -4.75%, significant at the 95 percent confidence level for both parametric and non-parametric tests. The reaction from the sample of U.K. banks was negative with a  $CAR_{0,+5}$  of -1.43% and t-stat of -2.84, however, the non-parametric test was insignificant. The reaction of U.S. banks to the final announcement by the Basle Committee was negative in the -10 to +5 day event



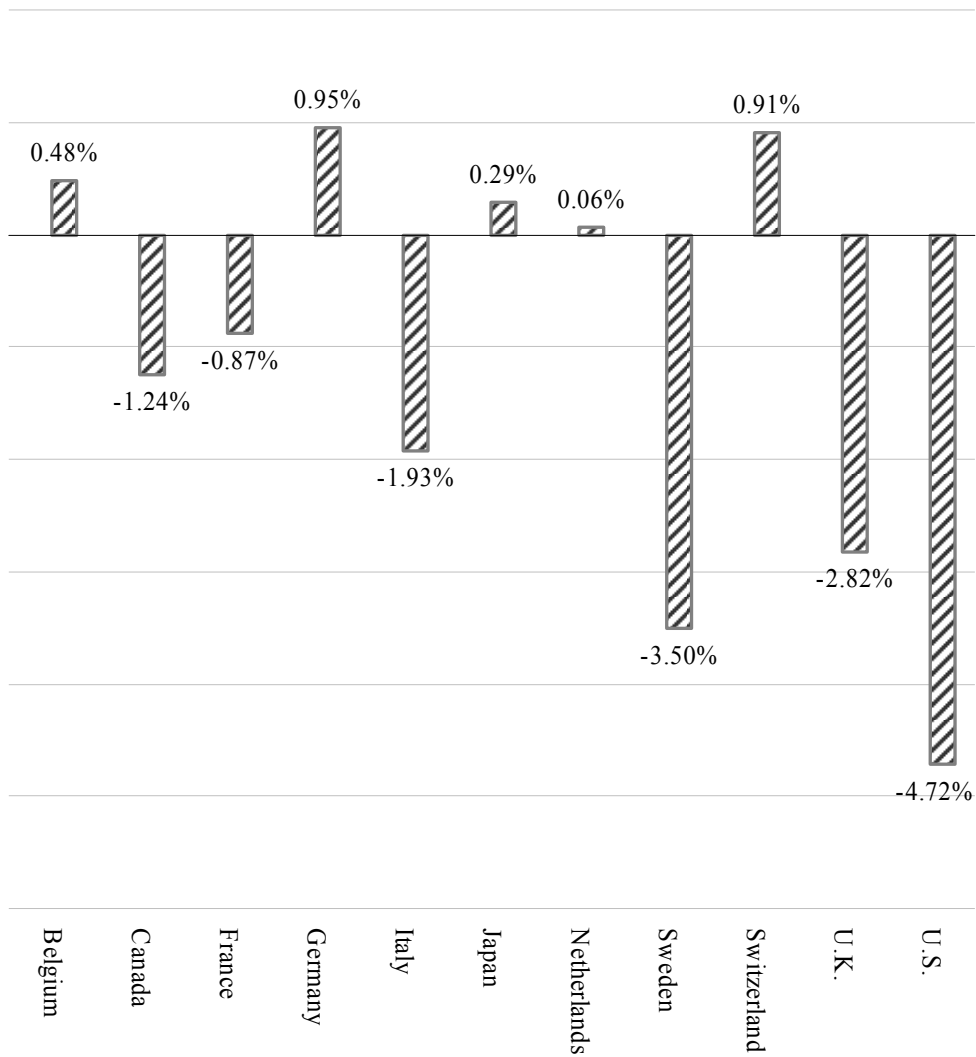
window with a  $CAR_{-10,+5}$  of -4.72%, and significant at the 95 percent confidence level for both parametric and non-parametric tests.

The CAR results of France, Germany, and Japan were positive. French bank returns were showed a significant CAR of +1.47% over the 3-day event window surrounding the announcement. Similarly over the same period, German banks reacted in a significantly positive manner, with a  $CAR_{-1,+1}$  of 1.77%. The reaction from Japanese banks was statistically significant in the  $CAR_{0,+5}$  period, with a significant return of +1.74% at the 95 percent confidence level on a parametric and non-parametric test.

**Table 4** *Reaction to the Fourth Announcement made by the Basle Committee*

	<u>Belgium</u>	<u>Canada</u>	<u>France</u>	<u>Germany</u>	<u>Italy</u>	<u>Japan</u>	<u>Netherlands</u>	<u>Sweden</u>	<u>Switzerland</u>	<u>U.K.</u>	<u>U.S.</u>
<u>Cumulative</u> <u>CAR (%)</u>											
<b>Days -10 to +5</b>	0.48%	-1.24%	-0.87%	0.95%	-1.93%	0.29%	0.06%	-3.50%	0.91%	-2.82%	-4.72%
<b>t-stat</b>	0.26	-0.30	-0.26	0.33	-0.40	0.07	0.02	-1.57	0.45	-0.68	-2.22 **
<b>gen. sign test</b>	0.63	-2.24 *	-1.01	1.34	-1.78	1.18	1.31	-2.57 *	1.64	-2.03	-2.46 **
<b>Days -5 to +5</b>	1.01%	0.28%	-0.64%	-0.05%	-0.63%	-0.21%	0.22%	-2.33%	0.97%	-0.81%	-1.40%
<b>t-stat</b>	1.82	0.28	-0.64	-0.07	-1.04	-0.32	0.47	-1.51	1.93	-1.87	-1.82 *
<b>gen. sign test</b>	0.60	1.62	-0.89	-0.50	-1.31	-1.21	1.15	-2.14 *	1.33	-1.68	-0.15
<b>Days -1 to +1</b>	0.42%	0.54%	1.47%	1.77%	-0.54%	0.66%	-0.45%	-1.47%	0.21%	0.56%	1.77%
<b>t-stat</b>	1.75	1.01	2.93 **	2.88 **	-1.08	1.19	-1.04	-1.08	1.47	1.56	1.37
<b>gen. sign test</b>	0.93	1.19	2.24 *	2.45 *	-1.11	1.45	-1.72	-2.00	1.20	0.16	1.48
<b>Days 0 to +5</b>	1.42%	-0.10%	-0.83%	-1.14%	-0.73%	1.74%	-1.20%	-4.75%	1.04%	-1.43%	-1.14%
<b>t-stat</b>	2.49 *	-0.13	-0.90	-1.69	-0.95	2.71 **	-0.69	-3.51**	2.10*	-2.84 **	-1.12
<b>gen. sign test</b>	1.80	-1.24	-1.08	-0.60	-0.82	2.40 **	-0.50	-4.24**	1.94	-1.87	-0.90

**Figure 7** Reaction to the Fourth Announcement, CAR -10 to + 5



**VI Summary of Market Risk Amendment Announcement Results**

As shown in Table 5 below, the cumulative reaction of the G-10 banks for each announcement is inconclusive. Overall, the first announcement by the Basle Committee proposing a standardized approach to measure market risk was met with a negative reaction. In contrast, the second proposal, in which the Basle Committee allowed banks to adopt an internal models approach, resulted in a positive shift in

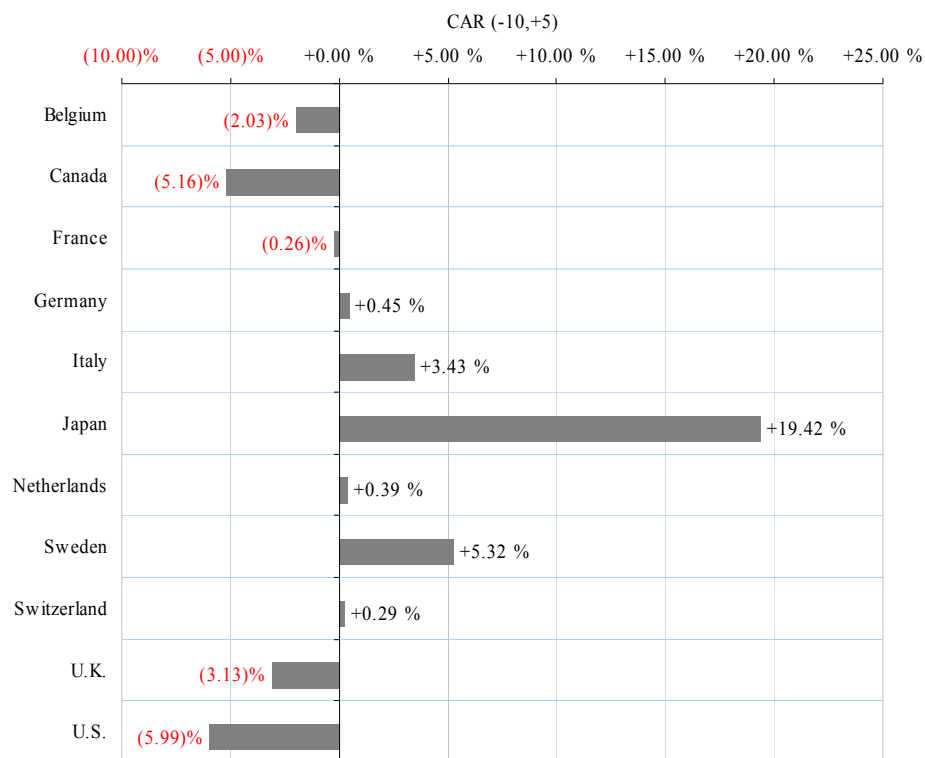
bank sample returns. Similarly, the third announcement, which was a joint report by the Basle Committee and IOSCO concerning the risk practices and reporting procedures of financial institutions led to positive abnormal returns across the sample of G-10 commercial banks. The final announcement, which formalized the Basle Committee's requirements on how banks must allocate capital to cover market risk was met with negative approval overall. These results suggest that the financial system recognizes the importance of risk management methodologies and practices, but reacts adversely when risk measurement strategies are limited by regulators.

However, the results are more telling when considered from a country-by-country perspective. Figure 8 depicts the overall CAR across the four Basle Committee announcements for each of the eleven countries. Japan's overall positive CAR of +19.42% is the most dramatic result and opens up a variety of research opportunities, such as exploring the risk and efficiency levels of these banks, which is examined further into this thesis. Although the reaction was not as significant as that of the Japanese bank sample, the returns from Italian and Swedish banks are also positive overall. The most significant negative reaction was from the sample of United States banks, with an overall CAR of -5.99%. This result most likely reflects that fact that the Basle Committee's new proposal for market risk was not in accordance with existing risk practices of U.S. banks and was not flexible or innovative enough for the level and complexity of risk these institutions were taking. The Canadian bank sample also had a negative reaction overall, with a CAR of -5.16%.

**Table 5** Cumulative Reaction across all 4 Basle Committee Announcements

Cumulative CAR (%)	<u>Belgium</u>	<u>Canada</u>	<u>France</u>	<u>Germany</u>	<u>Italy</u>	<u>Japan</u>	<u>Netherlands</u>	<u>Sweden</u>	<u>Switzerland</u>	<u>U.K.</u>	<u>U.S.</u>
Days -10 to +5	(2.03)%	(5.16)%	(0.26)%	+0.45 %	+3.43 %	+19.42 %	+0.39 %	+5.32 %	+0.29 %	(3.13)%	(5.99)%
Days -5 to +5	(1.25)%	(3.15)%	(5.30)%	+3.26 %	+0.48 %	+2.76 %	+0.56 %	+6.34 %	(0.58)%	+0.27 %	+0.51 %
Days -1 to +1	(0.86)%	+2.59 %	(0.97)%	+2.39 %	+0.88 %	+3.15 %	(0.16)%	+4.63 %	(2.03)%	(0.42)%	+0.88 %
Days 0 to +5	(0.12)%	(0.43)%	(8.31)%	(0.42)%	(0.17)%	+7.70 %	(1.66)%	+0.51 %	+1.20 %	+0.51 %	(2.83)%

**Figure 8** Cumulative Reaction across all 4 Basle Committee Announcements



The divergence in results across the G-10 countries make for interesting research possibilities. This thesis goes on to examine the risk and efficiency profiles of the

sample banks and determine the relationships between the banks' reaction to the 1996 Amendment, their efficiency levels, and also their risk profiles.

#### ***4.2 Analysis of Value-at-Risk (VaR) Results***

##### **I Introduction**

Risk is a multi-dimensional event and no single algorithm can estimate VaR by considering all possible market changes such as dataset quality, confidence intervals, and returns of financial instruments distributions (Kao-Tai Tsai, 2004). However, this study utilises four different VaR methodologies (parametric approach, historical simulation (HS), Extreme Value Theory (EVT), and Monte Carlo (MC) simulation, in order to mitigate some of the weaknesses inherent in the various approaches. For instance, the parametric approach assumes a normal distribution, and the historical simulation approach assumes past volatility will be similar to that of the future.

Estimating the VaR of a bank involves determining a probability distribution for the change in the value of the bank over a specific time-period. The value of the financial institution at time  $t$  depends on the risk factors, or market variables. For this study, the risk factors are exchange rates, interest rates, and market returns. Thus, the VaR estimation is calculated based on the distribution of the underlying risk factors.

Using a three-factor multi-index model, the key risk drivers for each bank were identified. The sensitivity of each bank to changes in interest rate, exchange rate, and the stock market is captured by factor coefficients. The VaR of each bank is computed by using the historical volatilities for the rate of change in interest rates, exchange rates, and each country's respective stock market. Each VaR statistic represents the

fraction of a bank's equity at risk over a one-week period with a 99% degree of confidence. The equity value of a bank is assumed to fluctuate with these three key individual risk factors given the historical volatilities and respective betas. The VaR is independent of bank size and is shown as a percentage, allowing for comparisons to be made across countries.

In Table 6, the estimated betas from the three-factor model in are shown for the sample of Belgian banks. Each coefficient represents the sensitivity of a bank's stock to a change in one individual factor. The market betas for Belgian banks are generally positive and suggest that banks' profits and equity values move in a similar direction to the general market index. The average market rate beta for the Belgian banks over the time period is 0.38. The interest rate betas do not show a large degree of statistical significance, but the beta factors that are significant are generally negative, which suggests that their stock performance is vulnerable to rising interest rates. The foreign exchange rate betas show no direction and the results are generally mixed.

The VaR results for Belgian banks are shown in Table 7. The weekly VaR in percent of bank equity at risk is shown for each VaR methodology – parametric, historical, extreme value theory (EVT), and Monte Carlo (MC) simulation. As can be seen from Table 7, the results from the parametric and historical distribution approaches are lower than the EVT and Monte Carlo results, consistent with the findings of Herring and Schuermann (2005). The EVT approach should show a higher risk level as it takes the worst-case scenario that has occurred for a specific year for each risk factor and assumes this occurs at one point in time. The Monte Carlo approach simulates the random behaviour of the three risk factors and estimates the impact of their changes

on each institution's equity value. The hypothetical values under each scenario make up a distribution of gains and losses from which VaR can be calculated. As shown in Figure 9, the average weekly VaR over the period 1992 to 1996 was close to 2% in the bank sample for Belgium. However, there is a sharp increase in risk for 1997 and 1998 up towards 5%.

Table 8 shows the Canadian bank factor betas for each risk coefficient. For the period 1992 to 1998 there is a strong positive relationship between Canadian banks equity returns and that of the market return. Over the period the average market beta is 0.51, but reached a high of 0.72 in 1998. Canadian bank's equity values have, on average, a negative relationship with interest rates. There is a statistically strong relationship with interest rates in the period 1992 to 1996 with an average beta of -0.36 over this timeframe. In the years 1997 and 1998, the relationship continues to be negative, but to a lesser degree, and is not statistically significant. This finding suggests that during 1997 and 1998, Canadian banks were less exposed to interest rate volatility, either through better hedging practices, or because profitability was less dependent on interest rate levels. For the Canadian bank sample, in the majority of cases the foreign exchange rate betas are negative and statistically significant. The average exchange rate beta is -0.34 and suggests that equity value suffers during periods of currency strength versus the U.S. dollar.

The VaR for Canadian banks is computed using the volatilities for the rate of change in interest rates, exchanges rates, and the stock market. The Canadian VaR results for the period 1992 to 1998 are shown in Table 9. Figure 10 displays the average weekly VaR for the Canadian bank sample by year. For the years 1992 to 1995, the VaR

percentages are relatively close to one another and range between 2- and 2.9%. There is a strong increase in risk for 1997 and 1998, with a weekly VaR of 3.39% and 5.93% respectively. In terms of the different VaR approaches, the historical simulation and Monte Carlo (MC) simulation results are very similar. The EVT approach yielded slightly higher risk levels. However, the parametric approach was consistently lower than any other approach with a weekly average VaR of close to 1.7% lower risk than the results from the MC estimation. For the Canadian sample, the difference between the parametric and MC simulation was 1.95%.

The estimated betas for the sample of French banks are shown in Table 10. With the exception of a few institutions, the results are generally positive, but few statistics are significant. Of particular interest is the level of significance in 1998, which is much higher than previous years with a statistically significant market beta of 0.43. This finding suggests that the larger French financial institutions were playing a greater role in the outcome of equity markets. The VaR results of the French bank sample are shown in Table 11. The trend improves gradually through the period 1992 to 1996. Once again the years 1997 and 1998 show a large increase in the average weekly VaR statistics across all four VaR methodologies. The VaR results in 1998 were more than double that of 1996, with an average MC result of 4.68% in 1998. The differences between the VaR approaches are consistent with that of Belgium and Canada. The EVT approach shows slightly stronger results as compared to the MC approach. The weekly average VaR statistics of the French banks steadily decreased between 1992 and 1996, moving up from an average weekly VaR statistic of -2.83% to -1.39%. However, the weekly VaR in 1997 under the MC approach was -3.36% and more than



double that of the previous year. The risk of the French sample of banks continued to increase in 1998 with a MC VaR of -4.56% and an EVT VaR in excess of -6%.

Table 12 details the factor coefficients for the sample of German banks. There is a positive market risk coefficient, with an average beta of 0.362, with most of the bank specific relationships statistically significant. Unlike the market coefficient results of Canada and France which increased especially in the years 1997 and 1998, the German coefficients for market risk are very consistent across the time period studied. This implies one of two things, either German banks were already a key part of the stock market, or their exposure to the financial crises through 1997 and 1998 was ultimately lower than other countries. However, as per the increase in overall VaR through 1997 and 1998, the latter cannot be the case. The interest rate coefficients are negative and suggest that German banks' equity risk is vulnerable to rising rates. The average interest rate beta for the German banks is -0.11 but with little evidence of statistical significance. The foreign exchange rate betas are more mixed on average and exhibit positive but relatively small coefficients.

The VaR results as shown in Table 13 and Figure 12 highlight the consistent theme in terms of a large increase in risk for the period 1997 and 1998. Under the MC approach, the average weekly VaR of the German bank sample hit a low of -1.47% in 1996 but then increased to -4.03% by 1998. The historical and parametric approaches continue to show lower VaR results as compared to the EVT and MC results, with an average difference of 1.7% between the parametric and MC result.

In Table 14, the analysis of the Italian bank sample indicates a positive market coefficient but lacks any consistency with regard to the statistical significance across the period of study. Only in 1998 is there a strong relationship with the general market with a beta of 0.45 versus an average coefficient of 0.12 over the period 1992 to 1997. In the period 1992 to 1997 the Italian bank sample does not show any sign of correlation between bank equity value and foreign exchange rate movements. However, in 1998 the bank sample experienced a significant relationship to exchange rate movements, which suggests that Italian banks were more exposed to exchange rate changes during this timeframe. The VaR results for the Italian bank sample are shown in Table 15 and Figure 13. The VaR of Italian banks actually decreases from close to -4% in 1992 to nearly -1% in 1995. However, the risk does increase through 1997 and 1998 with a VaR of over -5% in the last year of the study.

Table 16 details the factor coefficients for the Japanese bank sample. On average, the market risk coefficient is positive with the majority of years showing a statistically significant relationship. The average market risk beta in 1992 was 0.46 but moved down slightly by 1995 to 0.35. However, by 1998 the movement of the Japanese bank sample was 0.526 with all but one of the sample showing a strong statistical relationship. The interest rate betas were generally mixed, but with some interesting results in terms of the years 1992, 1993, 1994, and 1997 showing a positive relationship between equity values and interest rates. However, for the years 1995 and 1998 the results were negative across most of the Japanese bank sample. This is not surprising considering the financial volatility and problems Japan was experiencing. The banking system ultimately dictated the performance of the stock market and other industries. During the 1990s, Japan's economy experienced problems that resulted

from a large and rising volume of bad debts associated with the property and stock market declines in the late 1980s (Ito, 1992). The foreign exchange betas are on average negative, but with more statistically significant occurrences in the period 1996 to 1998 with an average coefficient of -0.39 highlighting that these banks suffer quite significantly during periods of currency depreciation against the US dollar.

The VaR results for Japanese commercial banks are shown in Table 17 and Figure 14. The VaR declined slightly between 1992 and 1994. However, the risk of these institutions began to increase from 1995 to 1998. In 1996, Japanese banks faced their riskiest time based on an average weekly VaR in excess of 11%, with some banks in the sample experiencing VaR scores in excess of 20%.

The period 1997 and 1998 was a time of financial crisis that consumed most of Asia, raising fears of a worldwide economic slowdown. By the mid-1990s many East Asian countries had large private current account deficits and the presence of fixed exchange rates encouraged external borrowing and subsequently foreign exchange risk in both financial and corporate sectors. However, due to recession in the early 1990s, the US raised interest rates in order to curb inflation. The result was a rise in the value of the US dollar, against which many East Asian currencies were pegged; this subsequently made the exports of these countries less competitive. The crisis had significant macro-level effects, including large reductions in currencies, equity values and other asset prices of key Asian countries, with Indonesia, South Korea and Thailand most affected. The crisis led to reluctance to lend to developing countries, economic slowdowns on a macro-level, and a decline in oil price to sub \$10/bbl. The reduction in oil revenue had a large impact on key producers such as Russia, which in turn

contributed to the Russian financial crisis in 1998. This in turn impacted the financial health of one of the largest US hedge funds, Long-Term Capital Management. As a result, it is no surprise to expect quite large increases in the weekly average VaR of the bank sample being studied across all G-10 countries.

The coefficient results for the Netherlands bank sample are shown in Table 18. The sample shows a very high market risk coefficient of close to one across most of the years. The relationship between interest rates is mostly negative with a few results statistically significant. In regard to the foreign exchange rate betas there are some mixed results, but the statistically significant results are positive and suggest that the equity values are enhanced in periods of currency appreciation. The VaR results are shown in Table 19 and Figure 15. The results are very similar to previous countries in terms of a large increase in risk is seen in 1997 and 1998 relative to previous years in the period this study examines. The financial landscape in the Netherlands underwent a major change in the 1990s. The process of deregulation made large advances as universal banks that provided a large number of financial services in commercial and investment banking were allowed to emerge.

In Table 20, the factor coefficients for the Swedish bank sample are shown. The results are generally mixed for the interest rate and exchange rate coefficients, but are on average positive in terms of market risk. In Sweden, banking and insurance have traditionally remained separate. In the early 1990s, banks and insurance companies were allowed to own shares in each other. In addition, savings banks and cooperative banks were permitted to change legal status and become limited liability companies in 1991. This change had a large impact on the structure of the banking industry, where

10 of the larger savings banks transformed into a new banking group with one parent holding company. The overall impact was a decrease in the number of large institutions down to four. As shown in Table 21 and Figure 16, the Swedish bank VaR results show less risk in the period 1993 to 1996, but demonstrate a larger average weekly EVT VaR in 1997 of over 7%. The MC and EVT results continue to show much larger risk results compared to the parametric and historical simulation approaches.

The factor results for Switzerland are shown in Table 22, where there are no clear relationships between bank equity and the three risk factors studied. The Swiss banking sector is characterized by a two-tier structure. The first tier is international and the large banks are universal with substantial investment banking activities. The second tier consists of a large group of domestically focused banks. In the early 1990s, Switzerland experienced asset deflation in the real estate market that led to a period of stagnation and perhaps reduced the risk exposure of these banks. The VaR results as per Table 23 and Figure 17 show an increase in risk between 1992 and 1998 where the average weekly VaR went from -2.11% to -4.06% under the MC approach. However, this risk level is quite low as compared to other countries in the sample.

The risk coefficients for the sample of UK banks studied are shown in Table 24. The market coefficient continues to be positive with a beta of close to 0.7 in 1998. Most of the banks in the sample show a statistically strong relationship with the general market movement. This is not surprising considering the domination of the financial sector by so few banks. Interestingly, the interest rate coefficient was strongly negative in 1992 and 1993. However, the results from 1994 onwards suggest that

these banks began to be less exposed to interest rate volatility, have become more sophisticated in their risk management practices, and are well hedged against this risk. The VaR results as per Table 25 and Figure 18 display the VaR results for each of the four methodologies adopted. The risk level of these banks actually declined between 1992 and 1995. However, the VaR of these banks more than doubled in the years 1997 and 1998 when compared to the relatively low 1996 numbers. The EVT approach yielded -8.32% in 1997, a significant move up versus the -1.51% number for the previous year.

Table 26 and Figure 19 display the VaR results for the sample of US banks. The factor coefficients are shown in Appendix II. The average weekly VaR under the parametric approach is in a very tight and low range with only two years showing an average weekly VaR above -0.5%. The historical simulation approach also yields relatively low results with an average weekly VaR of -0.9% and gradually strengthening to -1.99% in 1997. The largest EVT statistic was in 1997 with a -2.16% VaR. The MC results show the VaR moving up from -1.6% in 1992 to -2.14% in 1998. The MC results on average yield a VaR statistic of over 1% more than the parametric approach. There is a similar pattern to other countries in terms of the risk increasing in 1997 and 1998. However, the risk only increases by less than 0.5% over 1997 and 1998 versus the previous timeframe.

With respect to the hypotheses, there is enough evidence to support H5a, H6a and H7a. The results showed a significant increase in risk through the time-period studied, especially in 1996 and 1997. As banks moved into off-balance-sheet activity and away from more traditional sources of income, the equity values of banks were less

dependent on interest rate and foreign exchange rate volatility. However, this was only seen in countries such as Canada, Germany and the United Kingdom. The results also showed the parametric approach to consistently understate VaR as compared to the other methodologies employed in this study.

## **II VaR Results by Country Rank**

From Table 27 and 4.b.23 the VaR results are averaged by country and ranked accordingly. Across all countries the average VaR through the period 1992 to 1996 is -2.52%. However, in 1997 there is a significant increase in risk up to -4.31%. The VaR results for 1998 continue to increase and move up to -4.67%. In terms of ranking the countries, the sample of Japanese banks is ranked number 1 with the highest level of risk on a consistent basis with the highest risk ranking in 3 years out of the 7 years studied. The second highest risk rating is Sweden with a high risk rating especially in the years 1993, 1994 and 1995. The country with the lowest risk ranking is the United States with the lowest risk ranking in 3 of the 7 years studied. The US had the lowest risk ranking by a very long way with a sum of rank score of 13. The country with the second lowest risk ranking was Switzerland with a ranking score of 29. However, France and Germany were also very low in the risk ranking with scores of 30.

## **III VaR Conclusion**

This paper has investigated the risk profile of a sample of commercial banks within G-10 countries. All banks are publicly traded companies. The analysis covered a period of great financial market volatility - the period 1992 through to 1998 and the results indicate the extent to which market risk, interest rate and foreign exchange rate impact major commercial banks' equity values.

While the sign of the market beta was consistently positive across banks and countries, the interest rate and exchange rate betas were more mixed. The beta coefficients were then combined with the historical volatilities of the three risk drivers to generate a modified VaR analysis across banks and countries. This study also applied four different VaR methodologies in order to ensure a robust risk calculation was carried out. The VaR analysis is somewhat unique in that it allows comparisons to be made across banks and countries as it shows the percentage a bank's equity value could be drawn down over a specific time frame within a certain confidence level. The results of this section of the study support the growing body of evidence that, when properly constructed, VaR measures can be an effective tool for measuring bank risk.

The comparison of betas across countries should be done with caution based on the fact that different structures, legislations and stock market integration are not uniform. Nevertheless, the sample is diverse and does include countries with resemblance in terms of market structure and regulation.



**Table 6** Three Factor Betas: Belgian Bank Sample

Estimation of Three Factor Capital Asset Pricing Model

$$R_{it} = \alpha_{it} + \beta_{mi}R_{mjt} + \beta_{rt}R_{rjt} + \beta_{xt}R_{xjt} + u_{it}$$

Factor Betas by Bank by Year	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
<u>1992</u>						
Banque Belgoise	<b>0.327</b>	2.45**	<b>-0.135</b>	-0.96	<b>0.360</b>	2.73**
KBC	<b>0.383</b>	2.93**	<b>-0.367</b>	-2.79**	<b>0.530</b>	4.42**
Kredietbank	<b>0.245</b>	1.78	<b>-0.411</b>	-3.19**	<b>0.260</b>	1.91
<u>1993</u>						
Banque Belgoise	<b>0.080</b>	0.57	<b>0.022</b>	0.16	<b>0.118</b>	0.84
KBC	<b>0.480</b>	3.87**	<b>-0.054</b>	-0.38	<b>0.127</b>	0.91
Kredietbank	<b>0.259</b>	1.89	<b>-0.140</b>	-1.00	<b>0.079</b>	0.56
<u>1994</u>						
Banque Belgoise	<b>-0.168</b>	-1.20	<b>0.091</b>	0.65	<b>0.034</b>	0.24
KBC	<b>0.622</b>	5.61**	<b>-0.206</b>	-1.49	<b>-0.120</b>	-0.86
Kredietbank	<b>0.539</b>	4.53**	<b>-0.371</b>	-2.82**	<b>-0.323</b>	-2.41**
<u>1995</u>						
Banque Belgoise	<b>0.147</b>	1.05	<b>-0.294</b>	-2.18**	<b>0.202</b>	1.46
KBC	<b>0.653</b>	6.09**	<b>-0.224</b>	-1.63	<b>0.039</b>	0.28
Kredietbank	<b>0.298</b>	2.21**	<b>-0.043</b>	-0.30	<b>-0.417</b>	-3.24**
<u>1996</u>						
Banque Belgoise	<b>-0.014</b>	-0.10	<b>-0.005</b>	-0.03	<b>0.084</b>	0.60
KBC	<b>0.557</b>	4.74**	<b>-0.157</b>	-1.12	<b>0.320</b>	2.39**
Kredietbank	<b>0.370</b>	2.82**	<b>-0.114</b>	-0.81	<b>0.142</b>	1.02
<u>1997</u>						
Banque Belgoise	<b>0.389</b>	2.98**	<b>0.257</b>	1.88	<b>0.082</b>	0.58
KBC	<b>0.699</b>	6.90**	<b>0.031</b>	0.22	<b>0.298</b>	2.20**
Kredietbank	<b>0.730</b>	7.55**	<b>0.141</b>	1.01	<b>0.156</b>	1.12
<u>1998</u>						
Banque Belgoise	<b>0.427</b>	3.34**	<b>0.105</b>	0.74	<b>0.191</b>	1.38
KBC	<b>0.586</b>	5.11**	<b>0.071</b>	0.50	<b>0.166</b>	1.19
Kredietbank	<b>0.361</b>	2.74**	<b>0.095</b>	0.68	<b>-0.091</b>	-0.64

\*\* sig at the 95% confidence interval

\*\*\* sig. at the 99% confidence interval

$R_{it}$  is the return on bank stock  $i$  during time period  $t$

$B_{mi}R_{mjt}$  is the market beta and the return on the market index in country  $j$  at time  $t$

$B_{rt}R_{rjt}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$

$B_{xt}R_{xjt}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$

$\alpha_{it}, u_{it}$  is the bank specific constant and random error terms, respectively

**Table 7 Weekly VaR Results: Belgium**

Weekly VaR in percent of Bank Equity at Risk

$$VaR = c \left[ (\beta_{m,i} \sigma_{mj})^2 + (\beta_{r,i} \sigma_{rj})^2 + (\beta_{x,i} \sigma_{xj})^2 \right]^{1/2}$$

Bank VaR at 99% confidence		1992	1993	1994	1995	1996	1997	1998
<b>Belgium</b>								
Banque Belgoilaise	VaR, assuming a Normal Distribution	-0.88%	-0.16%	-0.24%	-0.28%	-0.12%	-0.99%	-1.51%
	Historical VaR	-1.79%	-0.34%	-0.44%	-0.77%	-0.22%	-2.41%	-3.26%
	EVT VaR	-1.91%	-0.41%	-0.49%	-1.07%	-0.26%	-2.76%	-3.57%
	VaR, Monte Carlo Simulation (1000 trials)	-2.83%	-1.20%	-1.25%	-1.12%	-0.82%	-4.05%	-5.60%
KBC	VaR, assuming a Normal Distribution	-0.74%	-0.54%	-0.78%	-0.65%	-0.77%	-1.77%	-1.84%
	Historical VaR	-1.54%	-1.00%	-1.65%	-1.34%	-1.71%	-4.46%	-3.67%
	EVT VaR	-1.72%	-1.26%	-1.74%	-1.59%	-2.20%	-5.23%	-3.90%
	VaR, Monte Carlo Simulation (1000 trials)	-2.28%	-2.52%	-2.44%	-2.30%	-2.75%	-5.08%	-5.88%
Kredietbank	VaR, assuming a Normal Distribution	-0.74%	-0.34%	-1.09%	-0.59%	-0.56%	-2.03%	-0.61%
	Historical VaR	-1.53%	-0.71%	-2.28%	-1.27%	-1.27%	-5.18%	-1.23%
	EVT VaR	-1.84%	-0.90%	-2.50%	-1.55%	-1.65%	-6.08%	-1.38%
	VaR, Monte Carlo Simulation (1000 trials)	-1.90%	-1.65%	-2.39%	-1.76%	-2.49%	-5.39%	-2.57%

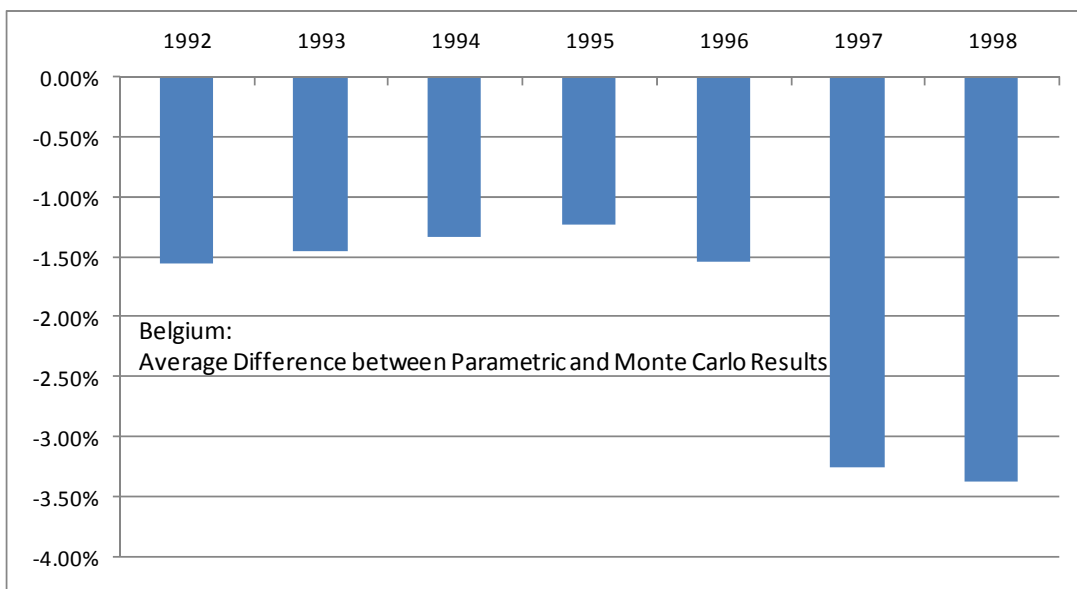
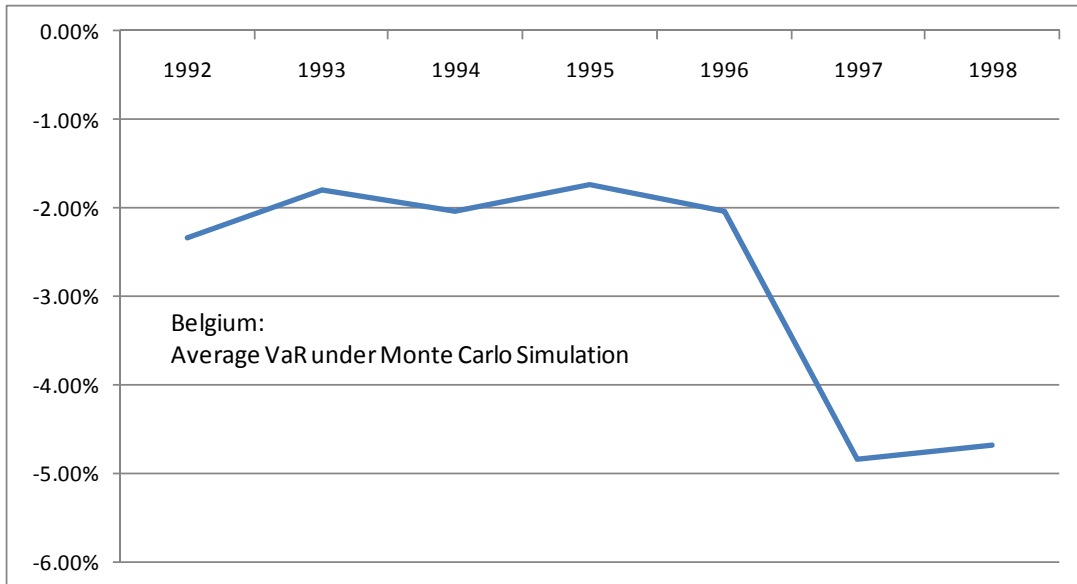
where c reflects a give level of statistical confidence

the betas pertain to each individual bank i

$\sigma_{m,i}$ ,  $\sigma_{r,i}$ ,  $\sigma_{x,i}$  represent the standard deviations of the market index, interest rate, and exchange rate in country i

These statistics are calculated from daily data obtained from FT Prices CD-Rom and Bloomberg.

**Figure 9** VaR results by Year. Parametric Vs Monte Carlo Results: Belgium



**Table 8 Three Factor Betas: Canadian Bank Sample**

Estimation of Three Factor Capital Asset Pricing Model

$$R_{it} = \alpha_{it} + \beta_{mt}R_{mjt} + \beta_{rt}R_{rjt} + \beta_{xt}R_{xjt} + u_{it}$$

Factor Betas by Bank by Year	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
<u>1992</u>						
Canadian Imperial Bank	<b>0.549</b>	<i>4.64**</i>	<b>-0.311</b>	<i>-2.31**</i>	<b>-0.236</b>	<i>-1.71</i>
National Bank of Canada	<b>0.428</b>	<i>3.35**</i>	<b>-0.162</b>	<i>-1.16</i>	<b>-0.036</b>	<i>-0.25</i>
Nova Scotia	<b>0.616</b>	<i>5.53**</i>	<b>-0.315</b>	<i>-2.34**</i>	<b>-0.253</b>	<i>-1.85</i>
Royal Bank of Canada	<b>0.537</b>	<i>4.51**</i>	<b>-0.285</b>	<i>-2.11**</i>	<b>-0.214</b>	<i>-1.55</i>
Toronto Dominion Bank	<b>0.477</b>	<i>3.84**</i>	<b>-0.386</b>	<i>-2.96**</i>	<b>-0.347</b>	<i>-2.61**</i>
<u>1993</u>						
Canadian Imperial Bank	<b>0.461</b>	<i>3.67**</i>	<b>-0.240</b>	<i>-1.75</i>	<b>-0.419</b>	<i>-3.26**</i>
National Bank of Canada	<b>0.259</b>	<i>1.90</i>	<b>-0.182</b>	<i>-1.31</i>	<b>-0.404</b>	<i>-3.12**</i>
Nova Scotia	<b>0.325</b>	<i>2.43**</i>	<b>-0.296</b>	<i>-2.19**</i>	<b>-0.498</b>	<i>-4.06**</i>
Royal Bank of Canada	<b>0.396</b>	<i>3.05**</i>	<b>-0.206</b>	<i>-1.49</i>	<b>-0.415</b>	<i>-3.22**</i>
Toronto Dominion Bank	<b>0.387</b>	<i>2.96**</i>	<b>-0.290</b>	<i>-2.15**</i>	<b>-0.367</b>	<i>-2.79**</i>
<u>1994</u>						
Canadian Imperial Bank	<b>0.608</b>	<i>5.42**</i>	<b>-0.355</b>	<i>-2.68**</i>	<b>-0.204</b>	<i>-1.48</i>
National Bank of Canada	<b>0.329</b>	<i>2.47**</i>	<b>-0.277</b>	<i>-2.04**</i>	<b>-0.320</b>	<i>-2.39**</i>
Nova Scotia	<b>0.572</b>	<i>4.93**</i>	<b>-0.424</b>	<i>-3.31**</i>	<b>-0.251</b>	<i>-1.84</i>
Royal Bank of Canada	<b>0.574</b>	<i>4.96**</i>	<b>-0.475</b>	<i>-3.81**</i>	<b>-0.366</b>	<i>-2.78**</i>
Toronto Dominion Bank	<b>0.579</b>	<i>5.02**</i>	<b>-0.369</b>	<i>-2.81**</i>	<b>-0.149</b>	<i>-1.07</i>
<u>1995</u>						
Canadian Imperial Bank	<b>0.397</b>	<i>3.05**</i>	<b>-0.532</b>	<i>-4.45**</i>	<b>-0.612</b>	<i>-5.47**</i>
National Bank of Canada	<b>0.315</b>	<i>2.34**</i>	<b>-0.578</b>	<i>-5.00**</i>	<b>-0.648</b>	<i>-6.02**</i>
Nova Scotia	<b>0.254</b>	<i>1.86</i>	<b>-0.418</b>	<i>-3.25**</i>	<b>-0.402</b>	<i>-3.11**</i>
Royal Bank of Canada	<b>0.435</b>	<i>3.42**</i>	<b>-0.582</b>	<i>-5.06**</i>	<b>-0.591</b>	<i>-5.18**</i>
Toronto Dominion Bank	<b>0.363</b>	<i>2.76**</i>	<b>-0.622</b>	<i>-5.62**</i>	<b>-0.626</b>	<i>-5.67**</i>
<u>1996</u>						
Canadian Imperial Bank	<b>0.451</b>	<i>3.58**</i>	<b>-0.413</b>	<i>-3.20**</i>	<b>-0.245</b>	<i>-1.79</i>
National Bank of Canada	<b>0.414</b>	<i>3.22**</i>	<b>-0.158</b>	<i>-1.13</i>	<b>-0.251</b>	<i>-1.84</i>
Nova Scotia	<b>0.506</b>	<i>4.15**</i>	<b>-0.343</b>	<i>-2.58**</i>	<b>-0.320</b>	<i>-2.38**</i>
Royal Bank of Canada	<b>0.544</b>	<i>4.58**</i>	<b>-0.479</b>	<i>-3.85**</i>	<b>-0.352</b>	<i>-2.66**</i>
Toronto Dominion Bank	<b>0.441</b>	<i>3.48**</i>	<b>-0.433</b>	<i>-3.40**</i>	<b>-0.137</b>	<i>-0.98</i>
<u>1997</u>						
Canadian Imperial Bank	<b>0.605</b>	<i>5.37**</i>	<b>-0.251</b>	<i>-1.83</i>	<b>-0.271</b>	<i>-1.99</i>
National Bank of Canada	<b>0.532</b>	<i>4.44**</i>	<b>-0.121</b>	<i>-0.86</i>	<b>-0.282</b>	<i>-2.08**</i>
Nova Scotia	<b>0.686</b>	<i>6.66**</i>	<b>-0.250</b>	<i>-1.82</i>	<b>-0.357</b>	<i>-2.70**</i>
Royal Bank of Canada	<b>0.609</b>	<i>5.43**</i>	<b>-0.207</b>	<i>-1.49</i>	<b>-0.432</b>	<i>-3.38**</i>
Toronto Dominion Bank	<b>0.676</b>	<i>6.48**</i>	<b>-0.244</b>	<i>-1.78</i>	<b>-0.395</b>	<i>-3.04**</i>
<u>1998</u>						
Canadian Imperial Bank	<b>0.760</b>	<i>8.26**</i>	<b>-0.047</b>	<i>-0.33</i>	<b>-0.198</b>	<i>-1.43</i>
National Bank of Canada	<b>0.700</b>	<i>6.93**</i>	<b>-0.223</b>	<i>-1.62</i>	<b>-0.384</b>	<i>-2.94**</i>
Nova Scotia	<b>0.726</b>	<i>7.47**</i>	<b>-0.258</b>	<i>-1.89</i>	<b>-0.287</b>	<i>-2.12**</i>
Royal Bank of Canada	<b>0.735</b>	<i>7.67**</i>	<b>-0.187</b>	<i>-1.35</i>	<b>-0.302</b>	<i>-2.24**</i>
Toronto Dominion Bank	<b>0.688</b>	<i>6.71**</i>	<b>-0.169</b>	<i>-1.21</i>	<b>-0.309</b>	<i>-2.30**</i>

\*\* sig at the 95% confidence interval

\*\*\* sig. at the 99% confidence interval

$R_{it}$  is the return on bank stock  $i$  during time period  $t$

$\beta_{mt}R_{mjt}$  is the market beta and the return on the market index in country  $j$  at time  $t$

$\beta_{rt}R_{rjt}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$

$\beta_{xt}R_{xjt}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$

$\alpha_{it}, u_{it}$  is the bank specific constant and random error terms, respectively

**Table 9 Weekly VaR Results: Canada**

Weekly VaR in percent of Bank Equity at Risk

$$VaR = c \left[ (\beta_{m,i} \sigma_{mij})^2 + (\beta_{r,i} \sigma_{rj})^2 + (\beta_{x,i} \sigma_{xj})^2 \right]^{1/2}$$

Bank VaR at 99% confidence		1992	1993	1994	1995	1996	1997	1998
<b>Canada</b>								
Canadian Imperial Bank	VaR, assuming a Normal Distribution	-1.41%	-1.11%	-1.09%	-1.35%	-0.99%	-1.46%	-2.82%
	Historical VaR	-3.56%	-2.61%	-3.17%	-3.06%	-1.97%	-3.86%	-7.46%
	EVT VaR	-4.44%	-3.16%	-3.47%	-3.15%	-2.49%	-4.46%	-8.16%
	VaR, Monte Carlo Simulation (1000 trials)	-2.50%	-2.35%	-3.19%	-1.77%	-2.05%	-3.31%	-5.67%
National Bank of Canada	VaR, assuming a Normal Distribution	-1.07%	-0.98%	-0.94%	-1.61%	-0.69%	-1.13%	-2.12%
	Historical VaR	-2.45%	-2.32%	-2.57%	-3.74%	-1.49%	-2.87%	-5.65%
	EVT VaR	-2.94%	-2.84%	-2.89%	-3.83%	-1.86%	-3.37%	-6.17%
	VaR, Monte Carlo Simulation (1000 trials)	-2.58%	-2.11%	-2.40%	-1.91%	-2.17%	-3.37%	-5.57%
Nova Scotia	VaR, assuming a Normal Distribution	-1.63%	-1.06%	-1.13%	-0.80%	-1.09%	-1.55%	-2.39%
	Historical VaR	-4.00%	-2.61%	-3.31%	-1.86%	-2.29%	-4.03%	-6.52%
	EVT VaR	-4.92%	-3.31%	-3.68%	-1.91%	-2.87%	-4.69%	-7.13%
	VaR, Monte Carlo Simulation (1000 trials)	-3.22%	-1.93%	-2.29%	-1.92%	-2.85%	-3.24%	-6.29%
Royal Bank of Canada	VaR, assuming a Normal Distribution	-1.44%	-1.00%	-1.33%	-1.39%	-1.20%	-1.42%	-2.19%
	Historical VaR	-3.57%	-2.33%	-3.84%	-3.17%	-2.46%	-3.58%	-5.86%
	EVT VaR	-4.42%	-2.81%	-4.31%	-3.26%	-3.09%	-4.18%	-6.40%
	VaR, Monte Carlo Simulation (1000 trials)	-2.63%	-2.65%	-2.71%	-2.52%	-2.58%	-3.48%	-5.85%
Toronto Dominion Bank	VaR, assuming a Normal Distribution	-1.30%	-0.99%	-1.26%	-1.39%	-1.07%	-1.63%	-2.42%
	Historical VaR	-3.55%	-2.44%	-3.72%	-3.24%	-2.03%	-4.19%	-6.43%
	EVT VaR	-4.53%	-3.12%	-4.10%	-3.32%	-2.59%	-4.88%	-7.03%
	VaR, Monte Carlo Simulation (1000 trials)	-2.51%	-2.09%	-3.51%	-1.91%	-2.19%	-3.54%	-6.26%

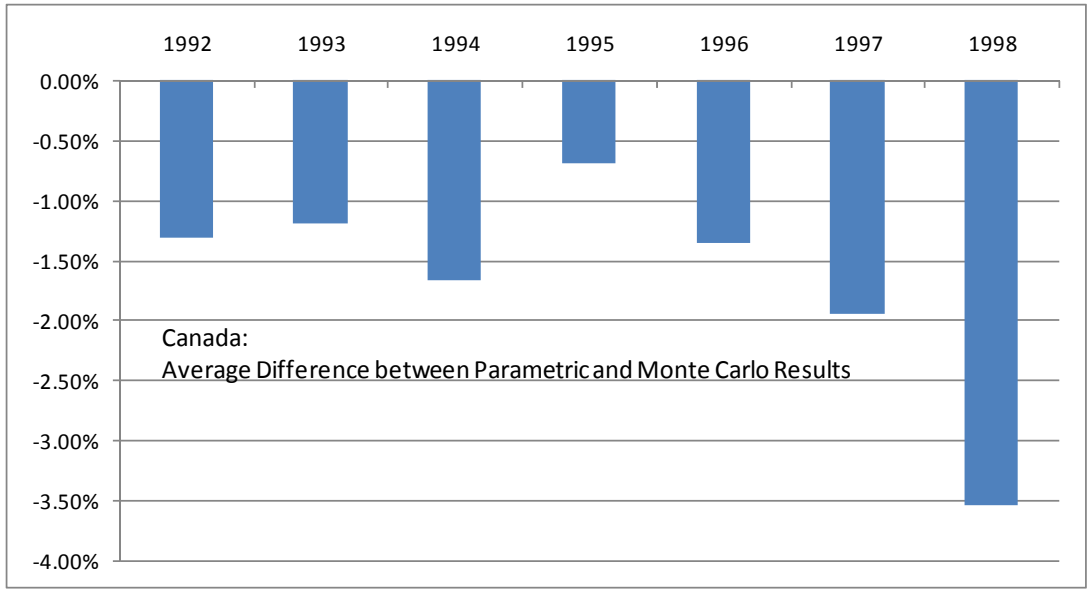
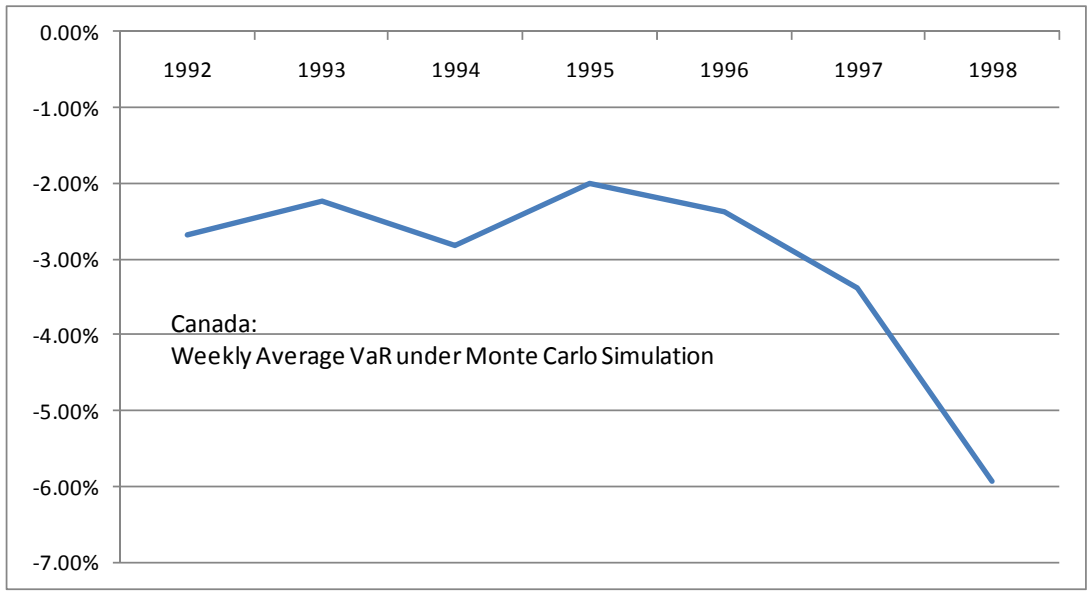
where  $c$  reflects a give level of statistical confidence

the betas pertain to each individual bank  $i$

$\sigma_{mij}, \sigma_{rj}, \sigma_{xj}$  represent the standard deviations of the market index, interest rate, and exchange rate in country  $j$

These statistics are calculated from daily data obtained from FT Prices CD-Rom and Bloomberg.

**Figure 10** VaR results by Year. Parametric Vs Monte Carlo Results: Canada



**Table 10 Three Factor Betas: French Bank Sample**

Estimation of Three Factor Capital Asset Pricing Model

$$R_{it} = \alpha_{it} + \beta_{m,t} R_{m,t} + \beta_{r,t} R_{r,t} + \beta_{f,t} R_{f,t} + u_{it}$$

Factor Betas by Bank by Year	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
<u>1992</u>						
Banque De La Reunion	<b>-0.265</b>	-1.94	<b>0.092</b>	0.65	<b>-0.265</b>	-1.94
Banque Nationale Du Paris	<b>0.132</b>	0.94	<b>-0.039</b>	-0.28	<b>0.220</b>	1.60
Credit Agricole	<b>0.198</b>	1.43	<b>0.201</b>	1.45	<b>0.052</b>	0.36
Credit Lyonnais	<b>0.140</b>	1.00	<b>-0.356</b>	-2.70**	<b>0.423</b>	3.30**
Natexis Banques	<b>0.335</b>	2.51**	<b>-0.097</b>	-0.69	<b>0.338</b>	2.54**
<u>1993</u>						
Banque De La Reunion	<b>-0.018</b>	-0.13	<b>-0.113</b>	-0.81	<b>0.210</b>	1.52
Banque Nationale Du Paris	<b>-0.162</b>	-1.16	<b>-0.090</b>	-0.64	<b>0.185</b>	1.33
Credit Agricole	<b>-0.052</b>	-0.36	<b>-0.117</b>	-0.84	<b>-0.005</b>	-0.04
Credit Lyonnais	<b>0.132</b>	0.94	<b>-0.234</b>	-1.70	<b>-0.097</b>	-0.69
Natexis Banques	<b>0.276</b>	2.03**	<b>-0.074</b>	-0.52	<b>0.049</b>	0.35
Societe Generale	<b>0.452</b>	3.59**	<b>0.061</b>	0.44	<b>0.062</b>	0.44
<u>1994</u>						
Banque De La Reunion	<b>0.097</b>	0.69	<b>-0.057</b>	-0.40	<b>0.108</b>	0.77
Banque Nationale Du Paris	<b>0.154</b>	1.10	<b>-0.148</b>	-1.06	<b>0.008</b>	0.05
Credit Agricole	<b>0.217</b>	1.57	<b>-0.051</b>	-0.36	<b>0.072</b>	0.51
Credit Lyonnais	<b>0.311</b>	2.32**	<b>-0.070</b>	-0.49	<b>0.296</b>	2.19**
Natexis Banques	<b>0.378</b>	2.89**	<b>0.000</b>	0.00	<b>0.345</b>	2.60**
Societe Generale	<b>0.523</b>	4.34**	<b>-0.492</b>	-3.99**	<b>0.087</b>	0.62
<u>1995</u>						
Banque De La Reunion	<b>-0.174</b>	-1.25	<b>-0.016</b>	-0.11	<b>-0.011</b>	-0.08
Banque Nationale Du Paris	<b>0.187</b>	1.35	<b>-0.363</b>	-2.76**	<b>0.178</b>	1.28
Credit Agricole	<b>0.195</b>	1.41	<b>-0.111</b>	-0.79	<b>0.037</b>	0.26
Credit Lyonnais	<b>0.018</b>	0.12	<b>0.031</b>	0.22	<b>0.086</b>	0.61
Natexis Banques	<b>0.210</b>	1.52	<b>-0.209</b>	-1.51	<b>0.124</b>	0.89
Societe Generale	<b>0.397</b>	3.06**	<b>-0.466</b>	-3.72**	<b>0.080</b>	0.57
<u>1996</u>						
Banque De La Reunion	<b>0.011</b>	0.08	<b>-0.063</b>	-0.45	<b>0.132</b>	0.94
Banque Nationale Du Paris	<b>0.067</b>	0.48	<b>0.037</b>	0.26	<b>-0.054</b>	-0.38
Credit Agricole	<b>0.014</b>	0.10	<b>0.143</b>	1.02	<b>-0.046</b>	-0.32
Credit Lyonnais	<b>-0.003</b>	-0.02	<b>-0.281</b>	-2.07**	<b>0.034</b>	0.24
Natexis Banques	<b>0.125</b>	0.89	<b>0.018</b>	0.13	<b>-0.158</b>	-1.13
Societe Generale	<b>0.420</b>	3.27**	<b>-0.279</b>	-2.05**	<b>0.172</b>	1.24
<u>1997</u>						
Banque De La Reunion	<b>0.130</b>	0.92	<b>-0.029</b>	-0.21	<b>-0.043</b>	-0.31
Banque Nationale Du Paris	<b>0.249</b>	1.82	<b>0.317</b>	2.36**	<b>0.189</b>	1.36
Credit Agricole	<b>0.169</b>	1.21	<b>-0.180</b>	-1.30	<b>0.227</b>	1.65
Credit Lyonnais	<b>0.128</b>	0.91	<b>0.087</b>	0.62	<b>0.118</b>	0.84
Natexis Banques	<b>0.607</b>	5.40**	<b>-0.316</b>	-2.36**	<b>0.289</b>	2.14**
Societe Generale	<b>0.634</b>	5.80**	<b>0.068</b>	0.48	<b>0.328</b>	2.45**
<u>1998</u>						
Banque De La Reunion	<b>0.072</b>	0.51	<b>0.076</b>	0.54	<b>-0.089</b>	-0.63
Banque Nationale Du Paris	<b>0.299</b>	2.21**	<b>0.448</b>	3.54**	<b>0.384</b>	2.94**
Credit Agricole	<b>0.384</b>	2.94**	<b>0.072</b>	0.51	<b>0.399</b>	3.07**
Credit Lyonnais	<b>0.564</b>	4.83**	<b>-0.031</b>	-0.22	<b>0.100</b>	0.71
Natexis Banques	<b>0.585</b>	5.10**	<b>0.062</b>	0.44	<b>0.308</b>	2.29**
Societe Generale	<b>0.720</b>	7.33**	<b>0.084</b>	0.59	<b>0.452</b>	3.58**

\*\* sig at the 95% confidence interval

\*\*\* sig. at the 99% confidence interval

$R_{it}$  is the return on bank stock  $i$  during time period  $t$   
 $\beta_{m,t} R_{m,t}$  is the market beta and the return on the market index in country  $j$  at time  $t$   
 $\beta_{r,t} R_{r,t}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$   
 $\beta_{f,t} R_{f,t}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$   
 $\alpha_{it}, u_{it}$  is the bank specific constant and random error terms, respectively

**Table 11 Weekly VaR Results: France**

Weekly VaR in percent of Bank Equity at Risk

$$VaR = c \left[ (\beta_{m,i} \sigma_{mj})^2 + (\beta_{r,i} \sigma_{rj})^2 + (\beta_{x,i} \sigma_{xj})^2 \right]^{1/2}$$

Bank VaR at 99% confidence		1992	1993	1994	1995	1996	1997	1998
<b>France</b>								
Banque De La Reunion	VaR, assuming a Normal Distribution	-0.77%	-0.49%	-0.23%	-0.22%	-0.24%	-0.33%	-0.40%
	Historical VaR	-2.40%	-1.04%	-0.58%	-0.60%	-0.51%	-0.92%	-1.09%
	EVT VaR	-2.61%	-1.06%	-0.60%	-0.79%	-0.62%	-1.41%	-1.59%
	VaR, Monte Carlo Simulation (1000 trials)	-1.94%	-2.18%	-1.48%	-0.91%	-1.07%	-1.86%	-1.76%
Banque Nationale Du Paris	VaR, assuming a Normal Distribution	-0.50%	-0.53%	-0.43%	-1.26%	-0.20%	-1.31%	-2.73%
	Historical VaR	-1.06%	-1.20%	-1.18%	-3.63%	-0.44%	-3.11%	-9.14%
	EVT VaR	-1.32%	-1.29%	-1.22%	-4.30%	-0.46%	-4.46%	-13.24%
	VaR, Monte Carlo Simulation (1000 trials)	-2.11%	-1.69%	-1.75%	-1.98%	-1.04%	-3.50%	-4.88%
Credit Agricole	VaR, assuming a Normal Distribution	-0.52%	-0.19%	-0.22%	-0.40%	-0.19%	-0.36%	-0.76%
	Historical VaR	-1.27%	-0.46%	-0.56%	-0.84%	-0.49%	-0.96%	-1.99%
	EVT VaR	-1.39%	-0.47%	-0.56%	-0.96%	-0.50%	-1.20%	-2.19%
	VaR, Monte Carlo Simulation (1000 trials)	-3.12%	-0.48%	-1.46%	-1.29%	-1.67%	-1.65%	-2.78%
Credit Lyonnais	VaR, assuming a Normal Distribution	-1.27%	-0.62%	-1.02%	-0.37%	-1.18%	-0.87%	-2.79%
	Historical VaR	-3.14%	-1.38%	-2.48%	-1.05%	-2.77%	-2.14%	-6.07%
	EVT VaR	-4.31%	-1.44%	-2.55%	-1.13%	-3.59%	-3.06%	-6.76%
	VaR, Monte Carlo Simulation (1000 trials)	-2.82%	-1.23%	-2.99%	-2.51%	-0.73%	-2.86%	-5.66%
Natexis Banques	VaR, assuming a Normal Distribution	-0.87%	-0.49%	-0.86%	-0.94%	-0.55%	-2.09%	-2.08%
	Historical VaR	-1.72%	-0.81%	-2.09%	-2.40%	-1.30%	-5.81%	-4.91%
	EVT VaR	-2.13%	-0.92%	-2.14%	-2.79%	-1.35%	-8.36%	-5.46%
	VaR, Monte Carlo Simulation (1000 trials)	-2.90%	-1.97%	-2.37%	-2.24%	-1.67%	-5.44%	-5.20%
Societe Generale	VaR, assuming a Normal Distribution	-1.32%	-0.64%	-1.26%	-1.24%	-0.84%	-1.71%	-3.76%
	Historical VaR	-2.76%	-1.03%	-3.45%	-3.23%	-1.65%	-4.56%	-9.10%
	EVT VaR	-3.63%	-1.19%	-3.56%	-3.84%	-1.96%	-6.97%	-10.09%
	VaR, Monte Carlo Simulation (1000 trials)	-4.07%	-2.29%	-3.13%	-1.87%	-2.06%	-4.87%	-7.07%

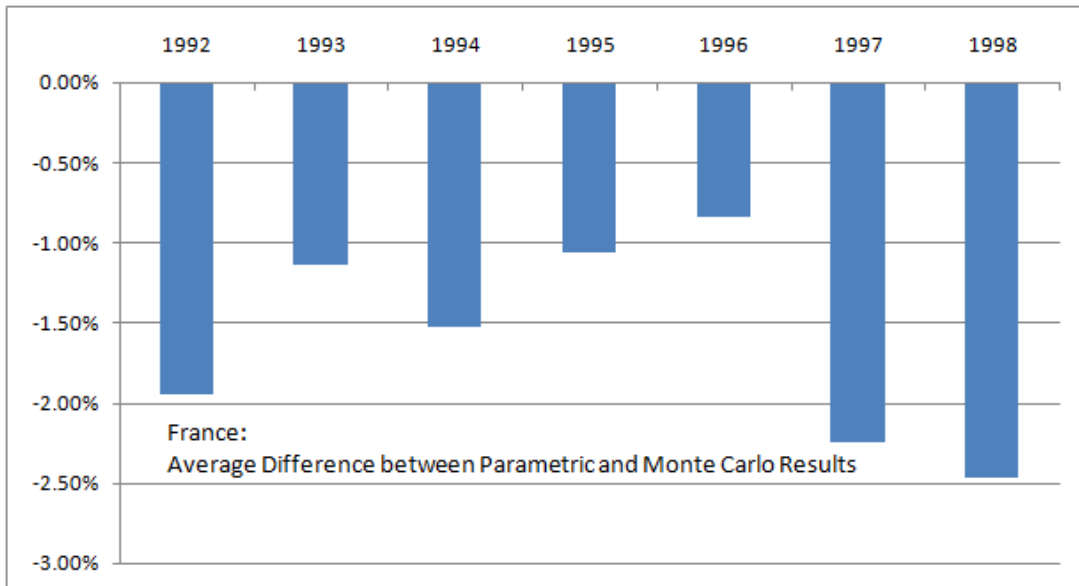
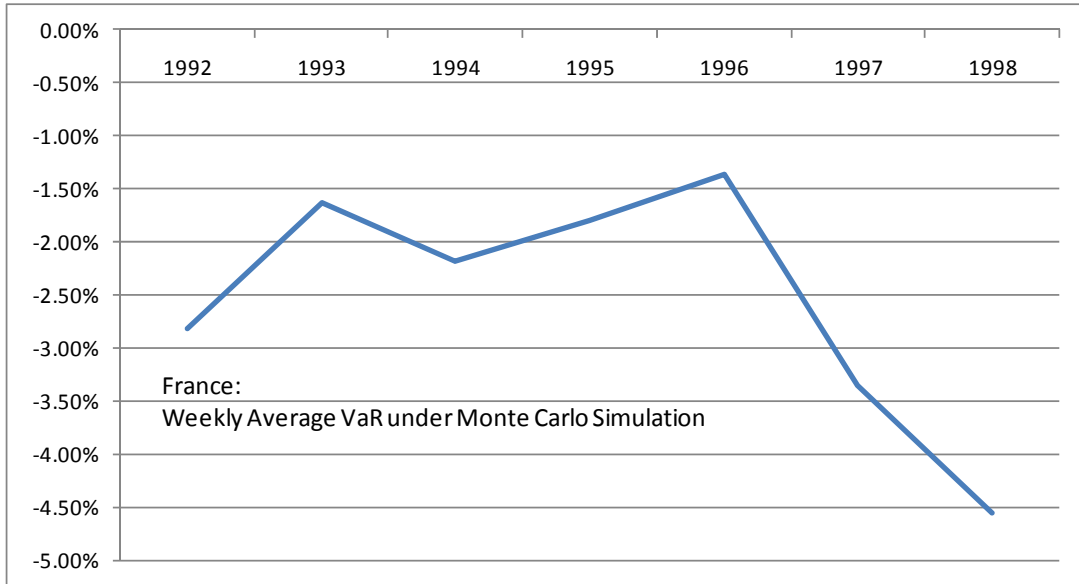
where  $c$  reflects a give level of statistical confidence  
the betas pertain to each individual bank  $i$

$\sigma_{mj}, \sigma_{rj}, \sigma_{xj}$  represent the standard deviations of the market index, interest rate, and exchange rate in country  $j$

These statistics are calculated from daily data obtained from FT Prices CD-Rom and Bloomberg.



**Figure 11** VaR results by Year. Parametric Vs Monte Carlo Results: France



**Table 12 Three Factor Betas: German Bank Sample**

Estimation of Three Factor Capital Asset Pricing Model

$$R_{it} = \alpha_{it} + \beta_{m,t} R_{mjt} + \beta_{r,t} R_{rjt} + \beta_{fx,t} R_{fxjt} + u_{it}$$

Factor Betas by Bank by Year	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
<u>1992</u>						
Commerzbank	0.447	3.53**	-0.318	-2.37**	0.521	4.31**
Dresdner	0.465	3.71**	-0.303	-2.25**	0.389	2.98**
Hypothecken	0.319	2.38**	-0.323	-2.41**	0.339	2.55**
Vereninsbank	0.326	2.44**	-0.140	-1.00	0.266	1.95
Vereins	0.003	0.02	-0.154	-1.10	-0.055	-0.39
<u>1993</u>						
Commerzbank	0.323	2.41**	-0.163	-1.17	0.126	0.90
Dresdner	0.450	3.57**	-0.277	-2.04**	0.292	2.16**
Hypothecken	0.532	4.44**	-0.190	-1.37	0.173	1.24
Vereninsbank	0.484	3.91**	-0.077	-0.55	0.247	1.80
Vereins	0.084	0.60	-0.327	-2.45**	0.086	0.61
<u>1994</u>						
Commerzbank	0.391	3.00**	-0.244	-1.78	0.059	0.42
Dresdner	0.522	4.32**	-0.181	-1.30	0.113	0.81
Hypothecken	0.325	2.43**	-0.169	-1.22	0.118	0.84
Vereninsbank	0.409	3.17**	-0.146	-1.05	0.101	0.72
Vereins	0.294	2.18**	-0.241	-1.76	0.202	1.46
<u>1995</u>						
Commerzbank	0.416	3.24**	-0.018	-0.12	0.080	0.56
Dresdner	0.464	3.71**	-0.081	-0.57	0.140	1.00
Hypothecken	0.483	3.90**	-0.039	-0.27	0.281	2.07**
Vereninsbank	0.452	3.58**	-0.061	-0.43	0.188	1.36
Vereins	0.324	2.42**	-0.247	-1.81	0.034	0.24
<u>1996</u>						
Commerzbank	0.463	3.70**	0.000	0.00	0.056	0.39
Dresdner	0.337	2.53**	0.110	0.79	-0.102	-0.72
Hypothecken	0.258	1.89	0.018	0.13	-0.018	-0.13
Vereninsbank	0.183	1.31	0.222	1.61	-0.102	-0.73
Vereins	0.163	1.17	-0.115	-0.82	-0.086	-0.61
<u>1997</u>						
Commerzbank	0.441	3.48**	-0.047	-0.33	0.328	2.45**
Dresdner	0.515	4.25**	-0.152	-1.09	0.407	3.15**
Hypothecken	0.377	2.88**	-0.112	-0.80	0.255	1.86
Vereninsbank	0.341	2.57**	-0.096	-0.68	0.204	1.48
Vereins	0.188	1.36	-0.115	-0.82	0.333	2.50**
<u>1998</u>						
Commerzbank	0.514	4.23**	-0.057	-0.41	0.263	1.93
Dresdner	0.525	4.36**	-0.147	-1.05	0.182	1.31
Hypothecken	0.582	4.11**	0.332	2.02**	0.278	1.66
Vereninsbank	0.147	1.05	-0.087	-0.62	0.168	1.20
Vereins	0.136	0.97	-0.023	-0.17	-0.078	-0.55

\*\* sig at the 95% confidence interval

\*\*\* sig. at the 99% confidence interval

$R_{it}$  is the return on bank stock  $i$  during time period  $t$

$\beta_{m,t} R_{mjt}$  is the market beta and the return on the market index in country  $j$  at time  $t$

$\beta_{r,t} R_{rjt}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$

$\beta_{fx,t} R_{fxjt}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$

$\alpha_{it}, u_{it}$  is the bank specific constant and random error terms, respectively

**Table 13 Weekly VaR Results: Germany**

Weekly VaR in percent of Bank Equity at Risk

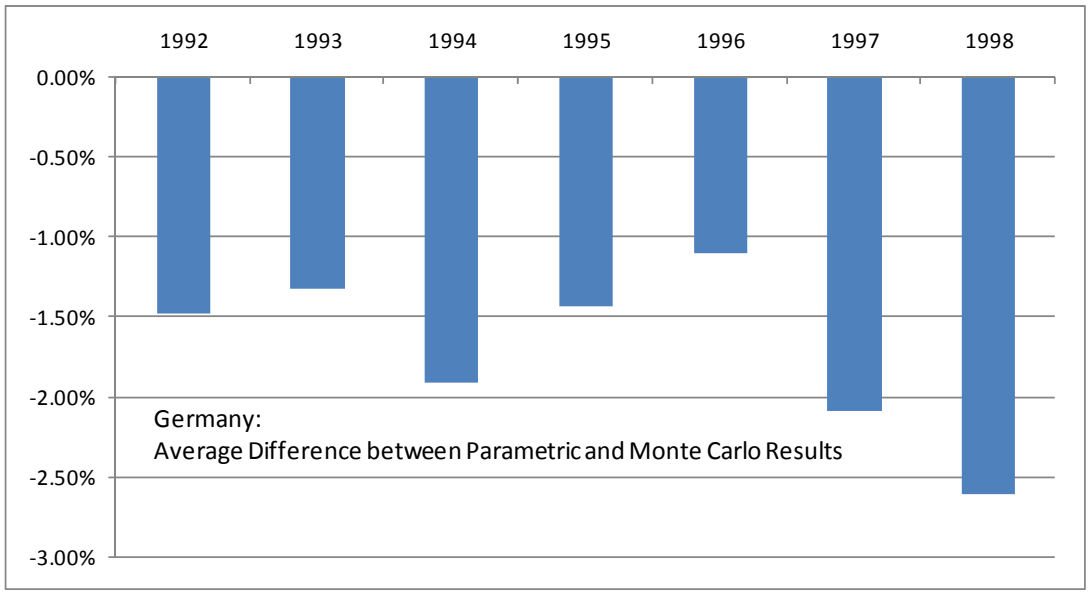
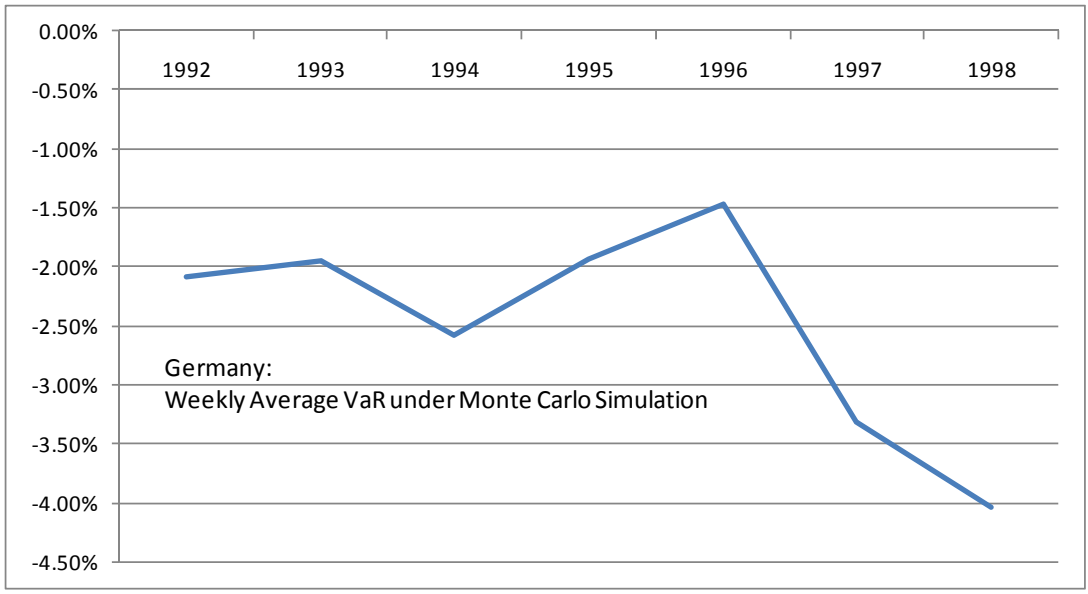
$$VaR = c \left[ (\beta_{m,i} \sigma_{mj})^2 + (\beta_{r,i} \sigma_{rj})^2 + (\beta_{x,i} \sigma_{xj})^2 \right]^{1/2}$$

Bank VaR at 99% confidence		1992	1993	1994	1995	1996	1997	1998
<b>Germany</b>								
Commerzbank	VaR, assuming a Normal Distribution	-1.08%	-0.55%	-0.66%	-0.46%	-0.56%	-1.38%	-1.34%
	Historical VaR	-1.97%	-0.91%	-1.54%	-0.74%	-0.98%	-3.53%	-3.13%
	EVT VaR	-2.12%	-1.02%	-1.61%	-0.78%	-1.09%	-5.27%	-3.43%
	VaR, Monte Carlo Simulation (1000 trials)	-3.38%	-2.00%	-2.94%	-1.83%	-1.75%	-3.85%	-3.75%
Dresdner	VaR, assuming a Normal Distribution	-0.84%	-0.82%	-0.91%	-0.48%	-0.35%	-1.93%	-1.93%
	Historical VaR	-1.45%	-1.40%	-2.25%	-0.80%	-0.68%	-5.00%	-4.32%
	EVT VaR	-1.59%	-1.53%	-2.31%	-0.85%	-0.74%	-7.37%	-4.81%
	VaR, Monte Carlo Simulation (1000 trials)	-2.48%	-2.60%	-3.18%	-1.85%	-1.45%	-4.20%	-5.59%
Hypotheke	VaR, assuming a Normal Distribution	-0.57%	-0.71%	-0.61%	-0.73%	-0.40%	-1.43%	-3.00%
	Historical VaR	-0.97%	-1.16%	-1.45%	-1.40%	-0.70%	-3.78%	-8.94%
	EVT VaR	-1.06%	-1.31%	-1.51%	-1.51%	-0.77%	-5.64%	-12.38%
	VaR, Monte Carlo Simulation (1000 trials)	-2.20%	-2.17%	-2.43%	-2.56%	-1.48%	-3.22%	-6.83%
Vereninsbank	VaR, assuming a Normal Distribution	-0.47%	-0.66%	-0.76%	-0.64%	-0.44%	-1.03%	-0.70%
	Historical VaR	-0.83%	-1.11%	-1.86%	-1.13%	-1.11%	-2.74%	-1.78%
	EVT VaR	-0.90%	-1.25%	-1.91%	-1.22%	-1.17%	-4.13%	-1.93%
	VaR, Monte Carlo Simulation (1000 trials)	-2.25%	-2.06%	-2.53%	-2.20%	-1.92%	-3.36%	-2.50%
Vereins	VaR, assuming a Normal Distribution	-0.14%	-0.38%	-0.47%	-0.24%	-0.13%	-0.41%	-0.18%
	Historical VaR	-0.21%	-0.66%	-1.07%	-0.33%	-0.24%	-0.97%	-0.37%
	EVT VaR	-0.25%	-0.68%	-1.16%	-0.35%	-0.27%	-1.29%	-0.41%
	VaR, Monte Carlo Simulation (1000 trials)	-0.13%	-0.88%	-1.84%	-1.25%	-0.76%	-1.92%	-1.48%

where c reflects a give level of statistical confidence  
the betas pertain to each individual bank i

$\sigma_{m,i}$ ,  $\sigma_{r,i}$ ,  $\sigma_{x,i}$  represent the standard deviations of the market index, interest rate, and exchange rate in country j  
These statistics are calculated from daily data obtained from FT Prices CD-Rom and Bloomberg.

**Figure 12** VaR results by Year. Parametric Vs Monte Carlo Results: Germany



**Table 14 Three Factor Betas: Italian Bank Sample**

Estimation of Three Factor Capital Asset Pricing Model

$$R_{it} = \alpha_{it} + \beta_{m,t} R_{m,t} + \beta_{r,t} R_{r,t} + \beta_{f,t} R_{f,t} + u_{it}$$

Factor Betas by Bank by Year	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
<u>1992</u>						
Banca Agricoltura	<b>0.093</b>	0.66	<b>-0.325</b>	-2.43**	<b>0.247</b>	1.80
Banca Commerciale	<b>0.103</b>	0.73	<b>-0.216</b>	-1.57	<b>0.190</b>	1.37
Banca Di Roma	<b>0.036</b>	0.25	<b>-0.265</b>	-1.94	<b>0.062</b>	0.44
Banca Nazionale	<b>0.066</b>	0.46	<b>-0.320</b>	-2.39**	<b>0.232</b>	1.68
Credito Italiana	<b>0.270</b>	1.98	<b>-0.260</b>	-1.91	<b>0.475</b>	3.82**
<u>1993</u>						
Banca Agricoltura	<b>0.023</b>	0.16	<b>0.009</b>	0.07	<b>-0.396</b>	-3.05**
Banca Commerciale	<b>0.134</b>	0.95	<b>0.141</b>	1.01	<b>-0.165</b>	-1.18
Banca Di Roma	<b>0.186</b>	1.34	<b>0.036</b>	0.26	<b>-0.176</b>	-1.26
Banca Nazionale	<b>0.217</b>	1.57	<b>-0.116</b>	-0.83	<b>-0.104</b>	-0.74
Credito Italiana	<b>0.016</b>	0.11	<b>-0.070</b>	-0.50	<b>-0.125</b>	-0.89
<u>1994</u>						
Banca Agricoltura	<b>0.252</b>	1.84	<b>-0.192</b>	-1.38	<b>0.157</b>	1.12
Banca Commerciale	<b>0.009</b>	0.06	<b>-0.034</b>	-0.24	<b>0.123</b>	0.87
Banca Di Roma	<b>0.351</b>	2.65**	<b>-0.296</b>	-2.19**	<b>0.022</b>	0.16
Banca Nazionale	<b>-0.019</b>	-0.14	<b>-0.141</b>	-1.01	<b>0.043</b>	0.31
Credito Italiana	<b>0.352</b>	2.66**	<b>-0.229</b>	-1.67	<b>0.009</b>	0.06
<u>1995</u>						
Banca Agricoltura	<b>-0.037</b>	-0.26	<b>-0.101</b>	-0.72	<b>-0.262</b>	-1.92
Banca Commerciale	<b>-0.070</b>	-0.50	<b>-0.130</b>	-0.93	<b>-0.013</b>	-0.09
Banca Di Roma	<b>-0.050</b>	-0.35	<b>-0.172</b>	-1.23	<b>-0.081</b>	-0.57
Banca Nazionale	<b>0.024</b>	0.17	<b>-0.159</b>	-1.14	<b>-0.024</b>	-0.17
Credito Italiana	<b>0.084</b>	0.60	<b>-0.408</b>	-3.16**	<b>-0.153</b>	-1.10
<u>1996</u>						
Banca Agricoltura	<b>-0.001</b>	-0.01	<b>0.265</b>	1.94	<b>-0.063</b>	-0.45
Banca Commerciale	<b>-0.017</b>	-0.12	<b>-0.030</b>	-0.21	<b>-0.198</b>	-1.43
Banca Di Roma	<b>0.240</b>	1.75	<b>-0.190</b>	-1.37	<b>0.115</b>	0.82
Banca Nazionale	<b>0.168</b>	1.20	<b>-0.066</b>	-0.47	<b>-0.167</b>	-1.20
Credito Italiana	<b>0.244</b>	1.78	<b>-0.154</b>	-1.10	<b>0.011</b>	0.08
<u>1997</u>						
Banca Agricoltura	<b>0.160</b>	1.14	<b>-0.237</b>	-1.73	<b>0.218</b>	1.58
Banca Commerciale	<b>0.207</b>	1.50	<b>-0.099</b>	-0.70	<b>0.041</b>	0.29
Banca Di Roma	<b>0.235</b>	1.71	<b>0.068</b>	0.48	<b>0.137</b>	0.98
Banca Nazionale	<b>0.141</b>	1.00	<b>-0.018</b>	-0.13	<b>0.101</b>	0.72
Credito Italiana	<b>0.145</b>	1.04	<b>-0.193</b>	-1.39	<b>0.135</b>	0.96
<u>1998</u>						
Banca Agricoltura	<b>0.507</b>	4.16**	<b>0.018</b>	0.13	<b>0.363</b>	2.75**
Banca Commerciale	<b>0.296</b>	2.19**	<b>-0.018</b>	-0.13	<b>0.362</b>	2.74**
Banca Di Roma	<b>0.432</b>	3.38**	<b>-0.036</b>	-0.25	<b>0.468</b>	3.74**
Banca Nazionale	<b>0.466</b>	3.73**	<b>-0.024</b>	-0.17	<b>0.376</b>	2.87**
Credito Italiana	<b>0.582</b>	5.07**	<b>0.004</b>	0.03	<b>0.535</b>	4.48**

\*\* sig at the 95% confidence interval

\*\*\* sig. at the 99% confidence interval

$R_{it}$  is the return on bank stock  $i$  during time period  $t$

$\beta_{m,t} R_{m,t}$  is the market beta and the return on the market index in country  $j$  at time  $t$

$\beta_{r,t} R_{r,t}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$

$\beta_{f,t} R_{f,t}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$

$\alpha_{it}, u_{it}$  is the bank specific constant and random error terms, respectively

**Table 15 Weekly VaR Results: Italy**

Weekly VaR in percent of Bank Equity at Risk

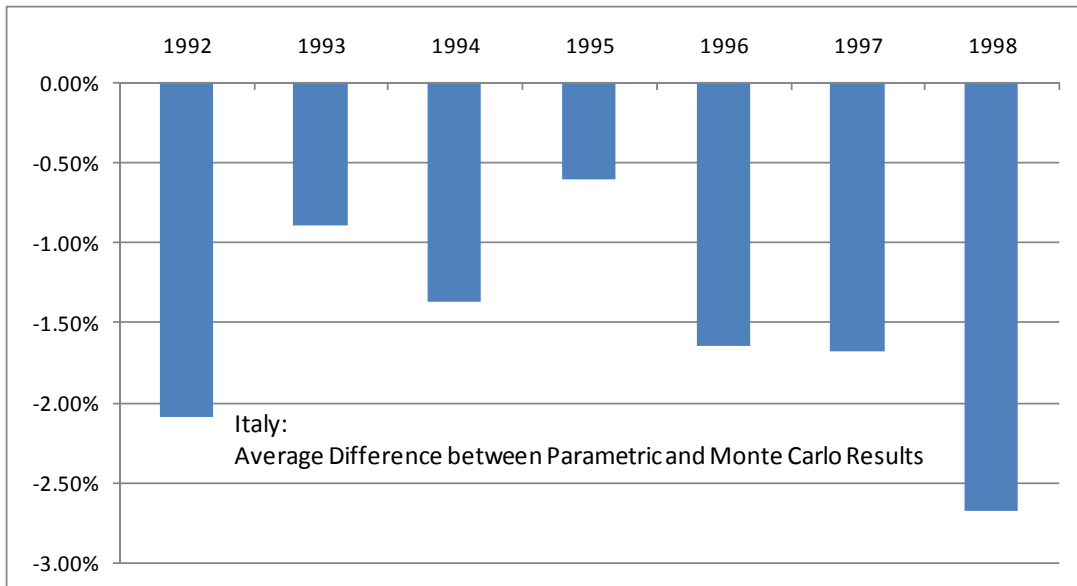
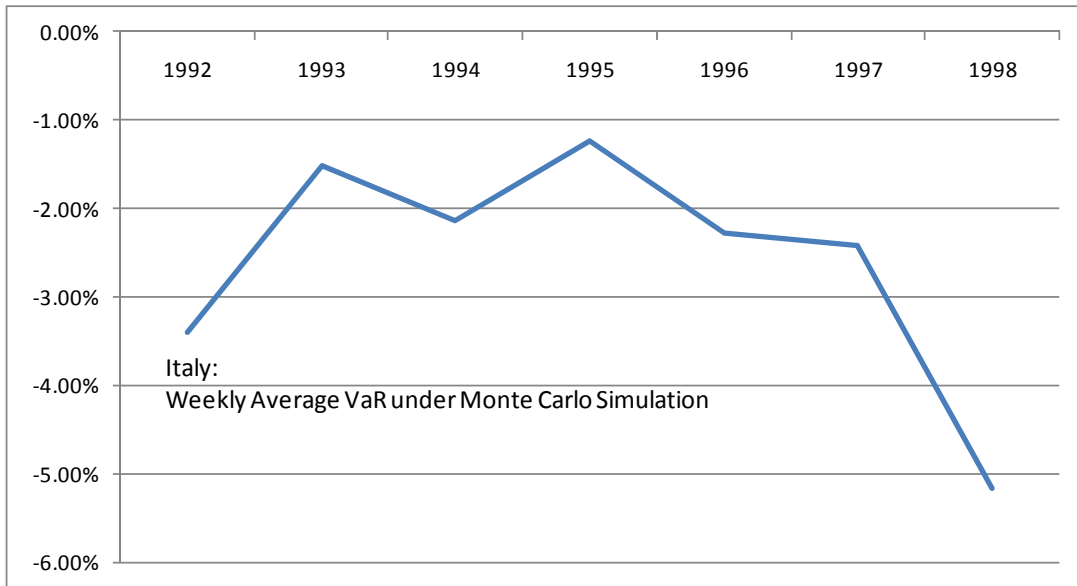
$$VaR = c \left[ (\beta_{m,i} \sigma_{mj})^2 + (\beta_{r,i} \sigma_{rj})^2 + (\beta_{x,i} \sigma_{xj})^2 \right]^{1/2}$$

Bank VaR at 99% confidence		1992	1993	1994	1995	1996	1997	1998
<b>Italy</b>								
Banca Agricoltura	VaR, assuming a Normal Distribution	-1.45%	-1.01%	-0.97%	-1.14%	-0.89%	-1.03%	-2.49%
	Historical VaR	-3.43%	-2.08%	-2.46%	-3.03%	-2.26%	-2.81%	-6.02%
	EVT VaR	-4.92%	-2.53%	-2.54%	-4.00%	-2.26%	-3.34%	-6.62%
	VaR, Monte Carlo Simulation (1000 trials)	-3.58%	-0.73%	-2.58%	-3.75%	-3.93%	-2.33%	-5.41%
Banca Commerciale	VaR, assuming a Normal Distribution	-0.70%	-0.68%	-0.28%	-0.23%	-0.32%	-0.57%	-1.64%
	Historical VaR	-1.57%	-1.40%	-0.53%	-0.69%	-0.60%	-1.62%	-4.28%
	EVT VaR	-2.22%	-1.59%	-0.57%	-0.85%	-0.62%	-2.40%	-4.65%
	VaR, Monte Carlo Simulation (1000 trials)	-2.70%	-2.78%	-1.34%	-1.12%	-1.85%	-2.36%	-3.89%
Banca Di Roma	VaR, assuming a Normal Distribution	-0.90%	-0.57%	-1.15%	-0.60%	-0.93%	-0.74%	-2.59%
	Historical VaR	-2.49%	-1.06%	-3.11%	-1.81%	-1.92%	-1.90%	-6.64%
	EVT VaR	-3.69%	-1.26%	-3.21%	-2.23%	-2.27%	-2.87%	-7.23%
	VaR, Monte Carlo Simulation (1000 trials)	-1.66%	-2.11%	-2.93%	0.00%	-2.32%	-2.69%	-4.73%
Banca Nazionale	VaR, assuming a Normal Distribution	-0.82%	-0.42%	-0.28%	-0.22%	-0.34%	-0.46%	-2.68%
	Historical VaR	-1.98%	-0.77%	-0.78%	-0.69%	-0.63%	-1.18%	-6.58%
	EVT VaR	-2.85%	-0.87%	-0.83%	-0.84%	-0.69%	-1.75%	-7.20%
	VaR, Monte Carlo Simulation (1000 trials)	-2.22%	-1.49%	-0.62%	-0.30%	-1.44%	-2.52%	-5.17%
Credito Italiana	VaR, assuming a Normal Distribution	-2.61%	-0.36%	-1.14%	-0.92%	-0.61%	-0.83%	-3.00%
	Historical VaR	-4.54%	-0.76%	-3.03%	-2.79%	-1.18%	-2.37%	-7.53%
	EVT VaR	-5.83%	-0.89%	-3.10%	-3.42%	-1.41%	-2.90%	-8.22%
	VaR, Monte Carlo Simulation (1000 trials)	-6.80%	-0.42%	-3.20%	-0.98%	-1.81%	-2.15%	-6.62%

where c reflects a give level of statistical confidence  
the betas pertain to each individual bank i

$\sigma_{mj}$ ,  $\sigma_{rj}$ ,  $\sigma_{xj}$  represent the standard deviations of the market index, interest rate, and exchange rate in country j  
These statistics are calculated from daily data obtained from FT Prices CD-Rom and Bloomberg.

**Figure 13** VaR results by Year. Parametric Vs Monte Carlo Results: Italy



**Table 16 Three Factor Betas: Japanese Bank Sample**

Estimation of Three Factor Capital Asset Pricing Model

$$R_{it} = \alpha_{it} + \beta_{mt}R_{mt} + \beta_{rt}R_{rt} + \beta_{ft}R_{ft} + u_{it}$$

Factor Betas by Bank by Year	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
<b>1992</b>						
77 Bank	0.287	2.12**	0.017	0.12	-0.361	-2.73**
Akita Bank	0.612	5.47**	0.142	1.01	-0.258	-1.89
Aomori	0.457	3.63**	0.442	3.49**	-0.333	-2.50**
Bank of Iwate	0.580	5.03**	0.247	1.80	-0.440	-3.46**
Chiba Bank	0.484	3.91**	0.203	1.46	-0.310	-2.30**
Hokkaido	0.558	4.75**	0.319	2.38**	-0.219	-1.58
Hokkoku	0.161	1.15	0.176	1.26	-0.191	-1.37
Hokuriku	0.300	2.22**	-0.065	-0.46	-0.149	-1.07
Joyo Bank	0.597	5.26**	0.293	2.16**	-0.253	-1.85
Kanto Bank	0.335	2.51**	0.284	2.09**	-0.257	-1.88
Michinoku	0.246	1.79	0.250	1.83	-0.258	-1.89
Mitsubishi Trust	0.729	7.53**	0.270	1.99	-0.280	-2.06**
Mitsui Trust	0.768	8.49**	0.183	1.31	-0.122	-0.87
Saporo	-0.302	-2.24**	0.067	0.47	0.084	0.59
Sumitomo Trust	0.693	6.79**	0.303	2.25**	-0.261	-1.91
Sumitomo	0.747	7.95**	0.186	1.34	-0.228	-1.65
Toho Bank	0.702	6.96**	0.096	0.68	-0.258	-1.89
Yamagata	0.510	4.20**	0.243	1.77	-0.359	-2.72**
Yamanashi	0.429	3.36**	0.164	1.18	-0.296	-2.19**
<b>1993</b>						
	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
77 Bank	0.292	2.16**	0.091	0.64	-0.415	-3.23**
Akita Bank	0.357	2.70**	0.199	1.44	-0.069	-0.49
Aomori	0.349	2.64**	0.198	1.43	-0.332	-2.49**
Bank of Iwate	0.431	3.38**	0.362	2.75**	-0.129	-0.92
Chiba Bank	0.247	1.80	-0.064	-0.46	-0.089	-0.63
Hokkaido	0.377	2.88**	0.112	0.80	-0.341	-2.56**
Hokkoku	0.195	1.40	0.078	0.55	-0.165	-1.18
Hokuriku	0.204	1.48	-0.066	-0.47	-0.207	-1.49
Joyo Bank	0.460	3.67**	0.273	2.00**	-0.048	-0.34
Kanto Bank	0.109	0.78	0.093	0.66	-0.238	-1.74
Michinoku	0.251	1.83	0.080	0.57	-0.321	-2.39**
Mitsubishi Trust	0.602	5.33**	0.160	1.14	-0.119	-0.85
Mitsui Trust	0.622	5.62**	0.199	1.43	-0.282	-2.08**
Saporo	0.044	0.31	0.127	0.90	-0.443	-3.49**
Sumitomo Trust	0.581	5.05**	0.183	1.32	-0.211	-1.53
Sumitomo	0.432	3.38**	0.132	0.94	-0.249	-1.82
Toho Bank	0.436	3.43**	0.215	1.56	-0.097	-0.69
Yamagata	0.388	2.98**	0.211	1.53	-0.235	-1.71
Yamanashi	0.370	2.82**	0.050	0.36	-0.194	-1.40
<b>1994</b>						
	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
77 Bank	0.272	2.00	0.038	0.27	-0.247	-1.80
Akita Bank	0.219	1.59	0.092	0.65	-0.152	-1.09
Aomori	0.209	1.51	0.216	1.57	-0.135	-0.96
Bank of Iwate	-0.037	-0.26	0.006	0.04	-0.131	-0.94
Chiba Bank	0.397	3.06**	0.024	0.17	-0.023	-0.16
Hokkaido	0.447	3.53**	0.021	0.15	-0.313	-2.33**
Hokkoku	0.185	1.33	0.298	2.21**	-0.329	-2.47**
Hokuriku	0.284	2.09**	-0.041	-0.29	-0.012	-0.09
Joyo Bank	0.453	3.59**	0.063	0.45	-0.087	-0.62
Kanto Bank	0.304	2.25**	0.088	0.63	-0.355	-2.68**
Michinoku	-0.007	-0.05	-0.151	-1.08	-0.368	-2.80**
Mitsubishi Trust	0.495	4.03**	0.069	0.49	0.053	0.37
Mitsui Trust	0.694	6.82**	0.004	0.03	0.259	1.90
Saporo	0.044	0.31	-0.054	-0.38	-0.083	-0.59
Sumitomo Trust	0.502	4.10**	0.004	0.03	0.077	0.54
Sumitomo	0.539	4.52**	-0.010	-0.07	0.154	1.10
Toho Bank	0.467	3.73**	0.146	1.05	-0.018	-0.13
Yamagata	0.269	1.98	0.142	1.01	-0.205	-1.48
Yamanashi	0.307	2.28**	0.143	1.02	-0.155	-1.11



1995	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
77 Bank	<b>0.326</b>	<i>2.44**</i>	<b>-0.167</b>	<i>-1.20</i>	<b>-0.378</b>	<i>-2.89**</i>
Akita Bank	<b>0.246</b>	<i>1.79</i>	<b>-0.102</b>	<i>-0.73</i>	<b>-0.367</b>	<i>-2.79**</i>
Aomori	<b>0.282</b>	<i>2.08**</i>	<b>-0.341</b>	<i>-2.57**</i>	<b>-0.425</b>	<i>-3.32**</i>
Bank of Iwate	<b>0.259</b>	<i>1.89</i>	<b>-0.209</b>	<i>-1.51</i>	<b>-0.448</b>	<i>-3.54**</i>
Chiba Bank	<b>0.445</b>	<i>3.52**</i>	<b>-0.194</b>	<i>-1.40</i>	<b>-0.096</b>	<i>-0.68</i>
Hokkaido	<b>0.396</b>	<i>3.05**</i>	<b>-0.161</b>	<i>-1.16</i>	<b>-0.177</b>	<i>-1.27</i>
Hokkoku	<b>0.485</b>	<i>3.92**</i>	<b>-0.190</b>	<i>-1.37</i>	<b>-0.104</b>	<i>-0.74</i>
Hokuriku	<b>0.214</b>	<i>1.55</i>	<b>-0.180</b>	<i>-1.29</i>	<b>-0.188</b>	<i>-1.36</i>
Joyo Bank	<b>0.287</b>	<i>2.12**</i>	<b>-0.386</b>	<i>-2.96**</i>	<b>-0.289</b>	<i>-2.14**</i>
Kanto Bank	<b>0.203</b>	<i>1.46</i>	<b>-0.143</b>	<i>-1.02</i>	<b>-0.100</b>	<i>-0.71</i>
Michinoku	<b>-0.001</b>	<i>-0.01</i>	<b>-0.161</b>	<i>-1.15</i>	<b>-0.443</b>	<i>-3.49**</i>
Mitsubishi Trust	<b>0.660</b>	<i>6.21**</i>	<b>-0.320</b>	<i>-2.39**</i>	<b>-0.018</b>	<i>-0.13</i>
Mitsui Trust	<b>0.608</b>	<i>5.41**</i>	<b>-0.324</b>	<i>-2.42**</i>	<b>0.003</b>	<i>0.02</i>
Saporo	<b>-0.025</b>	<i>-0.18</i>	<b>-0.145</b>	<i>-1.04</i>	<b>-0.436</b>	<i>-3.43**</i>
Sumitomo Trust	<b>0.654</b>	<i>6.12**</i>	<b>-0.310</b>	<i>-2.31**</i>	<b>0.019</b>	<i>0.13</i>
Sumitomo	<b>0.592</b>	<i>5.20**</i>	<b>-0.361</b>	<i>-2.74**</i>	<b>-0.134</b>	<i>-0.96</i>
Toho Bank	<b>0.354</b>	<i>2.67**</i>	<b>-0.218</b>	<i>-1.58</i>	<b>-0.222</b>	<i>-1.61</i>
Yamagata	<b>0.246</b>	<i>1.79</i>	<b>-0.189</b>	<i>-1.36</i>	<b>-0.172</b>	<i>-1.24</i>
Yamanashi	<b>0.435</b>	<i>3.42**</i>	<b>-0.352</b>	<i>-2.66**</i>	<b>-0.216</b>	<i>-1.56</i>

1996	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
77 Bank	<b>0.354</b>	<i>2.68**</i>	<b>0.103</b>	<i>0.73</i>	<b>-0.227</b>	<i>-1.65</i>
Akita Bank	<b>0.635</b>	<i>5.81**</i>	<b>0.208</b>	<i>1.50</i>	<b>-0.380</b>	<i>-2.91**</i>
Aomori	<b>0.401</b>	<i>3.09**</i>	<b>0.048</b>	<i>0.34</i>	<b>-0.252</b>	<i>-1.84</i>
Bank of Iwate	<b>0.213</b>	<i>1.54</i>	<b>0.272</b>	<i>2.00</i>	<b>-0.414</b>	<i>-3.21**</i>
Chiba Bank	<b>0.352</b>	<i>2.66**</i>	<b>-0.001</b>	<i>-0.01</i>	<b>-0.447</b>	<i>-3.54**</i>
Hokkaido	<b>0.306</b>	<i>2.28**</i>	<b>0.136</b>	<i>0.97</i>	<b>-0.389</b>	<i>-2.98**</i>
Hokkoku	<b>0.489</b>	<i>3.96**</i>	<b>0.116</b>	<i>0.83</i>	<b>-0.333</b>	<i>-2.50**</i>
Hokuriku	<b>0.186</b>	<i>1.34</i>	<b>0.153</b>	<i>1.10</i>	<b>-0.519</b>	<i>-4.30**</i>
Joyo Bank	<b>0.299</b>	<i>2.21**</i>	<b>0.189</b>	<i>1.36</i>	<b>-0.461</b>	<i>-3.68**</i>
Kanto Bank	<b>0.329</b>	<i>2.46**</i>	<b>0.138</b>	<i>0.98</i>	<b>-0.471</b>	<i>-3.77**</i>
Michinoku	<b>0.311</b>	<i>2.32**</i>	<b>0.084</b>	<i>0.60</i>	<b>-0.432</b>	<i>-3.38**</i>
Mitsubishi Trust	<b>0.589</b>	<i>5.16**</i>	<b>-0.007</b>	<i>-0.05</i>	<b>-0.236</b>	<i>-1.72</i>
Mitsui Trust	<b>0.694</b>	<i>6.82**</i>	<b>0.330</b>	<i>2.47**</i>	<b>-0.209</b>	<i>-1.51</i>
Saporo	<b>0.027</b>	<i>0.19</i>	<b>-0.064</b>	<i>-0.46</i>	<b>-0.289</b>	<i>-2.14**</i>
Sumitomo Trust	<b>0.582</b>	<i>5.06**</i>	<b>0.106</b>	<i>0.76</i>	<b>-0.162</b>	<i>-1.16</i>
Sumitomo	<b>0.512</b>	<i>4.22**</i>	<b>0.226</b>	<i>1.64</i>	<b>-0.396</b>	<i>-3.05**</i>
Toho Bank	<b>0.266</b>	<i>1.95</i>	<b>0.189</b>	<i>1.36</i>	<b>-0.421</b>	<i>-3.28**</i>
Yamagata	<b>0.216</b>	<i>1.57</i>	<b>0.231</b>	<i>1.68</i>	<b>-0.363</b>	<i>-2.75**</i>
Yamanashi	<b>0.361</b>	<i>2.74**</i>	<b>0.152</b>	<i>1.09</i>	<b>-0.414</b>	<i>-3.22**</i>

1997	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
77 Bank	<b>0.282</b>	2.08**	<b>0.251</b>	1.83	<b>-0.404</b>	-3.12**
Akita Bank	<b>0.461</b>	3.67**	<b>0.248</b>	1.81	<b>-0.386</b>	-2.96**
Aomori	<b>0.504</b>	4.12**	<b>0.129</b>	0.92	<b>-0.383</b>	-2.94**
Bank of Iwate	<b>0.432</b>	3.39**	<b>0.232</b>	1.69	<b>-0.388</b>	-2.98**
Chiba Bank	<b>0.446</b>	3.52**	<b>0.015</b>	0.10	<b>-0.328</b>	-2.46**
Hokkaido	<b>0.312</b>	2.32**	<b>0.168</b>	1.20	<b>-0.333</b>	-2.49**
Hokkoku	<b>0.330</b>	2.47**	<b>0.163</b>	1.17	<b>-0.433</b>	-3.40**
Hokuriku	<b>0.407</b>	3.15**	<b>0.452</b>	3.58**	<b>-0.244</b>	-1.78
Joyo Bank	<b>0.615</b>	5.52**	<b>0.263</b>	1.93	<b>-0.298</b>	-2.20**
Kanto Bank	<b>0.265</b>	1.95	<b>0.157</b>	1.13	<b>-0.327</b>	-2.45**
Michinoku	<b>0.342</b>	2.57**	<b>0.154</b>	1.10	<b>-0.509</b>	-4.18**
Mitsubishi Trust	<b>0.666</b>	6.31**	<b>0.174</b>	1.25	<b>-0.327</b>	-2.44**
Mitsui Trust	<b>0.657</b>	6.17**	<b>0.501</b>	4.09**	<b>-0.272</b>	-2.00**
Saporo	<b>-0.206</b>	-1.49	<b>0.099</b>	0.71	<b>-0.418</b>	-3.26**
Sumitomo Trust	<b>0.746</b>	7.92**	<b>0.253</b>	1.85	<b>-0.214</b>	-1.55
Sumitomo	<b>0.608</b>	5.41**	<b>0.203</b>	1.46	<b>-0.317</b>	-2.36**
Toho Bank	<b>0.532</b>	4.44**	<b>0.108</b>	0.77	<b>-0.475</b>	-3.82**
Yamagata	<b>0.426</b>	3.33**	<b>0.184</b>	1.33	<b>-0.392</b>	-3.02**
Yamanashi	<b>0.560</b>	4.79**	<b>0.294</b>	2.18**	<b>-0.291</b>	-2.15**

1998	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
77 Bank	<b>0.582</b>	5.06**	<b>-0.174</b>	-1.25	<b>-0.431</b>	-3.37**
Akita Bank	<b>0.293</b>	2.17**	<b>0.093</b>	0.66	<b>-0.331</b>	-2.48**
Aomori	<b>0.520</b>	4.30**	<b>-0.050</b>	-0.36	<b>-0.479</b>	-3.86**
Bank of Iwate	<b>0.498</b>	4.06**	<b>-0.096</b>	-0.68	<b>-0.257</b>	-1.88
Chiba Bank	<b>0.684</b>	6.64**	<b>-0.143</b>	-1.02	<b>-0.465</b>	-3.71**
Hokkaido	<b>0.411</b>	3.19**	<b>-0.085</b>	-0.60	<b>-0.369</b>	-2.80**
Hokkoku	<b>0.533</b>	4.46**	<b>-0.096</b>	-0.68	<b>-0.583</b>	-5.07**
Hokuriku	<b>0.586</b>	5.11**	<b>-0.303</b>	-2.25**	<b>-0.438</b>	-3.44**
Joyo Bank	<b>0.587</b>	5.13**	<b>-0.092</b>	-0.65	<b>-0.502</b>	-4.10**
Kanto Bank	<b>0.389</b>	2.99**	<b>0.018</b>	0.12	<b>-0.427</b>	-3.34**
Michinoku	<b>0.511</b>	4.20**	<b>0.056</b>	0.40	<b>-0.798</b>	-9.38**
Mitsubishi Trust	<b>0.671</b>	6.39**	<b>0.000</b>	0.00	<b>-0.515</b>	-4.25**
Mitsui Trust	<b>0.711</b>	7.14**	<b>-0.117</b>	-0.83	<b>-0.409</b>	-3.17**
Saporo	<b>0.193</b>	1.39	<b>0.025</b>	0.18	<b>-0.426</b>	-3.33**
Sumitomo Trust	<b>0.620</b>	5.59**	<b>-0.057</b>	-0.40	<b>-0.472</b>	-3.78**
Sumitomo	<b>0.755</b>	8.15**	<b>-0.122</b>	-0.87	<b>-0.501</b>	-4.09**
Toho Bank	<b>0.506</b>	4.15**	<b>-0.061</b>	-0.43	<b>-0.434</b>	-3.40**
Yamagata	<b>0.597</b>	5.26**	<b>-0.181</b>	-1.30	<b>-0.439</b>	-3.45**
Yamanashi	<b>0.346</b>	2.61**	<b>-0.060</b>	-0.42	<b>-0.468</b>	-3.75**

\*\* sig at the 95% confidence interval

\*\*\* sig. at the 99% confidence interval

$R_{it}$  is the return on bank stock  $i$  during time period  $t$

$B_{mt}R_{mjt}$  is the market beta and the return on the market index in country  $j$  at time  $t$

$B_{rt}R_{rjt}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$

$B_{xt}R_{xjt}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$

$\alpha_{it}, u_{it}$  is the bank specific constant and random error terms, respectively

**Table 17 Weekly VaR Results: Japan**

Weekly VaR in percent of Bank Equity at Risk

$$VaR = c \left[ (\beta_{m,i} \sigma_{mj})^2 + (\beta_{r,i} \sigma_{rj})^2 + (\beta_{x,i} \sigma_{xj})^2 \right]^{1/2}$$

Bank VaR at 99% confidence		1992	1993	1994	1995	1996	1997	1998
<b>Japan</b>								
77 Bank	VaR, assuming a Normal Distribution	-1.48%	-1.04%	-0.70%	-1.00%	-0.79%	-1.25%	-1.93%
	Historical VaR	-2.70%	-2.10%	-1.29%	-2.00%	-1.74%	-2.56%	-3.47%
	EVT VaR	-2.75%	-2.30%	-1.47%	-2.28%	-1.99%	-3.42%	-3.66%
	VaR, Monte Carlo Simulation (1000 trials)	-4.51%	-3.28%	-2.50%	-3.32%	-5.05%	-9.11%	-5.47%
Akita Bank	VaR, assuming a Normal Distribution	-1.86%	-1.12%	-0.42%	-0.77%	-1.18%	-1.53%	-1.42%
	Historical VaR	-3.70%	-2.96%	-0.83%	-1.45%	-2.60%	-3.17%	-2.64%
	EVT VaR	-3.81%	-3.82%	-0.96%	-1.59%	-2.97%	-4.10%	-2.88%
	VaR, Monte Carlo Simulation (1000 trials)	-6.41%	-3.87%	-2.05%	-2.17%	-5.04%	-10.97%	-9.25%
Aomori	VaR, assuming a Normal Distribution	-1.33%	-1.12%	-0.38%	-1.00%	-0.69%	-1.25%	-1.35%
	Historical VaR	-2.91%	-2.63%	-0.84%	-2.44%	-1.52%	-2.47%	-2.38%
	EVT VaR	-3.06%	-3.27%	-1.01%	-3.02%	-1.74%	-2.94%	-2.49%
	VaR, Monte Carlo Simulation (1000 trials)	-4.33%	-3.79%	-2.09%	-2.52%	-2.76%	-6.64%	-4.46%
Bank of Iwate	VaR, assuming a Normal Distribution	-2.01%	-1.57%	-0.22%	-1.11%	-0.62%	-1.37%	-1.28%
	Historical VaR	-3.99%	-4.58%	-0.39%	-2.33%	-1.26%	-2.82%	-2.24%
	EVT VaR	-4.12%	-6.35%	-0.44%	-2.71%	-1.50%	-3.63%	-2.33%
	VaR, Monte Carlo Simulation (1000 trials)	-6.73%	-5.13%	-0.25%	-2.44%	-6.20%	-9.69%	-3.82%
Chiba Bank	VaR, assuming a Normal Distribution	-1.70%	-0.69%	-0.58%	-1.06%	-1.11%	-1.74%	-2.96%
	Historical VaR	-3.41%	-1.44%	-1.12%	-2.20%	-2.37%	-3.39%	-5.21%
	EVT VaR	-3.53%	-1.47%	-1.32%	-2.60%	-2.82%	-3.89%	-5.46%
	VaR, Monte Carlo Simulation (1000 trials)	-5.81%	-2.46%	-3.19%	-3.95%	-2.62%	-5.18%	-6.27%
Hokkaido	VaR, assuming a Normal Distribution	-2.03%	-1.58%	-1.00%	-1.21%	-1.55%	-1.91%	-2.11%
	Historical VaR	-4.31%	-3.36%	-1.87%	-2.44%	-3.27%	-3.83%	-3.76%
	EVT VaR	-4.49%	-3.74%	-2.15%	-2.83%	-3.88%	-4.85%	-3.96%
	VaR, Monte Carlo Simulation (1000 trials)	-6.01%	-4.03%	-3.31%	-4.02%	-7.24%	-10.63%	-5.54%
Hokkoku	VaR, assuming a Normal Distribution	-0.54%	-0.41%	-0.53%	-1.10%	-1.14%	-1.15%	-1.67%
	Historical VaR	-1.14%	-0.91%	-1.11%	-2.21%	-2.50%	-2.20%	-2.98%
	EVT VaR	-1.19%	-1.07%	-1.31%	-2.58%	-2.87%	-2.68%	-3.15%
	VaR, Monte Carlo Simulation (1000 trials)	-2.80%	-2.17%	-2.20%	-4.32%	-4.39%	-7.41%	-4.45%
Hokuriku	VaR, assuming a Normal Distribution	-1.21%	-0.62%	-0.37%	-0.62%	-0.92%	-5.05%	-3.15%
	Historical VaR	-2.35%	-1.22%	-0.71%	-1.48%	-1.88%	-12.22%	-5.90%
	EVT VaR	-2.41%	-1.26%	-0.84%	-1.82%	-2.30%	-18.22%	-6.39%
	VaR, Monte Carlo Simulation (1000 trials)	-4.58%	-2.63%	-2.13%	-2.35%	-5.08%	-27.41%	-5.83%
Joyo Bank	VaR, assuming a Normal Distribution	-1.91%	-1.31%	-0.73%	-1.05%	-0.84%	-2.16%	-2.35%
	Historical VaR	-3.99%	-3.54%	-1.42%	-2.86%	-1.75%	-4.62%	-4.14%
	EVT VaR	-4.14%	-4.63%	-1.67%	-3.66%	-2.08%	-5.96%	-4.35%
	VaR, Monte Carlo Simulation (1000 trials)	-5.92%	-4.93%	-2.64%	-2.67%	-5.63%	-12.48%	-6.54%

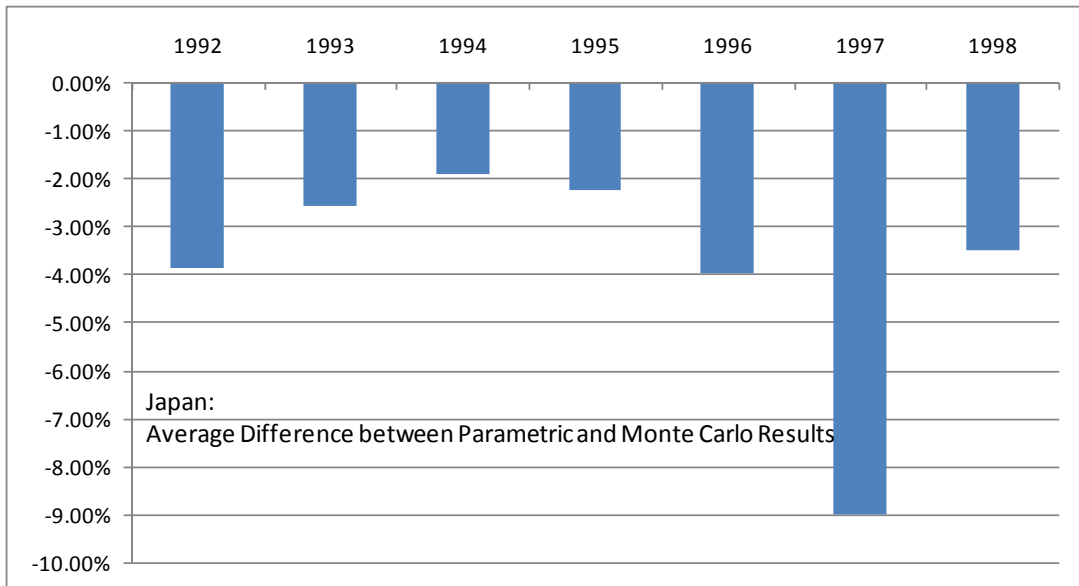
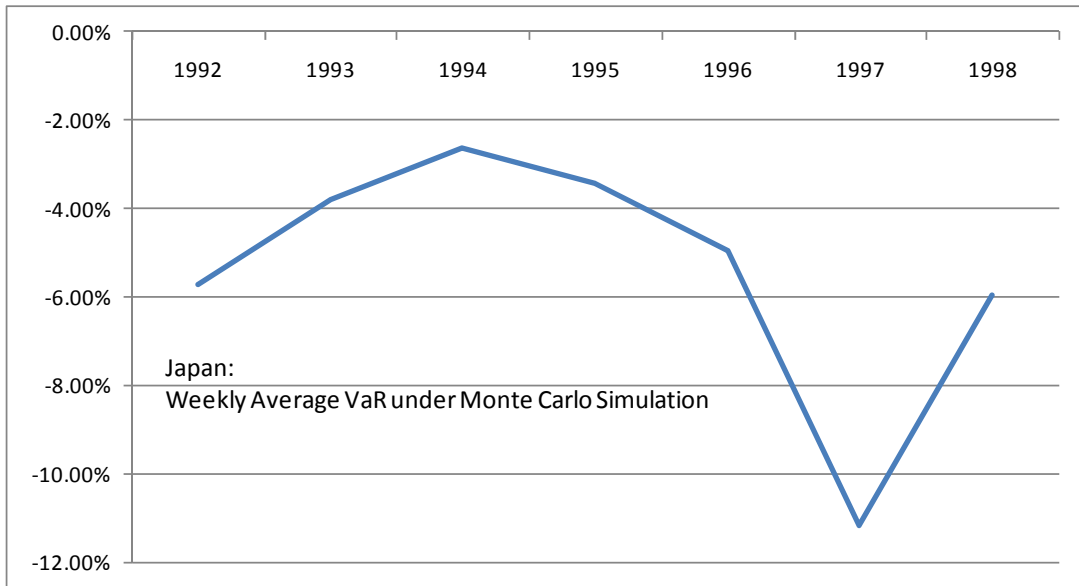
Kanto Bank	VaR, assuming a Normal Distribution	-1.23%	-0.73%	-0.89%	-0.62%	-1.14%	-1.93%	-1.73%
	Historical VaR	-2.64%	-1.60%	-1.64%	-1.48%	-2.41%	-3.82%	-3.08%
	EVT VaR	-2.76%	-1.96%	-1.86%	-1.83%	-2.88%	-4.83%	-3.24%
	VaR, Monte Carlo Simulation (1000 trials)	-5.00%	-2.56%	-2.53%	-2.48%	-4.83%	-12.17%	-4.32%
Michinoku	VaR, assuming a Normal Distribution	-0.74%	-0.59%	-0.37%	-0.74%	-0.69%	-0.78%	-1.51%
	Historical VaR	-1.58%	-1.21%	-0.66%	-1.53%	-1.47%	-1.46%	-2.74%
	EVT VaR	-1.66%	-1.34%	-0.70%	-1.75%	-1.75%	-1.73%	-2.92%
	VaR, Monte Carlo Simulation (1000 trials)	-3.09%	-1.91%	-1.25%	-1.32%	-3.45%	-5.43%	-5.67%
Mitsubishi Trust	VaR, assuming a Normal Distribution	-3.22%	-2.03%	-1.17%	-2.44%	-1.17%	-3.72%	-4.73%
	Historical VaR	-6.58%	-4.69%	-2.29%	-5.24%	-2.63%	-7.68%	-8.24%
	EVT VaR	-6.81%	-5.24%	-2.71%	-6.30%	-2.97%	-9.38%	-8.58%
	VaR, Monte Carlo Simulation (1000 trials)	-7.70%	-5.16%	-3.98%	-5.77%	-2.97%	-11.90%	-9.37%
Mitsui Trust	VaR, assuming a Normal Distribution	-3.37%	-2.13%	-1.85%	-2.13%	-1.57%	-5.11%	-6.14%
	Historical VaR	-6.86%	-4.90%	-3.71%	-4.73%	-3.45%	-11.88%	-10.69%
	EVT VaR	-7.08%	-5.61%	-4.38%	-5.76%	-3.85%	-16.90%	-11.11%
	VaR, Monte Carlo Simulation (1000 trials)	-8.21%	-4.70%	-4.40%	-5.64%	-9.49%	-25.93%	-10.27%
Saporo	VaR, assuming a Normal Distribution	-0.87%	-1.07%	-0.14%	-0.64%	-0.53%	-0.69%	-1.03%
	Historical VaR	-2.27%	-2.17%	-0.26%	-1.31%	-1.09%	-1.27%	-1.89%
	EVT VaR	-2.83%	-2.58%	-0.28%	-1.48%	-1.35%	-1.43%	-2.03%
	VaR, Monte Carlo Simulation (1000 trials)	-1.67%	-3.02%	-0.86%	-0.93%	-0.64%	-4.41%	-4.34%
Sumitomo Trust	VaR, assuming a Normal Distribution	-2.79%	-2.20%	-1.19%	-2.50%	-1.28%	-4.18%	-4.56%
	Historical VaR	-5.79%	-5.10%	-2.31%	-5.34%	-2.89%	-8.99%	-7.97%
	EVT VaR	-6.00%	-5.85%	-2.72%	-6.41%	-3.24%	-11.38%	-8.31%
	VaR, Monte Carlo Simulation (1000 trials)	-7.89%	-5.45%	-3.98%	-7.24%	-4.74%	-14.65%	-8.42%
Sumitomo	VaR, assuming a Normal Distribution	-3.16%	-1.11%	-0.96%	-1.95%	-1.23%	-3.03%	-3.79%
	Historical VaR	-6.38%	-2.49%	-1.90%	-4.49%	-2.65%	-6.30%	-6.62%
	EVT VaR	-6.58%	-2.81%	-2.25%	-5.52%	-3.05%	-7.85%	-6.91%
	VaR, Monte Carlo Simulation (1000 trials)	-9.77%	-4.05%	-3.60%	-4.93%	-6.20%	-13.29%	-5.60%
Toho Bank	VaR, assuming a Normal Distribution	-2.20%	-1.26%	-0.88%	-0.74%	-0.82%	-1.79%	-1.67%
	Historical VaR	-4.36%	-3.22%	-1.75%	-1.66%	-1.71%	-3.46%	-2.94%
	EVT VaR	-4.48%	-4.04%	-2.08%	-2.00%	-2.04%	-4.02%	-3.08%
	VaR, Monte Carlo Simulation (1000 trials)	-7.71%	-4.35%	-3.66%	-2.80%	-5.36%	-7.01%	-4.49%
Yamagata	VaR, assuming a Normal Distribution	-1.73%	-1.61%	-0.59%	-0.59%	-0.66%	-1.17%	-1.50%
	Historical VaR	-3.49%	-4.01%	-1.16%	-1.39%	-1.36%	-2.34%	-2.69%
	EVT VaR	-3.61%	-5.05%	-1.36%	-1.71%	-1.61%	-2.90%	-2.84%
	VaR, Monte Carlo Simulation (1000 trials)	-5.61%	-5.21%	-2.34%	-2.22%	-6.92%	-7.00%	-5.02%
Yamanashi	VaR, assuming a Normal Distribution	-1.40%	-0.85%	-0.68%	-1.04%	-0.82%	-1.67%	-1.48%
	Historical VaR	-2.77%	-1.81%	-1.37%	-2.57%	-1.75%	-3.63%	-2.66%
	EVT VaR	-2.86%	-1.88%	-1.62%	-3.22%	-2.06%	-4.82%	-2.83%
	VaR, Monte Carlo Simulation (1000 trials)	-4.91%	-3.34%	-2.87%	-3.92%	-5.72%	-11.07%	-4.13%

where  $c$  reflects a give level of statistical confidence  
the betas pertain to each individual bank  $i$

$$\sigma_{mjt} \sigma_{jt} \sigma_{it}$$

represent the standard deviations of the market index, interest rate, and exchange rate in country  $j$   
These statistics are calculated from daily data obtained from FT Prices CD-Rom and Bloomberg.

**Figure 14** VaR results by Year. Parametric Vs Monte Carlo Results: Japan



**Table 18** Three Factor Betas: The Netherlands Bank Sample

Estimation of Three Factor Capital Asset Pricing Model

$$R_{it} = \alpha_{it} + \beta_{mt} R_{mjt} + \beta_{rt} R_{rjt} + \beta_{xt} R_{xjt} + u_{it}$$

Factor Betas by Bank by Year	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
<u>1992</u>						
ABN Amro	<b>0.492</b>	4.00**	<b>-0.019</b>	-0.14	<b>0.315</b>	2.35**
ING Bank	<b>0.658</b>	6.18**	<b>-0.065</b>	-0.46	<b>0.117</b>	0.84
Staal Bank	<b>0.137</b>	0.98	<b>-0.238</b>	-1.73	<b>-0.176</b>	-1.26
<u>1993</u>						
ABN Amro	<b>0.663</b>	6.26**	<b>0.072</b>	0.51	<b>0.159</b>	1.14
ING Bank	<b>0.695</b>	6.84**	<b>0.173</b>	1.24	<b>0.127</b>	0.90
Staal Bank	<b>0.244</b>	1.78	<b>0.018</b>	0.12	<b>-0.048</b>	-0.34
<u>1994</u>						
ABN Amro	<b>0.589</b>	5.16**	<b>-0.117</b>	-0.83	<b>0.080</b>	0.57
ING Bank	<b>0.823</b>	10.26**	<b>-0.415</b>	-3.23**	<b>-0.079</b>	-0.56
Staal Bank	<b>0.064</b>	0.46	<b>0.006</b>	0.04	<b>-0.049</b>	-0.35
<u>1995</u>						
ABN Amro	<b>0.582</b>	5.05**	<b>-0.245</b>	-1.78	<b>0.067</b>	0.48
ING Bank	<b>0.638</b>	5.86**	<b>-0.377</b>	-2.88**	<b>0.245</b>	1.79
Staal Bank	<b>0.087</b>	0.62	<b>0.208</b>	1.51	<b>0.294</b>	2.17**
<u>1996</u>						
ABN Amro	<b>0.654</b>	6.12**	<b>-0.418</b>	-3.25**	<b>0.363</b>	2.76**
ING Bank	<b>0.892</b>	13.95**	<b>-0.279</b>	-2.06**	<b>0.502</b>	4.10**
Staal Bank						
<u>1997</u>						
ABN Amro	<b>0.810</b>	9.75**	<b>-0.249</b>	-1.82	<b>0.160</b>	1.15
ING Bank	<b>0.952</b>	22.01**	<b>-0.296</b>	-2.19**	<b>0.171</b>	1.23
Staal Bank						
<u>1998</u>						
ABN Amro	<b>0.782</b>	8.87**	<b>0.024</b>	0.17	<b>0.429</b>	3.36**
ING Bank	<b>0.974</b>	30.67**	<b>0.032</b>	0.22	<b>0.514</b>	4.24**
Staal Bank						

\*\* sig at the 95% confidence interval  
 \*\*\* sig. at the 99% confidence interval

$R_{it}$  is the return on bank stock  $i$  during time period  $t$   
 $B_{mt}R_{mjt}$  is the market beta and the return on the market index in country  $j$  at time  $t$   
 $B_{rt}R_{rjt}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$   
 $B_{xt}R_{xjt}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$   
 $\alpha_{it}, u_{it}$  is the bank specific constant and random error terms, respectively

**Table 19 Weekly VaR Results: The Netherlands**

Weekly VaR in percent of Bank Equity at Risk

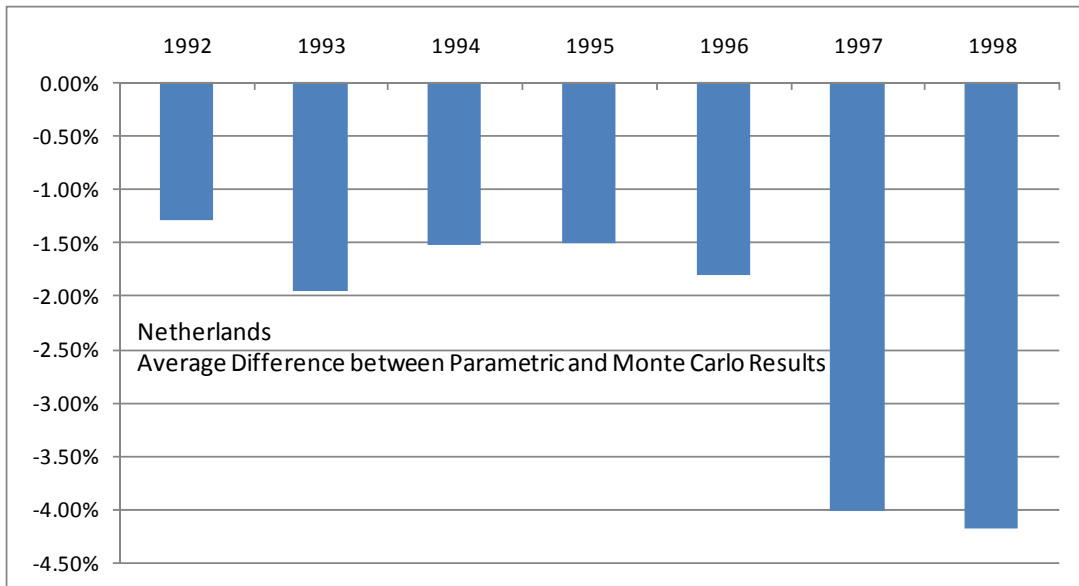
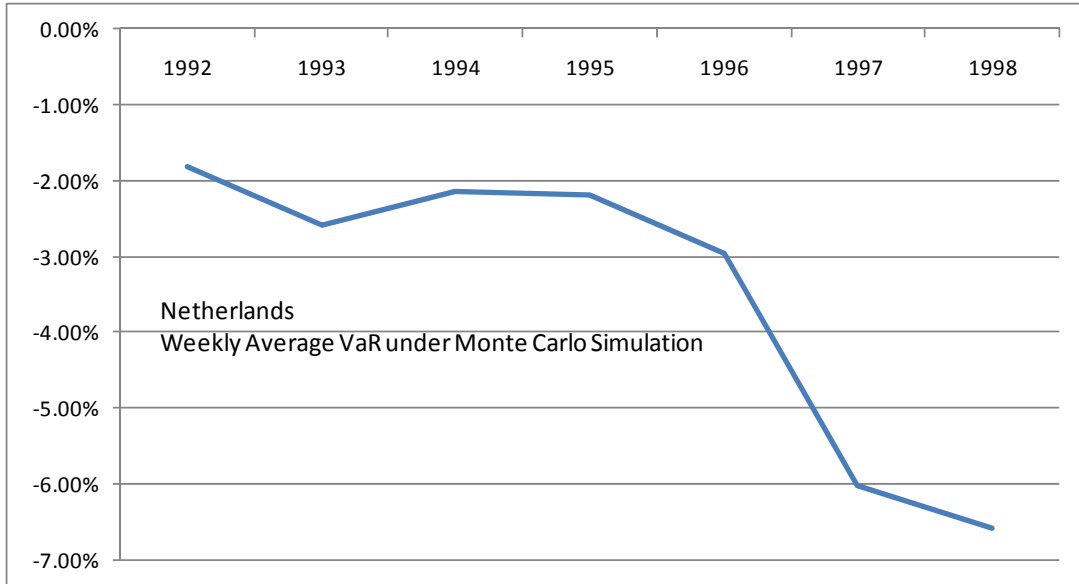
$$VaR = c \left[ (\beta_{m,i} \sigma_{m_i})^2 + (\beta_{r,i} \sigma_{r_j})^2 + (\beta_{x,i} \sigma_{x_j})^2 \right]^{1/2}$$

Bank VaR at 99% confidence		1992	1993	1994	1995	1996	1997	1998
<b>Netherlands</b>								
ABN Amro	VaR, assuming a Normal Distribution	-0.77%	-0.97%	-0.85%	-0.74%	-1.33%	-2.36%	-2.50%
	Historical VaR	-1.70%	-1.73%	-1.86%	-1.58%	-3.04%	-4.51%	-6.16%
	EVT VaR	-1.80%	-2.15%	-1.95%	-2.02%	-3.84%	-4.66%	-6.50%
	VaR, Monte Carlo Simulation (1000 trials)	-2.69%	-3.03%	-2.79%	-2.27%	-3.06%	-6.81%	-7.18%
ING Bank	VaR, assuming a Normal Distribution	-0.50%	-0.49%	-0.89%	-0.56%	-0.96%	-1.69%	-2.33%
	Historical VaR	-1.11%	-0.94%	-2.16%	-1.23%	-2.07%	-3.22%	-5.71%
	EVT VaR	-1.18%	-1.20%	-2.31%	-1.57%	-2.63%	-3.33%	-6.02%
	VaR, Monte Carlo Simulation (1000 trials)	-1.86%	-2.48%	-2.65%	-1.85%	-2.85%	-5.25%	-6.01%
Staal Bank	VaR, assuming a Normal Distribution	-0.32%	-0.42%	-0.16%	-0.73%			
	Historical VaR	-0.71%	-0.75%	-0.32%	-1.88%			
	EVT VaR	-0.84%	-0.94%	-0.34%	-2.03%			
	VaR, Monte Carlo Simulation (1000 trials)	-0.90%	-2.24%	-1.02%	-2.42%			

where  $c$  reflects a give level of statistical confidence  
the betas pertain to each individual bank  $i$

$\sigma_{m_i}, \sigma_{r_j}, \sigma_{x_j}$  represent the standard deviations of the market index, interest rate, and exchange rate in country  $j$   
These statistics are calculated from daily data obtained from FT Prices CD-Rom and Bloomberg.

**Figure 15** VaR results by Year. Parametric Vs Monte Carlo Results: Netherlands





**Table 20 Three Factor Betas: Sweden Bank Sample**

Estimation of Three Factor Capital Asset Pricing Model

$$R_{it} = \alpha_{it} + \beta_{mt} R_{mjt} + \beta_{rt} R_{rjt} + \beta_{xt} R_{xjt} + u_{it}$$

Factor Betas by Bank by Year	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
<u>1992</u>						
Ostgota Enskilda Bank	<b>0.144</b>	1.03	<b>-0.035</b>	-0.25	<b>0.068</b>	0.48
Skandia Bank	<b>0.251</b>	1.83	<b>-0.541</b>	-4.55**	<b>0.449</b>	3.55**
Skandinaviska Bank	<b>0.137</b>	0.98	<b>-0.115</b>	-0.82	<b>0.159</b>	1.14
Svenska Bank	<b>-0.144</b>	-1.03	<b>-0.089</b>	-0.63	<b>0.191</b>	1.38
<u>1993</u>						
Ostgota Enskilda Bank	<b>0.032</b>	0.22	<b>-0.290</b>	-2.15**	<b>-0.095</b>	-0.68
Skandia Bank	<b>0.239</b>	1.74	<b>-0.274</b>	-2.02**	<b>-0.149</b>	-1.07
Skandinaviska Bank	<b>-0.008</b>	-0.06	<b>-0.169</b>	-1.21	<b>-0.247</b>	-1.81
Svenska Bank	<b>0.165</b>	1.18	<b>0.043</b>	0.31	<b>-0.053</b>	-0.37
<u>1994</u>						
Ostgota Enskilda Bank	<b>0.171</b>	1.22	<b>-0.116</b>	-0.82	<b>-0.361</b>	-2.74**
Skandia Bank	<b>0.339</b>	2.55**	<b>-0.320</b>	-2.39**	<b>-0.362</b>	-2.75**
Skandinaviska Bank	<b>0.282</b>	2.08**	<b>-0.468</b>	-3.74**	<b>-0.429</b>	-3.36**
Svenska Bank	<b>0.234</b>	1.70	<b>-0.473</b>	-3.79**	<b>-0.534</b>	-4.46**
<u>1995</u>						
Ostgota Enskilda Bank	<b>0.217</b>	1.57	<b>-0.149</b>	-1.06	<b>-0.176</b>	-1.26
Skandia Bank	<b>0.395</b>	3.04**	<b>-0.360</b>	-2.73**	<b>-0.311</b>	-2.32**
Skandinaviska Bank	<b>0.367</b>	2.79**	<b>-0.248</b>	-1.81	<b>-0.072</b>	-0.51
Svenska Bank	<b>0.497</b>	4.05**	<b>-0.306</b>	-2.28**	<b>-0.180</b>	-1.29
<u>1996</u>						
Ostgota Enskilda Bank	<b>0.055</b>	0.39	<b>-0.261</b>	-1.91	<b>-0.392</b>	-3.01**
Skandia Bank	<b>0.251</b>	1.83	<b>-0.141</b>	-1.01	<b>-0.350</b>	-2.64**
Skandinaviska Bank	<b>0.350</b>	2.64**	<b>-0.535</b>	-4.48**	<b>-0.523</b>	-4.34**
Svenska Bank	<b>0.314</b>	2.34**	<b>-0.351</b>	-2.65**	<b>-0.467</b>	-3.74**
<u>1997</u>						
Ostgota Enskilda Bank						
Skandia Bank	<b>0.597</b>	5.26**	<b>0.300</b>	2.22**	<b>0.074</b>	0.52
Skandinaviska Bank	<b>0.429</b>	3.36**	<b>0.025</b>	0.18	<b>0.034</b>	0.24
Svenska Bank	<b>0.582</b>	5.05**	<b>0.031</b>	0.22	<b>-0.116</b>	-0.82
<u>1998</u>						
Ostgota Enskilda Bank						
Skandia Bank	<b>0.569</b>	4.89**	<b>-0.027</b>	-0.19	<b>0.197</b>	1.42
Skandinaviska Bank	<b>0.549</b>	4.64**	<b>-0.198</b>	-1.42	<b>0.114</b>	0.81
Svenska Bank	<b>0.664</b>	6.27**	<b>-0.233</b>	-1.69	<b>0.016</b>	0.12

\*\* sig at the 95% confidence interval

\*\*\* sig. at the 99% confidence interval

$R_{it}$  is the return on bank stock  $i$  during time period  $t$

$B_{mt}R_{mjt}$  is the market beta and the return on the market index in country  $j$  at time  $t$

$B_{rt}R_{rjt}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$

$B_{xt}R_{xjt}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$

$\alpha_{it}, u_{it}$  is the bank specific constant and random error terms, respectively

**Table 21 Weekly VaR Results: Sweden**

Weekly VaR in percent of Bank Equity at Risk

$$VaR = c \left[ (\beta_{m,i} \sigma_{mj})^2 + (\beta_{r,i} \sigma_{rj})^2 + (\beta_{x,i} \sigma_{xj})^2 \right]^{1/2}$$

Bank VaR at 99% confidence		1992	1993	1994	1995	1996	1997	1998
<b>Sweden</b>								
Ostgota Enskilda Bank	VaR, assuming a Normal Distribution	-0.79%	-2.07%	-1.25%	-0.75%	-1.04%		
	Historical VaR	-1.31%	-5.05%	-2.65%	-1.56%	-2.41%		
	EVT VaR	-1.56%	-5.69%	-2.91%	-1.84%	-3.10%		
	VaR, Monte Carlo Simulation (1000 trials)	-3.18%	-0.89%	-2.49%	-1.63%	-0.61%		
Skandia Bank	VaR, assuming a Normal Distribution	-3.39%	-1.32%	-1.57%	-1.30%	-1.00%	-2.17%	-2.50%
	Historical VaR	-8.43%	-2.85%	-4.15%	-2.94%	-2.33%	-5.55%	-5.48%
	EVT VaR	-11.59%	-3.23%	-4.93%	-3.52%	-2.95%	-8.68%	-6.31%
	VaR, Monte Carlo Simulation (1000 trials)	-6.64%	-2.06%	-2.66%	-2.32%	-1.63%	-4.19%	-6.71%
Skandinaviska Bank	VaR, assuming a Normal Distribution	-1.14%	-3.02%	-1.98%	-1.14%	-1.74%	-1.26%	-2.24%
	Historical VaR	-2.32%	-7.15%	-5.57%	-2.43%	-3.47%	-3.51%	-4.83%
	EVT VaR	-3.01%	-7.97%	-6.95%	-2.86%	-4.33%	-5.56%	-5.52%
	VaR, Monte Carlo Simulation (1000 trials)	-3.42%	0.00%	-2.64%	-2.48%	-2.04%	-3.45%	-5.64%
Svenska Bank	VaR, assuming a Normal Distribution	-1.29%	-0.82%	-2.38%	-1.39%	-1.36%	-1.62%	-1.85%
	Historical VaR	-3.28%	-1.42%	-6.37%	-2.87%	-2.92%	-4.49%	-3.97%
	EVT VaR	-3.72%	-1.62%	-7.90%	-3.36%	-3.67%	-7.05%	-4.49%
	VaR, Monte Carlo Simulation (1000 trials)	-3.79%	-2.59%	-2.17%	-2.38%	-1.76%	-4.68%	-5.59%

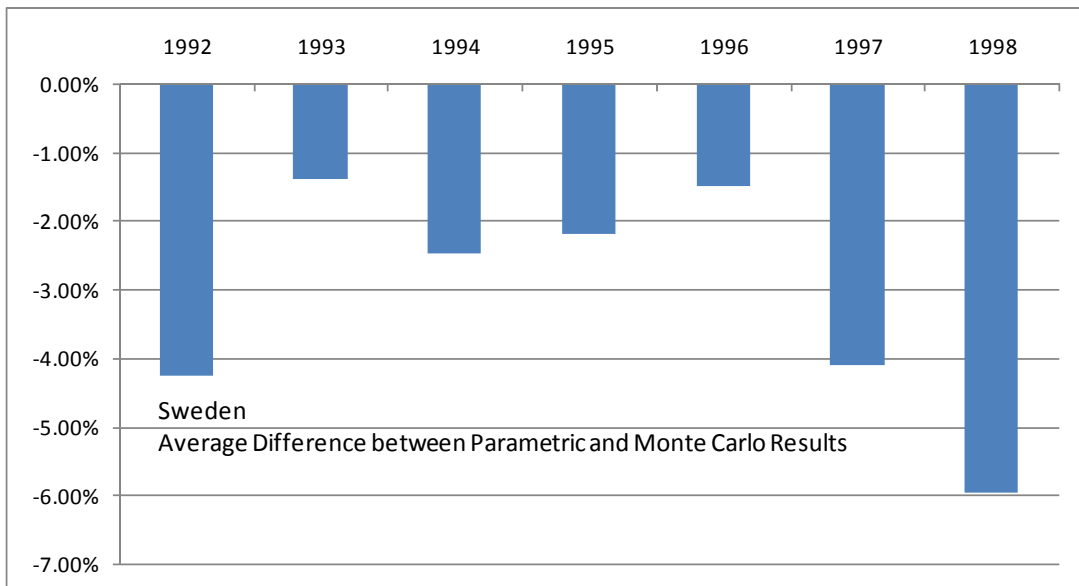
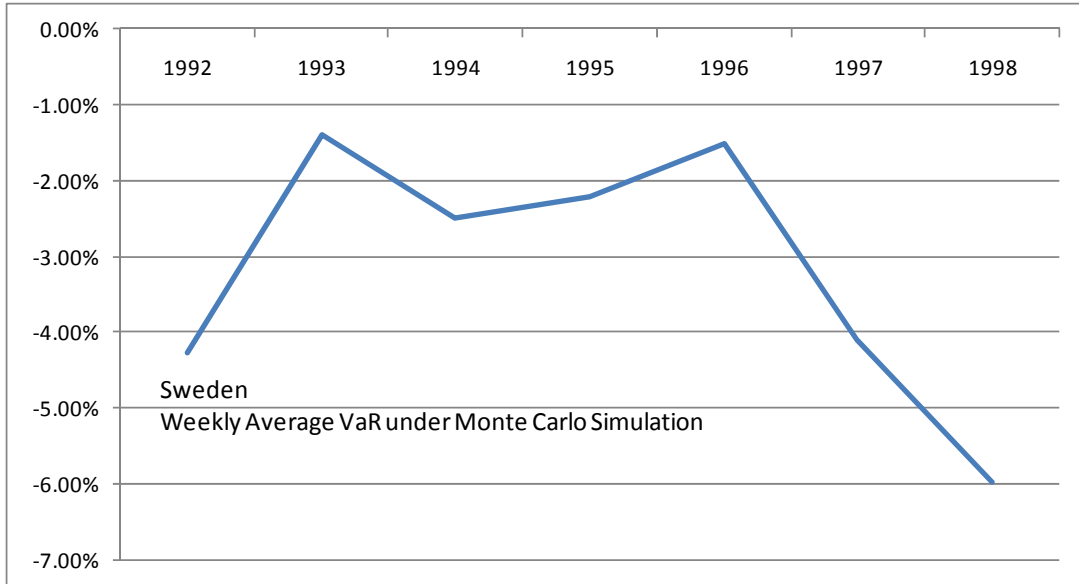
where c reflects a give level of statistical confidence

the betas pertain to each individual bank i

$\sigma_{m,i}$ ,  $\sigma_{r,i}$ ,  $\sigma_{x,i}$  represent the standard deviations of the market index, interest rate, and exchange rate in country j

These statistics are calculated from daily data obtained from FT Prices CD-Rom and Bloomberg.

**Figure 16** VaR results by Year. Parametric Vs Monte Carlo Results: Sweden



**Table 22 Three Factor Betas: Switzerland Bank Sample**

Estimation of Three Factor Capital Asset Pricing Model

$$R_{it} = \alpha_{it} + \beta_{mi} R_{mjt} + \beta_{ri} R_{rjt} + \beta_{fi} R_{fjt} + u_{it}$$

Factor Betas by Bank by Year	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
<u>1992</u>						
Coop Bank	<b>0.067</b>	0.47	<b>-0.064</b>	-0.45	<b>-0.001</b>	-0.01
Credit Suisse	<b>0.346</b>	2.61**	<b>-0.198</b>	-1.43	<b>0.109</b>	0.77
Bank Linth	<b>-0.005</b>	-0.04	<b>0.063</b>	0.45	<b>-0.090</b>	-0.64
Neue Aargauer	<b>0.690</b>	6.73**	<b>-0.230</b>	-1.67	<b>0.291</b>	2.15**
UBS	<b>0.717</b>	7.26**	<b>-0.174</b>	-1.25	<b>0.316</b>	2.36**
<u>1993</u>						
Coop Bank	<b>0.194</b>	1.40	<b>-0.110</b>	-0.79	<b>-0.059</b>	-0.42
Credit Suisse	<b>0.474</b>	3.80**	<b>-0.059</b>	-0.42	<b>0.100</b>	0.71
Bank Linth	<b>-0.183</b>	-1.32	<b>0.085</b>	0.60	<b>-0.064</b>	-0.45
Neue Aargauer	<b>0.694</b>	6.82**	<b>-0.326</b>	-2.44**	<b>0.401</b>	3.10**
UBS	<b>0.635</b>	5.81**	<b>-0.065</b>	-0.46	<b>0.417</b>	3.24**
<u>1994</u>						
Coop Bank	<b>0.337</b>	2.53**	<b>0.001</b>	0.01	<b>-0.103</b>	-0.73
Credit Suisse	<b>0.681</b>	6.58**	<b>-0.227</b>	-1.65	<b>-0.214</b>	-1.55
Bank Linth	<b>0.146</b>	1.04	<b>0.120</b>	0.86	<b>-0.109</b>	-0.78
Neue Aargauer	<b>0.611</b>	5.45**	<b>-0.233</b>	-1.69	<b>-0.143</b>	-1.02
UBS	<b>0.701</b>	6.95**	<b>-0.209</b>	-1.51	<b>-0.075</b>	-0.53
<u>1995</u>						
Coop Bank	<b>0.028</b>	0.20	<b>-0.230</b>	-1.67	<b>-0.160</b>	-1.14
Credit Suisse	<b>0.418</b>	3.25**	<b>-0.250</b>	-1.82	<b>-0.334</b>	-2.51**
Bank Linth	<b>-0.047</b>	-0.33	<b>0.200</b>	1.44	<b>-0.121</b>	-0.87
Neue Aargauer						
UBS	<b>0.566</b>	4.85**	<b>-0.033</b>	-0.23	<b>0.040</b>	0.28
<u>1996</u>						
Coop Bank	<b>0.188</b>	1.35	<b>-0.223</b>	-1.61	<b>-0.122</b>	-0.87
Credit Suisse	<b>0.208</b>	1.51	<b>0.036</b>	0.25	<b>-0.210</b>	-1.52
Bank Linth	<b>0.177</b>	1.27	<b>0.245</b>	1.79	<b>0.138</b>	0.98
Neue Aargauer						
UBS	<b>0.574</b>	4.95**	<b>-0.055</b>	-0.39	<b>0.013</b>	0.09
<u>1997</u>						
Coop Bank	<b>0.005</b>	0.04	<b>0.038</b>	0.27	<b>0.262</b>	1.92
Credit Suisse	<b>0.612</b>	5.47**	<b>0.009</b>	0.06	<b>0.031</b>	0.22
Bank Linth	<b>-0.118</b>	-0.84	<b>0.105</b>	0.74	<b>-0.082</b>	-0.58
Neue Aargauer						
UBS	<b>0.727</b>	7.49**	<b>0.012</b>	0.08	<b>0.226</b>	1.64
<u>1998</u>						
Coop Bank	<b>0.441</b>	3.48**	<b>0.121</b>	0.86	<b>0.272</b>	2.00**
Credit Suisse	<b>0.744</b>	7.88**	<b>0.165</b>	1.18	<b>0.286</b>	2.11**
Bank Linth	<b>0.191</b>	1.38	<b>0.015</b>	0.10	<b>0.184</b>	1.32
Neue Aargauer						
UBS						

\*\* sig at the 95% confidence interval

\*\*\* sig. at the 99% confidence interval

$R_{it}$  is the return on bank stock  $i$  during time period  $t$

$\beta_{mi} R_{mjt}$  is the market beta and the return on the market index in country  $j$  at time  $t$

$\beta_{ri} R_{rjt}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$

$\beta_{fi} R_{fjt}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$

$\alpha_{it}, u_{it}$  is the bank specific constant and random error terms, respectively

**Table 23 Weekly VaR Results: Switzerland**

Weekly VaR in percent of Bank Equity at Risk

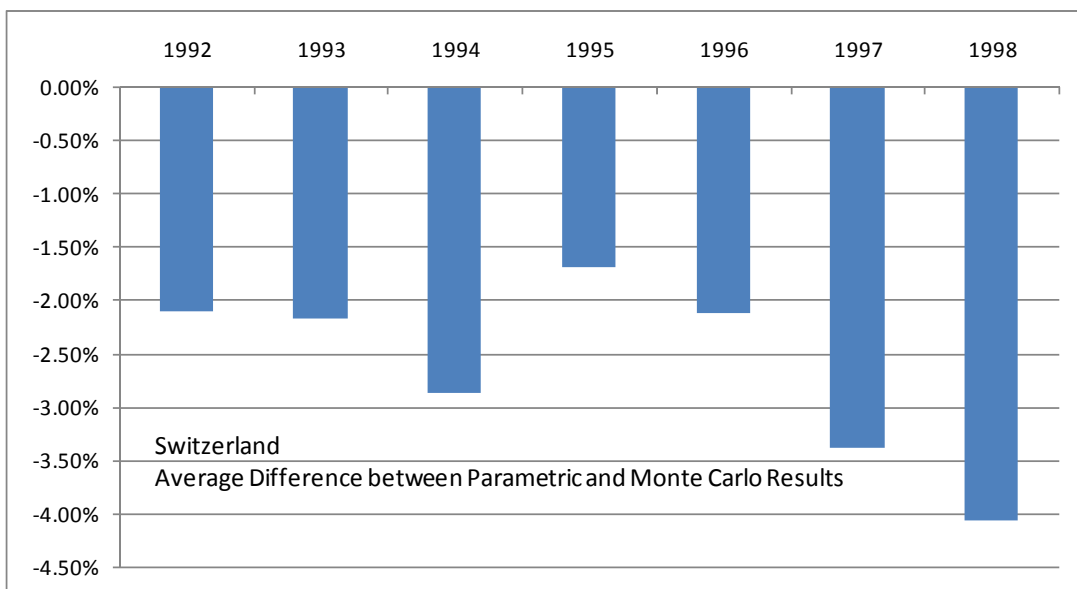
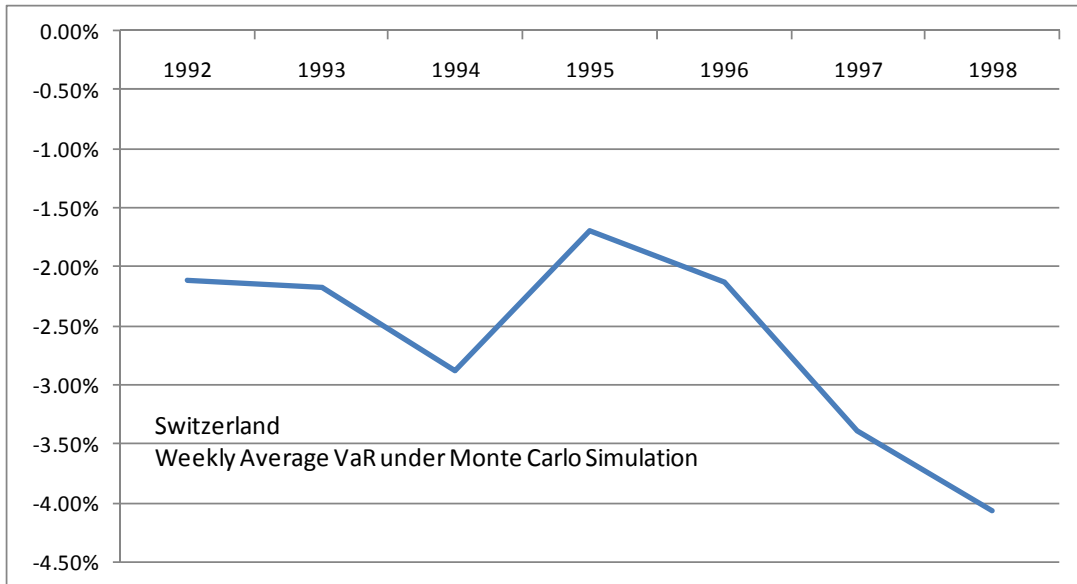
$$VaR = c \left[ (\beta_{m,i} \sigma_{mj})^2 + (\beta_{r,i} \sigma_{rj})^2 + (\beta_{x,i} \sigma_{xj})^2 \right]^{1/2}$$

Bank VaR at 99% confidence		1992	1993	1994	1995	1996	1997	1998
<b>Switzerland</b>								
Coop Bank	VaR, assuming a Normal Distribution	-0.05%	-0.20%	-0.13%	-0.14%	-0.16%	-0.14%	-0.43%
	Historical VaR	-0.11%	-0.38%	-0.29%	-0.28%	-0.32%	-0.35%	-1.11%
	EVT VaR	-0.12%	-0.43%	-0.31%	-0.33%	-0.35%	-0.47%	-1.22%
	VaR, Monte Carlo Simulation (1000 trials)	-0.85%	-1.22%	-1.40%	-0.21%	-0.84%	-1.20%	-2.66%
Credit Suisse	VaR, assuming a Normal Distribution	-0.86%	-0.80%	-1.61%	-0.92%	-0.39%	-1.49%	-2.84%
	Historical VaR	-2.02%	-1.59%	-3.51%	-2.20%	-0.86%	-3.00%	-7.14%
	EVT VaR	-2.13%	-1.84%	-3.80%	-3.21%	-0.92%	-3.83%	-7.88%
	VaR, Monte Carlo Simulation (1000 trials)	-2.93%	-2.87%	-4.11%	-2.61%	-1.63%	-5.39%	-7.39%
Bank Linth	VaR, assuming a Normal Distribution	-0.05%	-0.22%	-0.17%	-0.17%	-0.54%	-0.05%	-0.25%
	Historical VaR	-0.12%	-0.51%	-0.35%	-0.50%	-1.22%	-0.11%	-0.70%
	EVT VaR	-0.14%	-0.55%	-0.36%	-0.62%	-1.46%	-0.13%	-0.75%
	VaR, Monte Carlo Simulation (1000 trials)	-0.64%	-1.31%	-1.26%	-1.79%	-3.63%	-1.14%	-2.13%
Neue Aargauer	VaR, assuming a Normal Distribution	-0.78%	-0.77%	-1.28%				
	Historical VaR	-1.85%	-1.49%	-2.80%				
	EVT VaR	-1.93%	-1.69%	-3.04%				
	VaR, Monte Carlo Simulation (1000 trials)	-2.75%	-2.29%	-3.55%				
UBS	VaR, assuming a Normal Distribution	-1.03%	-0.94%	-1.51%	-0.68%	-0.73%	-1.61%	
	Historical VaR	-2.44%	-1.87%	-3.30%	-1.78%	-1.47%	-3.32%	
	EVT VaR	-2.53%	-2.15%	-3.58%	-2.83%	-1.66%	-4.26%	
	VaR, Monte Carlo Simulation (1000 trials)	-3.39%	-3.15%	-4.03%	-2.16%	-2.41%	-5.84%	

where c reflects a give level of statistical confidence  
the betas pertain to each individual bank i

$\sigma_{m,i}, \sigma_{r,i}, \sigma_{x,i}$  represent the standard deviations of the market index, interest rate, and exchange rate in country j  
These statistics are calculated from daily data obtained from FT Prices CD-Rom and Bloomberg.

**Figure 17** VaR results by Year. Parametric Vs Monte Carlo Results: Switzerland



**Table 24 Three Factor Betas: United Kingdom Bank Sample**

Estimation of Three Factor Capital Asset Pricing Model

$$R_{it} = \alpha_{it} + \beta_{mi} R_{mjt} + \beta_{rt} R_{rjt} + \beta_{xt} R_{xjt} + u_{it}$$

Factor Betas by Bank by Year	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
<u>1992</u>						
Barclays	<b>0.522</b>	4.33**	-0.077	-0.55	-0.038	-0.27
HSBC	<b>0.284</b>	2.09**	-0.442	-3.48**	-0.389	-2.98**
Lloyds Bank	<b>0.634</b>	5.79**	-0.214	-1.55	<b>0.046</b>	0.32
Royal Bank of Scotland	<b>0.688</b>	6.71**	-0.291	-2.15**	-0.179	-1.28
Standard Chartered	<b>0.553</b>	4.70**	-0.390	-2.99**	-0.249	-1.82
<u>1993</u>						
Barclays	<b>0.410</b>	3.18**	-0.271	-1.99	-0.010	-0.07
HSBC	<b>0.662</b>	6.25**	-0.364	-2.76**	-0.144	-1.03
Lloyds Bank	<b>0.586</b>	5.11**	-0.258	-1.89	-0.038	-0.27
Royal Bank of Scotland	<b>0.541</b>	4.55**	-0.232	-1.69	-0.078	-0.55
Standard Chartered	<b>0.364</b>	2.76**	-0.119	-0.85	<b>0.213</b>	1.54
<u>1994</u>						
Barclays	<b>0.568</b>	4.88**	-0.073	-0.51	-0.098	-0.69
HSBC	<b>0.444</b>	3.50**	-0.272	-2.00	-0.221	-1.60
Lloyds Bank	<b>0.474</b>	3.81**	-0.259	-1.90	-0.248	-1.81
Royal Bank of Scotland	<b>0.297</b>	2.20**	-0.090	-0.64	-0.010	-0.07
Standard Chartered	<b>0.640</b>	5.89**	-0.238	-1.73	-0.143	-1.02
<u>1995</u>						
Barclays	<b>0.599</b>	5.29**	-0.258	-1.89	<b>0.033</b>	0.24
HSBC	<b>0.486</b>	3.93**	-0.360	-2.73**	-0.119	-0.85
Lloyds Bank	<b>0.355</b>	2.68**	-0.167	-1.19	-0.020	-0.14
Royal Bank of Scotland	<b>0.326</b>	2.44**	-0.067	-0.47	-0.008	-0.05
Standard Chartered	<b>0.406</b>	3.15**	-0.275	-2.02**	-0.069	-0.49
<u>1996</u>						
Barclays	<b>0.496</b>	4.04**	-0.141	-1.01	-0.181	-1.30
HSBC	<b>0.320</b>	2.39**	<b>0.017</b>	0.12	-0.255	-1.86
Lloyds Bank						
Royal Bank of Scotland	<b>0.387</b>	2.96**	-0.083	-0.59	-0.071	-0.51
Standard Chartered	<b>0.200</b>	1.44	-0.200	-1.44	-0.256	-1.87
<u>1997</u>						
Barclays	<b>0.605</b>	5.37**	<b>0.036</b>	0.26	-0.446	-3.53**
HSBC	<b>0.764</b>	8.36**	-0.016	-0.11	-0.248	-1.81
Lloyds Bank						
Royal Bank of Scotland	<b>0.595</b>	5.23**	-0.010	-0.07	-0.070	-0.49
Standard Chartered	<b>0.605</b>	5.37**	<b>0.137</b>	0.98	-0.149	-1.07
<u>1998</u>						
Barclays	<b>0.705</b>	7.04**	<b>0.021</b>	0.15	-0.328	-2.46**
HSBC	<b>0.725</b>	7.44**	<b>0.152</b>	1.09	-0.145	-1.04
Lloyds Bank						
Royal Bank of Scotland	<b>0.630</b>	5.74**	<b>0.141</b>	1.01	-0.267	-1.96
Standard Chartered	<b>0.636</b>	5.83**	<b>0.084</b>	0.60	-0.146	-1.04

\*\* sig at the 95% confidence interval

\*\*\* sig. at the 99% confidence interval

$R_{it}$  is the return on bank stock  $i$  during time period  $t$

$B_{mi}R_{mjt}$  is the market beta and the return on the market index in country  $j$  at time  $t$

$B_{rt}R_{rjt}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$

$B_{xt}R_{xjt}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$

$\alpha_{it}, u_{it}$  is the bank specific constant and random error terms, respectively

**Table 25 Weekly VaR Results: United Kingdom**

Weekly VaR in percent of Bank Equity at Risk

$$VaR = c \left[ (\beta_{m,i} \sigma_{m_j})^2 + (\beta_{r,i} \sigma_{r_j})^2 + (\beta_{x,i} \sigma_{x_j})^2 \right]^{1/2}$$

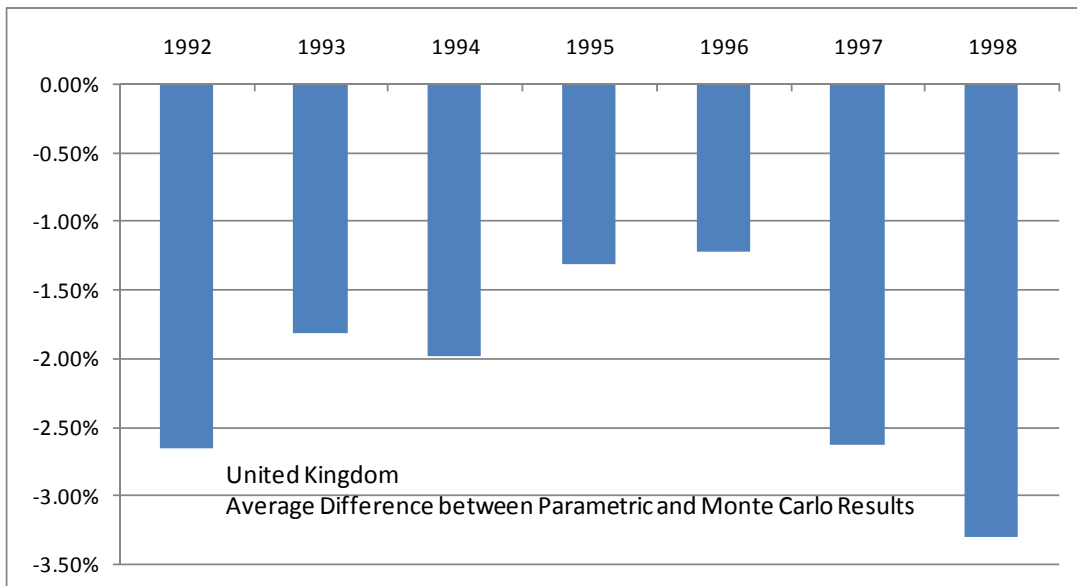
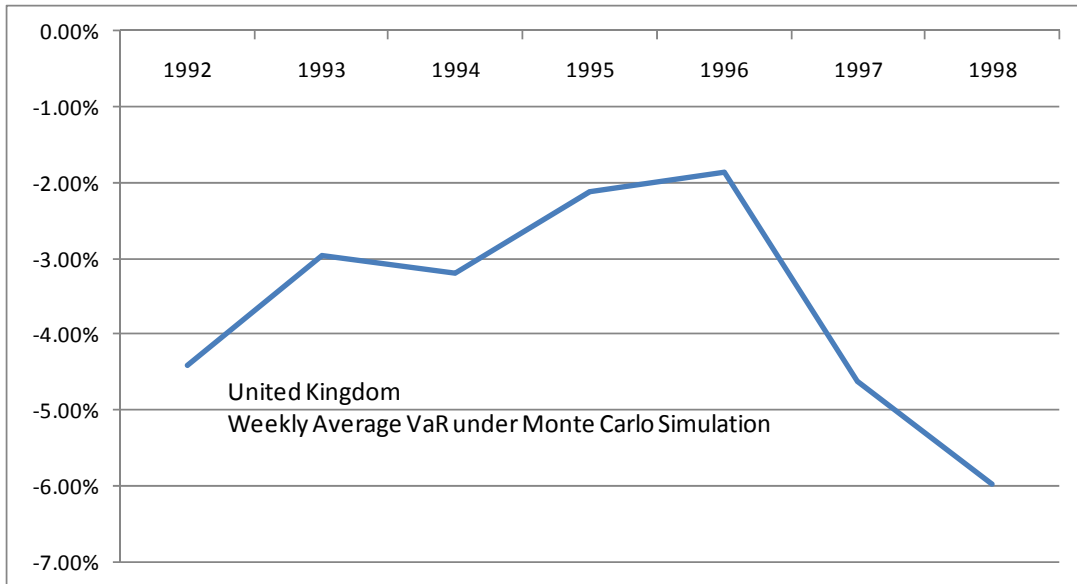
Bank VaR at 99% confidence		1992	1993	1994	1995	1996	1997	1998
<b>United Kingdom</b>								
Barclays	VaR, assuming a Normal Distribution	-1.56%	-1.03%	-1.03%	-0.83%	-0.78%	-1.84%	-2.78%
	Historical VaR	-2.39%	-1.66%	-2.61%	-1.63%	-1.52%	-4.54%	-6.12%
	EVT VaR	-2.71%	-1.87%	-2.64%	-1.74%	-1.71%	-6.85%	-6.78%
	VaR, Monte Carlo Simulation (1000 trials)	-5.61%	-2.68%	-2.73%	-2.04%	-2.13%	-4.49%	-5.18%
HSBC	VaR, assuming a Normal Distribution	-1.76%	-1.33%	-1.33%	-1.04%	-0.61%	-2.66%	-2.75%
	Historical VaR	-2.49%	-2.17%	-3.44%	-2.46%	-1.25%	-7.20%	-6.01%
	EVT VaR	-2.71%	-2.45%	-3.55%	-2.63%	-1.42%	-11.28%	-6.66%
	VaR, Monte Carlo Simulation (1000 trials)	-2.98%	-2.84%	-3.33%	-1.92%	-1.91%	-5.19%	-6.98%
Lloyds Bank	VaR, assuming a Normal Distribution	-1.56%	-1.17%	-0.93%	-0.60%			
	Historical VaR	-2.38%	-1.87%	-2.38%	-1.22%			
	EVT VaR	-2.69%	-2.14%	-2.44%	-1.30%			
	VaR, Monte Carlo Simulation (1000 trials)	-4.74%	-3.13%	-2.70%	-2.22%			
Royal Bank of Scotland	VaR, assuming a Normal Distribution	-2.05%	-1.37%	-0.64%	-0.56%	-0.62%	-1.46%	-2.04%
	Historical VaR	-3.07%	-2.21%	-1.65%	-0.93%	-1.14%	-4.06%	-4.51%
	EVT VaR	-3.46%	-2.52%	-1.68%	-0.99%	-1.28%	-6.43%	-4.98%
	VaR, Monte Carlo Simulation (1000 trials)	-4.75%	-3.45%	-2.70%	-2.09%	-2.17%	-4.30%	-5.55%
Standard Chartered	VaR, assuming a Normal Distribution	-1.91%	-0.86%	-2.15%	-1.03%	-0.57%	-2.06%	-3.12%
	Historical VaR	-2.79%	-1.58%	-5.51%	-2.36%	-1.39%	-5.53%	-6.77%
	EVT VaR	-3.11%	-1.86%	-5.62%	-2.52%	-1.62%	-8.70%	-7.53%
	VaR, Monte Carlo Simulation (1000 trials)	-4.04%	-2.74%	-4.54%	-2.40%	-1.28%	-4.55%	-6.21%

$$\sigma_{m_i} \sigma_{r_i} \sigma_{x_i}$$

where c reflects a give level of statistical confidence  
 the betas pertain to each individual bank i  
 represent the standard deviations of the market index, interest rate, and exchange rate in country j  
 These statistics are calculated from daily data obtained from FT Prices CD-Rom and Bloomberg.



**Figure 18** VaR results by Year. Parametric Vs Monte Carlo Results: United Kingdom



**Table 26 Weekly VaR Results: United States**

Weekly VaR in percent of Bank Equity at Risk

$$VaR = \left[ (\beta_{m,t} \sigma_{mj})^2 + (\beta_{r,t} \sigma_{rj})^2 + (\beta_{x,t} \sigma_{xj})^2 \right]^{1/2}$$

Bank VaR at 99% confidence		1992	1993	1994	1995	1996	1997	1998
<b>United States</b>								
Associated Bank	VaR, assuming a Normal Distribution	-0.38%	-0.39%	-0.22%	-0.38%	-0.62%	-0.26%	-0.30%
	Historical VaR	-0.68%	-0.79%	-0.51%	-0.57%	-1.40%	-0.48%	-0.68%
	EVT VaR	-0.75%	-0.82%	-0.54%	-0.63%	-1.60%	-0.53%	-0.73%
	VaR, Monte Carlo Simulation (1000 trials)	-1.52%	-0.72%	-1.43%	-1.78%	-1.61%	-0.95%	-1.64%
Bancorp South	VaR, assuming a Normal Distribution	-0.65%	-0.17%	-0.24%	-2.18%	-0.23%	-0.30%	-0.61%
	Historical VaR	-1.21%	-0.37%	-0.47%	-0.64%	-0.57%	-0.54%	-1.36%
	EVT VaR	-1.27%	-0.41%	-0.48%	-0.96%	-0.66%	-0.59%	-1.50%
	VaR, Monte Carlo Simulation (1000 trials)	-2.83%	-0.83%	-0.50%	-2.16%	-0.59%	-0.69%	-1.71%
Bank of America	VaR, assuming a Normal Distribution	-0.51%	-0.48%	-0.48%	-0.36%	-1.45%	-0.23%	-1.45%
	Historical VaR	-0.85%	-1.09%	-0.89%	-0.64%	-3.21%	-0.47%	-3.88%
	EVT VaR	-0.91%	-1.27%	-1.00%	-0.70%	-3.66%	-0.53%	-4.70%
	VaR, Monte Carlo Simulation (1000 trials)	-1.47%	-1.64%	-1.89%	-1.31%	-3.13%	-0.95%	-4.55%
Bank of New York	VaR, assuming a Normal Distribution	-0.28%	-0.18%	-0.90%	-0.44%	-0.49%	-0.81%	-0.38%
	Historical VaR	-0.50%	-0.39%	-2.17%	-0.76%	-1.34%	-1.47%	-0.97%
	EVT VaR	-0.56%	-0.44%	-2.29%	-0.81%	-1.39%	-1.56%	-1.13%
	VaR, Monte Carlo Simulation (1000 trials)	-0.23%	-1.10%	-0.42%	-1.51%	-1.63%	-1.21%	-2.18%
BB&T	VaR, assuming a Normal Distribution	-0.28%	-0.39%	-0.38%	-0.32%	-0.17%	-0.72%	-0.79%
	Historical VaR	-0.88%	-0.79%	-0.89%	-0.59%	-0.32%	-1.22%	-1.77%
	EVT VaR	-1.02%	-0.83%	-0.91%	-0.61%	-0.34%	-1.31%	-1.96%
	VaR, Monte Carlo Simulation (1000 trials)	-2.21%	-1.47%	-1.28%	-1.31%	-1.24%	-1.20%	-1.44%
BOK Financial	VaR, assuming a Normal Distribution			-0.50%	-0.21%	-0.90%	-0.36%	-0.27%
	Historical VaR			-0.93%	-0.43%	-1.45%	-0.84%	-0.63%
	EVT VaR			-1.04%	-0.47%	-1.58%	-1.00%	-0.67%
	VaR, Monte Carlo Simulation (1000 trials)			-1.81%	-1.06%	-2.86%	-2.43%	-1.84%
Charles Schwab	VaR, assuming a Normal Distribution	-0.44%	-1.09%	-1.40%	-1.69%	-0.58%	-0.79%	-1.21%
	Historical VaR	-0.82%	-2.45%	-2.64%	-4.12%	-1.34%	-1.38%	-3.23%
	EVT VaR	-0.91%	-2.95%	-2.89%	-4.47%	-1.49%	-1.49%	-3.91%
	VaR, Monte Carlo Simulation (1000 trials)	-1.67%	-2.24%	-3.45%	-2.62%	-1.67%	-1.47%	-4.31%
Colonial Bancorp	VaR, assuming a Normal Distribution	-0.44%	-0.45%	-0.36%	-0.52%	-2.12%	-0.62%	-0.35%
	Historical VaR	-0.87%	-0.91%	-0.66%	-1.18%	-5.72%	-1.14%	-0.90%
	EVT VaR	-1.00%	-0.95%	-0.73%	-1.29%	-5.94%	-1.19%	-1.04%
	VaR, Monte Carlo Simulation (1000 trials)	-1.05%	-1.25%	-1.43%	-0.89%	-2.86%	-1.55%	-2.16%
Comerica	VaR, assuming a Normal Distribution	-1.05%	-0.30%	-0.32%	-0.23%	-0.17%	-0.55%	-0.28%
	Historical VaR	-2.31%	-0.62%	-0.82%	-0.55%	-0.29%	-1.06%	-0.68%
	EVT VaR	-2.61%	-0.65%	-0.83%	-0.61%	-0.32%	-1.13%	-0.76%
	VaR, Monte Carlo Simulation (1000 trials)	-2.86%	-0.85%	-1.53%	-0.56%	-1.26%	-1.28%	-1.59%
Commerce Bancorp	VaR, assuming a Normal Distribution	-0.68%	-0.39%	-0.58%	-0.81%	-0.28%	-0.62%	-0.49%
	Historical VaR	-1.19%	-0.81%	-1.48%	-1.84%	-0.65%	-1.19%	-1.28%
	EVT VaR	-1.25%	-0.97%	-1.52%	-1.96%	-0.75%	-1.30%	-1.52%
	VaR, Monte Carlo Simulation (1000 trials)	-2.61%	0.00%	-1.92%	-2.62%	-1.32%	-1.32%	-2.54%

Commerce Bankshares	VaR, assuming a Normal Distribution	-0.24%	-1.00%	-0.30%	-0.15%	-0.45%	-0.79%	-0.27%
	Historical VaR	-0.42%	-2.42%	-0.58%	-0.34%	-1.22%	-1.51%	-0.62%
	EVT VaR	-0.44%	-2.95%	-0.62%	-0.37%	-1.29%	-1.70%	-0.65%
	VaR, Monte Carlo Simulation (1000 trials)	-1.69%	-2.51%	-0.94%	-0.20%	-1.12%	-1.78%	-1.52%
Compass Bankshares	VaR, assuming a Normal Distribution	-0.26%	-0.15%	-0.23%	-0.24%	-0.18%	-0.82%	-0.29%
	Historical VaR	-0.48%	-0.30%	-0.55%	-0.53%	-0.34%	-1.59%	-0.67%
	EVT VaR	-0.51%	-0.31%	-0.57%	-0.56%	-0.38%	-1.76%	-0.71%
	VaR, Monte Carlo Simulation (1000 trials)	-1.46%	-0.10%	-0.60%	-1.14%	-1.31%	-1.34%	-1.50%
Countrywide	VaR, assuming a Normal Distribution	-1.07%	-1.35%	-0.97%	-0.58%	-0.31%	-0.72%	-1.31%
	Historical VaR	-1.93%	-3.18%	-1.96%	-1.44%	-0.70%	-1.49%	-3.50%
	EVT VaR	-2.12%	-3.92%	-1.98%	-1.60%	-0.75%	-1.58%	-4.24%
	VaR, Monte Carlo Simulation (1000 trials)	-2.56%	-2.98%	-0.16%	-0.89%	-0.38%	-2.02%	-4.07%
Downey Financial	VaR, assuming a Normal Distribution	-0.30%	-0.15%	-0.74%	-0.44%	-0.56%	-0.68%	-0.34%
	Historical VaR	-0.93%	-0.32%	-1.87%	-1.04%	-1.35%	-1.31%	-0.78%
	EVT VaR	-1.07%	-0.38%	-1.89%	-1.15%	-1.56%	-1.47%	-0.84%
	VaR, Monte Carlo Simulation (1000 trials)	-2.12%	0.00%	-2.21%	-1.15%	-0.82%	-0.52%	-1.64%
Fifth Third	VaR, assuming a Normal Distribution	-0.92%	-0.51%	-0.20%	-0.41%	-0.21%	-0.83%	-0.23%
	Historical VaR	-2.02%	-1.02%	-0.44%	-0.98%	-0.42%	-1.64%	-0.54%
	EVT VaR	-2.28%	-1.07%	-0.48%	-1.05%	-0.46%	-1.87%	-0.56%
	VaR, Monte Carlo Simulation (1000 trials)	-2.66%	-1.49%	-0.91%	-1.57%	-1.43%	-1.15%	-1.77%
First Horizon	VaR, assuming a Normal Distribution	-0.67%	-0.11%	-0.51%	-0.72%	-0.38%	-0.91%	-0.32%
	Historical VaR	-1.22%	-0.26%	-1.29%	-1.12%	-0.79%	-1.63%	-0.81%
	EVT VaR	-1.34%	-0.30%	-1.33%	-1.22%	-0.87%	-1.77%	-0.92%
	VaR, Monte Carlo Simulation (1000 trials)	-1.84%	-0.97%	-1.66%	-2.26%	-2.13%	-1.17%	-2.00%
Fulton Financial	VaR, assuming a Normal Distribution	-0.26%	-0.39%	-0.64%	-0.46%	-0.73%	-0.26%	-0.24%
	Historical VaR	-0.59%	-0.93%	-1.37%	-1.08%	-1.68%	-0.53%	-0.56%
	EVT VaR	-0.69%	-1.15%	-1.41%	-1.16%	-1.81%	-0.59%	-0.59%
	VaR, Monte Carlo Simulation (1000 trials)	-0.38%	-1.35%	-1.71%	-1.84%	-2.55%	-0.88%	-1.90%
Huntington Bankshares	VaR, assuming a Normal Distribution	-0.63%	-0.29%	-0.79%	-0.25%	-0.44%	-0.91%	-0.23%
	Historical VaR	-1.48%	-0.62%	-1.93%	-0.58%	-1.07%	-1.69%	-0.55%
	EVT VaR	-1.72%	-0.70%	-1.95%	-0.63%	-1.24%	-1.77%	-0.58%
	VaR, Monte Carlo Simulation (1000 trials)	-2.02%	-1.07%	-1.83%	-0.59%	-1.14%	-1.66%	-1.46%
Keycorp Financial	VaR, assuming a Normal Distribution	-0.19%	-0.47%	-0.21%	-0.32%	-0.33%	-1.22%	-0.26%
	Historical VaR	-0.36%	-0.92%	-0.47%	-0.76%	-0.72%	-2.69%	-0.63%
	EVT VaR	-0.38%	-0.95%	-0.50%	-0.82%	-0.83%	-2.94%	-0.69%
	VaR, Monte Carlo Simulation (1000 trials)	-1.27%	-0.32%	-1.44%	-1.92%	-1.75%	-3.27%	-1.63%
Marshall and Isley	VaR, assuming a Normal Distribution	-0.19%	-1.93%	-0.33%	-0.27%	-0.22%	-0.20%	-0.23%
	Historical VaR	-0.55%	-4.16%	-0.66%	-0.60%	-0.57%	-0.44%	-0.54%
	EVT VaR	-0.63%	-4.94%	-0.70%	-0.64%	-0.60%	-0.51%	-0.56%
	VaR, Monte Carlo Simulation (1000 trials)	-1.40%	-2.08%	-1.25%	-1.71%	-1.24%	-1.40%	-2.48%
Merrill Lynch	VaR, assuming a Normal Distribution	-0.43%	-0.96%	-0.69%	-0.82%	-0.49%	-2.66%	-0.78%
	Historical VaR	-0.84%	-2.01%	-1.77%	-1.44%	-0.98%	-5.08%	-1.73%
	EVT VaR	-0.95%	-2.34%	-1.79%	-1.53%	-1.13%	-5.59%	-1.92%
	VaR, Monte Carlo Simulation (1000 trials)	-1.02%	-1.11%	-1.89%	-2.04%	-3.03%	-4.51%	-1.67%
National City	VaR, assuming a Normal Distribution	-0.13%	-0.79%	-0.72%	-0.22%	-0.29%	-0.22%	-0.39%
	Historical VaR	-0.24%	-1.58%	-1.41%	-0.49%	-0.73%	-0.42%	-0.99%
	EVT VaR	-0.26%	-1.72%	-1.49%	-0.53%	-0.81%	-0.44%	-1.16%
	VaR, Monte Carlo Simulation (1000 trials)	-1.20%	-2.90%	-1.90%	-0.85%	-1.00%	-1.32%	-2.32%
Northern Trust	VaR, assuming a Normal Distribution	-0.29%	-0.48%	-0.37%	-0.29%	-1.43%	-0.74%	-0.49%
	Historical VaR	-0.55%	-1.03%	-0.94%	-0.71%	-2.88%	-1.41%	-1.28%
	EVT VaR	-0.61%	-1.13%	-0.95%	-0.77%	-3.22%	-1.51%	-1.52%
	VaR, Monte Carlo Simulation (1000 trials)	-1.45%	-1.25%	-1.34%	-0.67%	-4.69%	-1.64%	-3.59%

PnC FinServices	VaR, assuming a Normal Distribution	-0.94%	-0.31%	-0.32%	-0.30%	-0.29%	-0.89%	-0.23%
	Historical VaR	-2.65%	-0.63%	-0.76%	-0.60%	-0.56%	-1.53%	-0.54%
	EVT VaR	-3.06%	-0.66%	-0.76%	-0.62%	-0.65%	-1.63%	-0.56%
	VaR, Monte Carlo Simulation (1000 trials)	-2.77%	-0.89%	-0.92%	-1.09%	-2.00%	-0.99%	-1.91%
Popular Inc	VaR, assuming a Normal Distribution	-0.33%	-0.19%	-0.31%	-0.24%	-0.57%	-0.32%	-0.32%
	Historical VaR	-0.59%	-0.39%	-0.58%	-0.53%	-1.29%	-0.66%	-0.81%
	EVT VaR	-0.62%	-0.41%	-0.60%	-0.56%	-1.39%	-0.69%	-0.92%
	VaR, Monte Carlo Simulation (1000 trials)	-1.85%	-0.94%	-1.12%	-1.29%	-1.47%	-1.58%	-2.10%
Regions Financial	VaR, assuming a Normal Distribution	-0.36%	-0.59%	-0.31%	-0.22%	-0.23%	-0.77%	-0.67%
	Historical VaR	-0.72%	-1.28%	-0.61%	-0.40%	-0.58%	-1.40%	-1.78%
	EVT VaR	-0.81%	-1.45%	-0.64%	-0.42%	-0.64%	-1.55%	-2.14%
	VaR, Monte Carlo Simulation (1000 trials)	-0.80%	-2.12%	-1.17%	-0.87%	-0.93%	-2.05%	-2.97%
Sovereign Bancorp	VaR, assuming a Normal Distribution	-1.11%	-0.37%	-1.05%	-0.41%	-0.37%	-0.45%	-0.34%
	Historical VaR	-1.84%	-0.81%	-2.03%	-0.75%	-0.94%	-0.80%	-0.86%
	EVT VaR	-1.99%	-0.97%	-2.16%	-0.79%	-1.05%	-0.88%	-0.98%
	VaR, Monte Carlo Simulation (1000 trials)	-2.19%	-0.99%	-2.51%	-1.17%	-0.14%	-0.89%	-1.83%
State Street	VaR, assuming a Normal Distribution	-0.45%	-0.54%	-0.10%	-0.29%	-0.31%	-2.38%	-0.27%
	Historical VaR	-0.75%	-1.11%	-0.25%	-0.60%	-2.32%	-4.56%	-0.65%
	EVT VaR	-0.80%	-1.19%	-0.26%	-0.63%	-0.74%	-5.00%	-0.71%
	VaR, Monte Carlo Simulation (1000 trials)	-1.66%	-1.82%	-0.59%	-1.29%	-1.51%	-4.23%	-2.00%
Suntrust Bank	VaR, assuming a Normal Distribution	-0.42%	-0.18%	-0.22%	-0.16%	-1.14%	-0.68%	-0.27%
	Historical VaR	-1.13%	-0.43%	-0.46%	-0.39%	-2.32%	-1.22%	-0.67%
	EVT VaR	-1.29%	-0.51%	-0.50%	-0.42%	-2.65%	-1.29%	-0.74%
	VaR, Monte Carlo Simulation (1000 trials)	-2.12%	-0.95%	-0.96%	-0.90%	-3.08%	-1.65%	-1.80%
Synovus Bank	VaR, assuming a Normal Distribution	-0.44%	-0.78%	-0.26%	-0.39%	-1.36%	-1.00%	-0.31%
	Historical VaR	-0.85%	-1.62%	-0.51%	-0.76%	-3.20%	-1.96%	-0.76%
	EVT VaR	-0.98%	-1.88%	-0.57%	-0.82%	-3.58%	-2.07%	-0.86%
	VaR, Monte Carlo Simulation (1000 trials)	-0.94%	-1.07%	-1.36%	-1.23%	-1.38%	-2.10%	-1.98%
TCF Financial	VaR, assuming a Normal Distribution	-0.53%	-0.23%	-0.25%	-0.90%	-0.21%	-0.91%	-0.73%
	Historical VaR	-1.47%	-0.56%	-0.51%	-1.81%	-0.38%	-1.85%	-1.62%
	EVT VaR	-1.68%	-0.69%	-0.56%	-1.94%	-0.44%	-1.98%	-1.80%
	VaR, Monte Carlo Simulation (1000 trials)	-2.18%	-1.62%	-1.31%	-3.09%	-1.42%	-2.45%	-1.47%
US Bancorp	VaR, assuming a Normal Distribution	-0.37%	-0.49%	-0.64%	-0.31%	-0.10%	-0.25%	-0.36%
	Historical VaR	-0.70%	-1.07%	-1.30%	-0.71%	-0.26%	-0.48%	-0.82%
	EVT VaR	-0.78%	-1.21%	-1.36%	-0.75%	-0.30%	-0.51%	-0.88%
	VaR, Monte Carlo Simulation (1000 trials)	-1.60%	-1.33%	-1.73%	-1.70%	-0.20%	-1.08%	-1.54%
Wachovia	VaR, assuming a Normal Distribution	-0.50%	-1.06%	-0.47%	-0.35%	-0.39%	-0.32%	-0.24%
	Historical VaR	-0.91%	-2.37%	-0.95%	-0.85%	-0.92%	-0.60%	-0.56%
	EVT VaR	-0.98%	-2.70%	-1.01%	-0.91%	-1.03%	-0.65%	-0.59%
	VaR, Monte Carlo Simulation (1000 trials)	-2.13%	-2.11%	-1.80%	-1.74%	-1.42%	-1.02%	-1.82%
Washington Mutual	VaR, assuming a Normal Distribution	-0.39%	-0.36%	-0.41%	-0.35%	-0.60%	-0.66%	-0.23%
	Historical VaR	-0.86%	-0.81%	-0.97%	-0.73%	-1.04%	-1.35%	-0.55%
	EVT VaR	-1.02%	-0.96%	-0.97%	-0.82%	-1.15%	-1.47%	-0.57%
	VaR, Monte Carlo Simulation (1000 trials)	-0.28%	-1.68%	-0.90%	-1.23%	-2.53%	-1.39%	-2.00%
Wells Fargo	VaR, assuming a Normal Distribution	-0.48%	-1.67%	-0.68%	-0.17%	-0.57%	-0.65%	-0.34%
	Historical VaR	-0.82%	-3.43%	-1.29%	-0.35%	-1.43%	-1.29%	-0.86%
	EVT VaR	-0.88%	-3.74%	-1.45%	-0.36%	-1.61%	-1.40%	-0.99%
	VaR, Monte Carlo Simulation (1000 trials)	-1.65%	-3.80%	-2.88%	-1.18%	-0.90%	-2.27%	-1.97%
Zion Corp	VaR, assuming a Normal Distribution	-0.27%	-1.44%	-0.39%	-0.27%	-0.17%	-4.62%	-0.63%
	Historical VaR	-0.54%	-3.39%	-0.77%	-0.65%	-0.43%	-8.78%	-1.67%
	EVT VaR	-0.59%	-4.15%	-0.78%	-0.70%	-0.45%	-9.56%	-2.00%
	VaR, Monte Carlo Simulation (1000 trials)	-1.65%	-2.54%	-0.96%	-1.34%	-1.05%	-4.85%	-3.08%

where  $c$  reflects a give level of statistical confidence

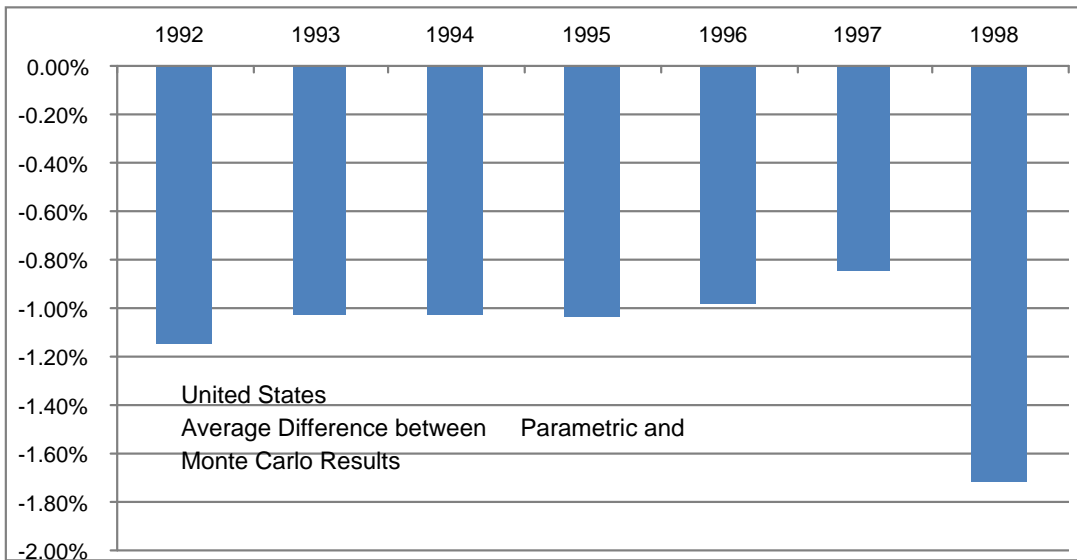
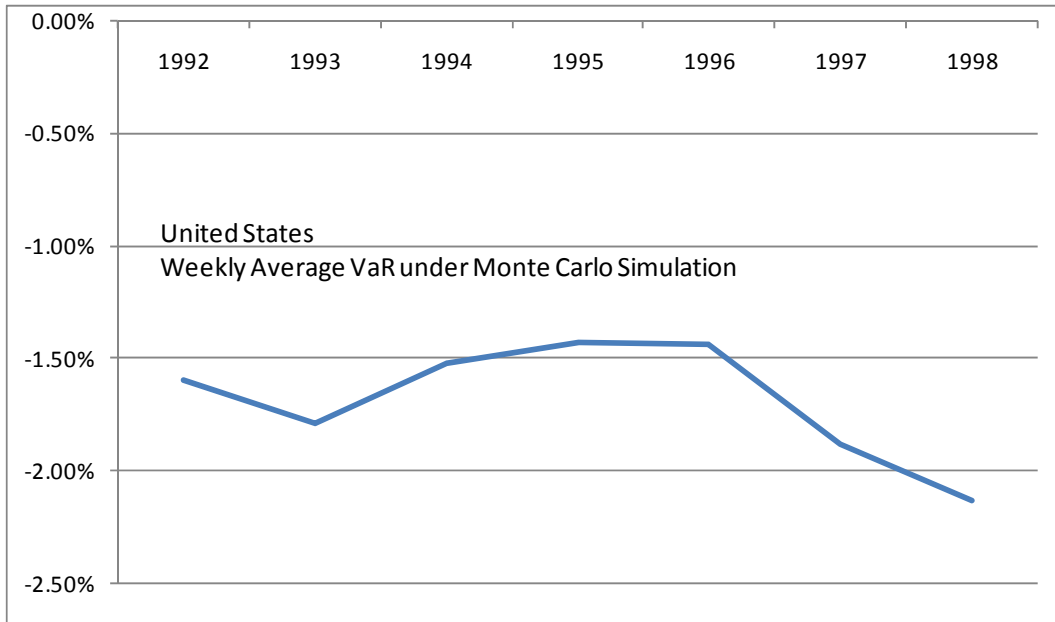
the betas pertain to each individual bank  $i$

represent the standard deviations of the market index, interest rate, and exchange rate in country  $j$

These statistics are calculated from daily data obtained from FT Prices CD-Rom and Bloomberg.

$$\sigma_{m_j}, \sigma_{r_j}, \sigma_{e_j}$$

**Figure 19** VaR results by Year. Parametric Vs Monte Carlo Results: United States



**Table 27 Weekly VaR Results: Total Bank Sample**

Weekly VaR in percent of a Bank Equity at Risk.							
Mean VaR of Sample Banks by Country (Monte Carlo Simulation Results)							
	1992	1993	1994	1995	1996	1997	1998
Belgium	-2.34%	-1.79%	-2.02%	-1.73%	-2.02%	-4.84%	-4.68%
Canada	-2.69%	-2.23%	-2.82%	-2.01%	-2.37%	-3.39%	-5.93%
France	-2.83%	-1.64%	-2.20%	-1.80%	-1.37%	-3.36%	-4.56%
Germany	-2.09%	-1.94%	-2.58%	-1.94%	-1.47%	-3.31%	-4.03%
Italy	-3.39%	-1.51%	-2.14%	-1.23%	-2.27%	-2.41%	-5.16%
Japan	-5.72%	-3.79%	-2.62%	-3.42%	-4.97%	-11.18%	-5.96%
Netherlands	-1.82%	-2.58%	-2.15%	-2.18%	-2.95%	-6.03%	-6.59%
Sweden	-4.26%	-4.26%	-4.26%	-4.26%	-4.26%	-4.26%	-4.26%
Switzerland	-2.11%	-2.11%	-2.11%	-2.11%	-2.11%	-2.11%	-2.11%
United Kingdom	-4.42%	-2.97%	-3.20%	-2.13%	-1.87%	-4.63%	-5.98%
United States	-1.60%	-1.79%	-1.52%	-1.43%	-1.44%	-1.88%	-2.14%
Average	-3.02%	-2.42%	-2.51%	-2.20%	-2.46%	-4.31%	-4.67%

**Table 28 Weekly VaR Results: Lowest VaR Ranking by Country by Year**

Country Ranking by Lowest VaR									
	1992	1993	1994	1995	1996	1997	1998	Sum of Ranks	
Belgium	5	3	2	3	5	9	6	33	
Canada	6	7	9	6	8	6	8	50	
France	7	2	6	4	1	5	5	30	
Germany	3	5	7	5	3	4	3	30	
Italy	8	1	4	1	7	3	7	31	
Japan	11	10	8	10	11	11	9	70	<b>Highest VaR</b>
Netherlands	2	8	5	9	9	10	11	54	
Sweden	9	11	11	11	10	7	4	63	2nd Highest VaR
Switzerland	4	6	3	7	6	2	1	29	2nd Lowest VaR
United Kingdom	10	9	10	8	4	8	10	59	
United States	1	4	1	2	2	1	2	13	<b>Lowest VaR</b>

### ***4.3 Analysis of DEA Bank Efficiency Results***

#### **I Introduction**

This study uses data envelopment analysis (DEA) to investigate the efficiency of the G-10 commercial banking industry over the period 1992 to 1998. This study also examines the impact of off-balance-sheet (OBS) activities and estimates the efficiency of the bank sample with and without an OBS variable to determine if any differences exist. Furthermore, Tobit regression is used to explain the efficiency of banks.

The discussion of the empirical results on the efficiency of commercial banks in G-10 is structured as follows: First, the efficiency of the full sample of banks obtained through an input-oriented approach with CRS and VRS, and with and without the inclusion of the off-balance sheet variable. Secondly, this study investigates determinants of efficiency using Tobit regression.

#### **II First Stage DEA Results**

DEA can be implemented by assuming either constant returns to scale (CRS) or variable returns to scale (VRS). This study indicates overall technical efficiency (TE) of each bank under CRS. Banker et al (1984) suggested the use of VRS that splits overall technical efficiency into a product of two components. The first is pure technical efficiency (PTE), sometimes referred to as technical efficiency, and relates to the ability of management to optimise the bank's given resources. The second is scale efficiency (SE) and refers to exploiting scale economies by operating at a point where the production frontier exhibits CRS. In several recent papers, DEA models are estimated under the assumption of VRS, while arguing CRS is only valid when all DMUs are operating at an optimal level. However, CRS allows the comparison

between large and small firms (Miller and Noulas, 1996). In the present study, the technical efficiency estimates are obtained under both CRS and VRS assumptions.

Figures 20 through to 23 present the results from the four models that correspond to input/outputs selected on the basis of the intermediation approach. The average technical efficiency obtained by the CRS approach (excl. OBS activity) ranges between 0.57 (inefficiency score of 0.43) in 1992 and 0.73 (inefficiency score of 0.27) in 1998, with an overall mean over the study period equal to 0.61, as per Table 29. The CRS model results when OBS is included as an output variable increase with an average efficiency score of 0.72, with a low score of 0.68 (0.32 inefficiency) in 1992 and the highest efficiency score seen in 1998 with 0.80 (0.20 inefficiency) as shown in Table 30. These global frontier results are similar to those of Lozano-Vivas et al (2002) who report an average inefficiency score of 0.34, while Weill et al (2004) report an average inefficiency score of 0.35.

The corresponding figures for technical efficiency under the VRS approach (excluding OBS) ranges between 0.61 in 1992 and efficiency improves up to 0.79 by 1998, with an overall mean efficiency of 0.67 (represented by the inefficiency score of 0.33 per Table 31). The average efficiency score when OBS is incorporated into the VRS model ranges between 0.71 and 0.85. The average efficiency score for the period of 1992 to 1998 is 0.76.

The efficiency scores increase significantly when off-balance sheet items are considered as an additional output, with a mean of 0.72 under the CRS approach, and 0.76 under the VRS approach. The inclusion of OBS activity as an additional output



increases the efficiency score on average by 0.11 under the CRS approach and by 0.09 under the VRS approach. Under both CRS and VRS, the inclusion of OBS activity as an output variable results in a statistically significant result when the mean differences are compared. This result supports H8a in terms of OBS activity increasing the overall efficiency score of the sample and is consistent with the findings of Clark and Siems (2002). Therefore, in the sample period studied, banks could improve technical efficiency by 39% under CRS and by 33% under VRS, when excluding OBS activity as a variable. However, it is important to incorporate OBS items as an output variable (Clark and Siems, 2002) and under this approach, the sample on average could improve technical efficiency by 28% under the CRS approach, and by 24% under the VRS method.

Figures 20 to 23 allow for the comparison of efficiency scores by country by year. The results indicate that in 1992, under the CRS intermediation approach, Belgium (inefficiency of 0.14) and Sweden (inefficiency of 0.23) had the highest TE levels in 1992, whereas Italy was the lowest performer with an average inefficiency score of 0.6. However, under a CRS approach that includes OBSA, Italy has a less extreme level of inefficiency, and although at the low end of the efficiency range, is similar to the inefficiency scores of Japan, the Netherlands and the United States. Under the VRS approach, Italy and the United States have the highest inefficiency score, 0.59 and 0.40 respectively. Once again when OBSA variables the results for Italy are less extreme in terms of inefficiency levels. However, the United States continues to perform poorly in 1992 with an inefficiency score of 0.38. The low efficiency score would be expected considering the US was just moving out of a recession. (Unfortunately, no data was available for Canadian banks in the year 1992).

In 1993, the total efficiency score improves very slightly across all four DEA models, by close to 1% when compared to 1992. Italy continues to perform poorly in 1993 with an average inefficiency score of 0.56 and 0.55 under CRS and VRS models with OBS activity, but does improve with the inclusion of OBSA with the inefficiency score moving down close to 0.3. When including OBSA Canada and the United States continue to be on the high end of the inefficiency scores with Canada scoring 0.30 and 0.37 for the CRS and VRS approach. The United States reported an inefficiency score of 0.32 and 0.31 for CRS and VRS approaches, including OBSA. Belgium and Sweden continued to perform well in 1993 with inefficiency scores of sub 0.25 for CRS and VRS models without OBS, and below 0.2 when including OBS.

Overall efficiency scores continued to improve in 1994 with efficiency improvements of 2% and over 4% in CRS and VRS models. For the models that included OBSA, the efficiency level improved by 1% and 4% under CRS and VRS respectively. In terms of the analysis by country, a similar theme continued with Italy being at the high end of the range of inefficiency scores (0.55) with the Netherlands and France also performing relatively poorly with inefficiency scores of above 0.5 under the CRS intermediation approach. Along with Italy, France and the United States performed relatively poorly under the CRS and VRS approaches the included OBSA. Once again Belgium and Sweden performed well through 1994 in terms of efficiency scores relative to other countries in the sample. The poor performance of Italy and France relative to other countries is consistent with the findings of Allen and Rai (1996) and Bikker (2002). Berg et al (1993) found Sweden to perform better other Nordic countries in terms of bank efficiency. Bukh et al (1995) also found Sweden to outperform Norway, Finland, and Denmark with an average efficiency score of 0.85.

For 1995, it is interesting to note that the trend of improving efficiency from 1992 is broken and inefficiency increases on average by 2% across all four models. Under TE without OBS, Italy, France and the Netherlands have inefficiency scores above 0.5. Under CRS with OBS, these countries remain at the high end of the range in terms of inefficiency, but with scores closer to 0.4. Under the VRS intermediation approach, Italy, France and Canada are the poorest performers. Once OBS is taken into account, the overall inefficiency scores improve, but in terms of ranking countries, the results remain the same with Belgium and Sweden shows the greatest level of efficiency, whereas, Italy, France and Canada continue to underperform. The results for Canada are somewhat conflicting with previous evidence: Bikker (2002) finds relatively high efficiency levels in Germany, Sweden and Canada.

In 1996, the results show an overall improvement in efficiency scores, with the CRS and VRS results improving by over 1.5% and close to 5% respectively. When OBS is included the efficiency score improve by nearly 1% and 2% respectively under CRS and VRS. France, Canada, Italy and the Netherlands continue to under-perform with inefficiency scores of close to 0.5 (CRS). Under VRS, the Netherlands is more efficient, however, France, Canada and Italy have inefficiency scores above 0.4. The countries that do not perform well under CRS continue to hold a low efficiency ranking when considered under VRS and VRS\_OBS. In 1996, Belgium, Sweden and Switzerland perform well with inefficiency scores of sub 0.3.

Based on how volatile the financial markets were through 1997 the expectation would be for inefficiency levels to increase quite dramatically. However, the technical efficiency score continues to improve through time could argue that there is a time

trend variable in the efficiency results. The theme continues with Belgium and the Nordic countries of Sweden and Switzerland show strong efficiency results as compared to other countries. Italy, France and Canada under-perform in all four efficiency models.

One interesting result is the change in efficiency levels through time by country. Canadian inefficiency generally increases under the CRS model, whereas it improves slightly under the VRS model. France has a very consistent inefficiency score of close to 0.4 until 1998 when efficiency scores improve dramatically along with other countries. The efficiency scores of German banks improved through the study period and generally performed well with scores of less than 0.3. Italy was one of the lowest ranked countries on a consistent basis with inefficiency scores in excess of 0.5 for many of the years when not including OBS. This result is consistent with Bikker (2002). When including OBS, Italy struggled to get an inefficiency score below 0.4. The results for Japan were interesting in that efficiency scores on average were quite strong considering the level of volatility this country had through the latter part of the 1990s. The average inefficiency score was 0.31 across all years and models. 1995 did see a move up in the inefficiency score, but on average Japan performed quite well versus other countries in the sample. The Netherlands did perform quite poorly through the study period with an average inefficiency score of 0.32, but as high as 0.48 under the CRS approach. The trend was similar to others in terms of a general efficiency improvement through time. Sweden and Switzerland were consistently on the high end of the efficiency range with Sweden having an average inefficiency score of 0.19 and Switzerland with 0.26. The United Kingdom performed quite well through the study period with an inefficiency score of 0.3 across all four DEA

approaches. As per the other countries, the United Kingdom banks saw an increase in overall efficiency through 1997 and 1998. The United States was one of countries that showed a clear trend in improvement through the period of study with an inefficiency score of 0.44 in 1992 (CRS) and improving to 0.31 by 1998. There was a strong change in efficiency scores to the upside from 1996 through to 1998. On average the US bank sample had an average inefficiency score of 0.32, which is similar to the findings of Aly et al (1990) and Berger (1995) who find inefficiency scores of 0.35 and 0.39 respectively.

### **III Stock Performance and DEA scores**

Table 32 details the results of regressing bank efficiency scores on the stock performance of each bank. Based on the results, H9a is rejected as no statistically significant relationship is found. This is in contrast to the findings of Beccalli, Casu, and Girardone (2006), whose results suggest that percentage change in stock prices reflect percentage change in cost efficiency, particularly those derived from DEA. However, other studies have indicated significant results when examining the percentage change in stock prices against the percentage change in efficiency levels. The expectation would be for efficient banks to be more profitable and therefore generate higher shareholder returns. A small amount of studies have examined the relationship between efficiency and share performance, especially on a cross-country sample. Adenso-Diez and Gascon (1997) establish a link between stock performance in Spanish banks and efficiency. However, the main findings suggest that the most influential variable in determining stock performance is bank specific risk. Beccalli, Casu, and Girardone (2006) investigate bank stock performance against the yearly change in efficiency. However, instead of using annual returns, the study looks at

yearly returns by using the sum of daily returns for the period of investigation, due to daily returns having a smaller volatility. The results of Beccalli, Casu, and Girardone (2006) suggest that changes in stock performance reflect changes in bank efficiency. This thesis regressed annual returns against bank efficiency and may be why insignificant results were found for this relationship.

#### **IV Second Stage DEA Results**

In order to investigate the determinants of efficiency this study constructs an econometric model with technical efficiency as the dependent variable. As in previous studies, due to the limited nature of the efficiency measure (i.e. 0 and 1) Tobit analysis is employed. This study examines the influence of the external environment of each country to determine the impact on efficiency. The other variables that are regressed against efficiency are the VaR results and also a dummy variable for when the 1996 Market Risk Amendment was introduced.

Table 33 presents the Tobit regression results for the CRS and CRS\_OBS approaches. Table 34 presents the Tobit regression results for the VRS and VRS\_OBS approaches. The results shown in Tables 33 and 34 are for the total sample of banks across all G-10 countries. The results by country are shown in the Appendices III to XII for reference.

Bos and Kool (2006) stated that this second-stage approach allows for tests of significance of each environmental variable as well as the combined impact of all these variables on efficiency. This study regresses GDP, CPI, unemployment rates, and industrial production on the efficiency scores. Industrial production has a

negative, but weak, statistical relationship with inefficiency. The sample results also show that inflation (CPI) is positively related with inefficiency. Lensink et al, (2007) find that inflation has a negative impact on profit efficiency and the growth of GDP is positively correlated with profit efficiency. The argument being that in countries that are more prosperous, banks have better access to new technology and capital which ultimately have positive influence on efficiency levels. In terms of inflation, stable macroeconomic conditions and financial development contribute to higher efficiency, and a higher degree of market competition (Flamini, McDonald, and Schumacher, 2008). Inflation is an indicator of macroeconomic stability, and is directly related to the interest rate levels and, thus, interest expense and revenue of financial institutions. As a result, macroeconomic instability would, in general, have an adverse impact on banking sector performance. Claessens and Laeven (2004) show that a higher inflation level tends to lower bank efficiency. A bank's ability to manage interest rate risk under inflationary conditions can also affect its cost structure and would be an interesting avenue for future research.

This set of results for the macro-economic variables does suggest efficiency scores are dependent on non-bank specific factors. The results from the Tobit regression support H10a based on the strength of the relationship between efficiency and inflation and to a certain degree, industrial production. Yildirim and Philippatos (2007) note that under favourable economic conditions, such as strong GDP and industrial production, will positively affect the demand for bank services, and improve bank efficiency. In terms of inflation, Kasman and Yildirim (2006) argue that high inflation may affect bank behaviour and induce banks to compete excessively to improve margins, but end

up impacting overall efficiency. The findings of this study support Kasman and Yildirim (2006).

One key finding is the relationship between inefficiency and VaR. Table 34 shows a statistically significant relationship, which is positive. Due to the fact that the VaR measure is inherently negative, this relationship suggests that as risk declines, i.e. VaR trends towards zero, the level of inefficiency (efficiency) increases (declines). It has been argued that the incorporation of risk is very important in studies of banking efficiency and failure to account for risk can have a significant impact on relative efficiency scores (Drake and Simper, 2003). DEA measures of efficiency are based on estimates of the degree to which the bank under analysis could have produced more outputs relative to its input levels or to the degree that the bank could have used less input for its overall output level. In terms of profitability and return a certain level of risk needs to be taken. As risk is increased within the institution, either through trading or diversifying the business, the expectation would be for the level of performance to subsequently increase and hence the expectation of a statistical relationship between a bank's VaR and level of efficiency. Furthermore, Barth, et al (2004) found that restrictions on banking activities tend to reduce banking sector efficiency. Given a bank's ability to produce, the amount of risk it takes on can change the efficiency results significantly. This result supports H11a and indicates that one of the key determinants of efficiency is risk.

The Tobit results indicate that the higher capital stringency from the Market Risk Amendment increases (decreases) bank (in)efficiency based on the negative coefficient, which is statistically significant at the 1% level of confidence, and



supports H12a. This result is consistent with the findings of previous studies on bank performance and efficiency in terms of regulation enhancing private monitoring and subsequently technical efficiency (Levine, 2004).

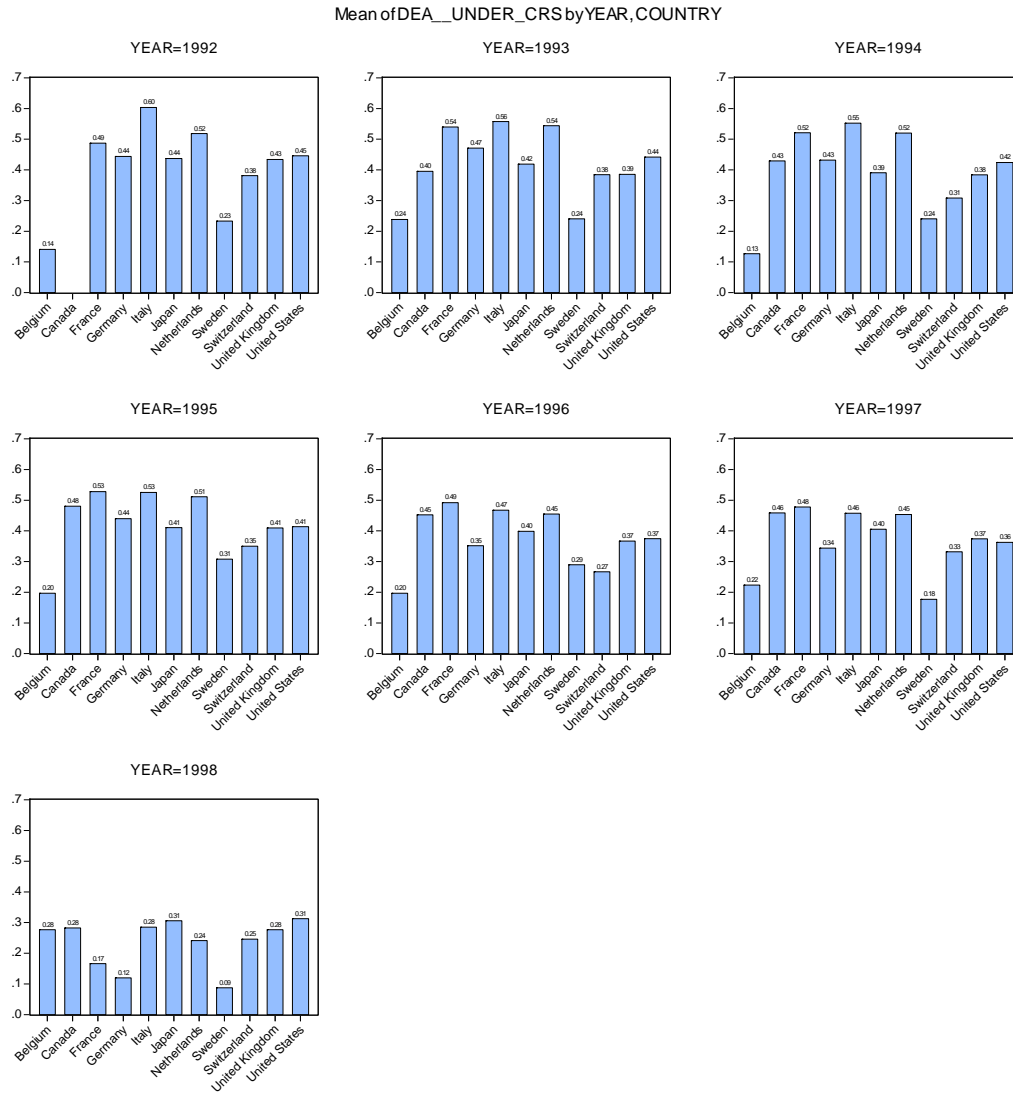
### **V DEA Results Conclusion**

A vast majority of bank efficiency studies focus on individual countries, and mainly the United States. Although in recent years a growing number of studies examine cross-country samples. Many of these studies recognise the importance of considering environmental variables when estimating efficiency. This study employs DEA and Tobit regression to examine the impact of regulations, risk and macro-economic variables on commercial banks' efficiency.

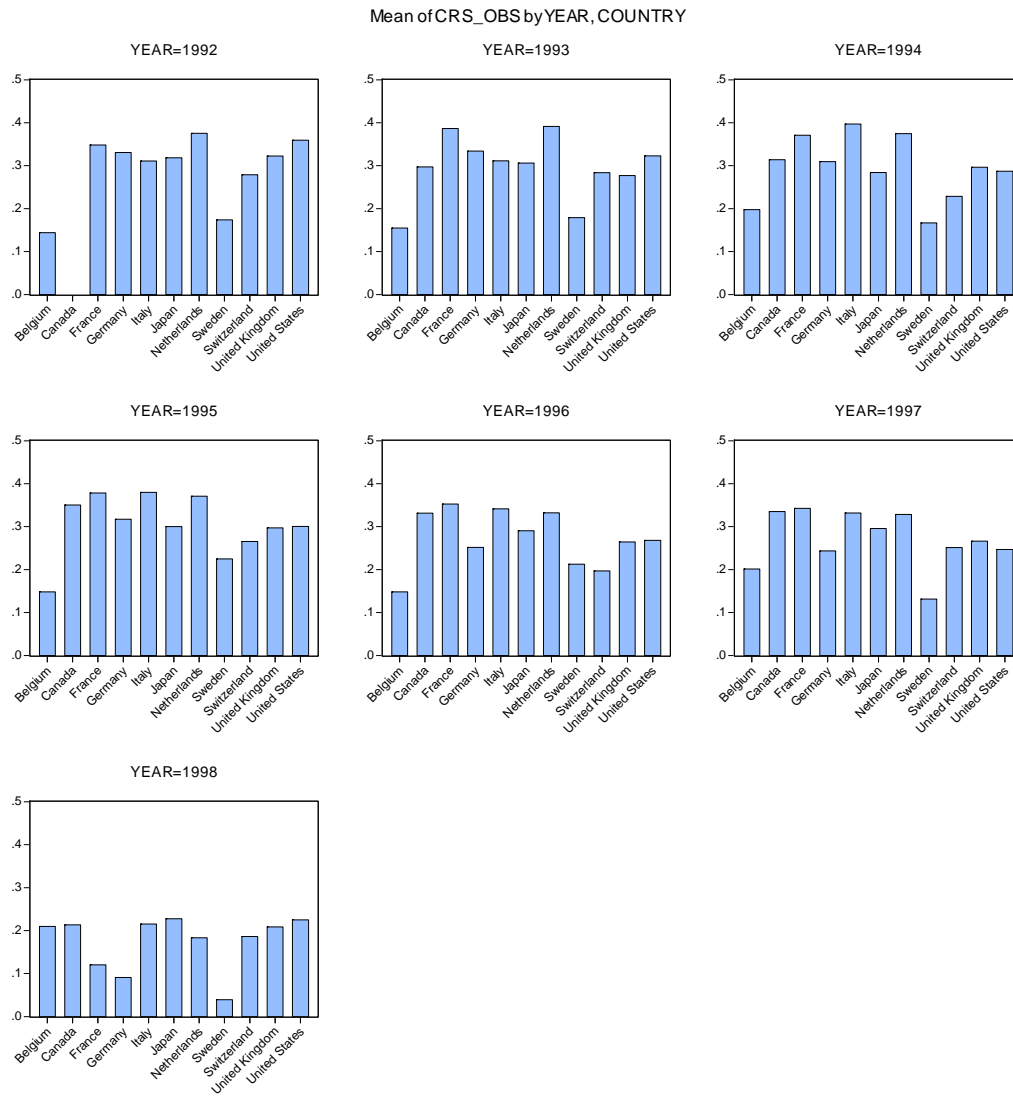
The results of DEA indicate that the average bank in sample could improve its overall technical efficiency by 0.39 under CRS and 0.33 under VRS. The inclusion of an OBSA variable improves the efficiency score significantly.

The results from the Tobit model suggests inflation has a strong negative impact on efficiency, whereas, there is a somewhat positive relationship with industrial production. The results provide evidence in favour of the 1996 Market Risk Amendment and the impact on efficiency. Finally, the findings support the inclusion of a risk variable to explain efficiency levels, and VaR has a positive impact on bank efficiency.

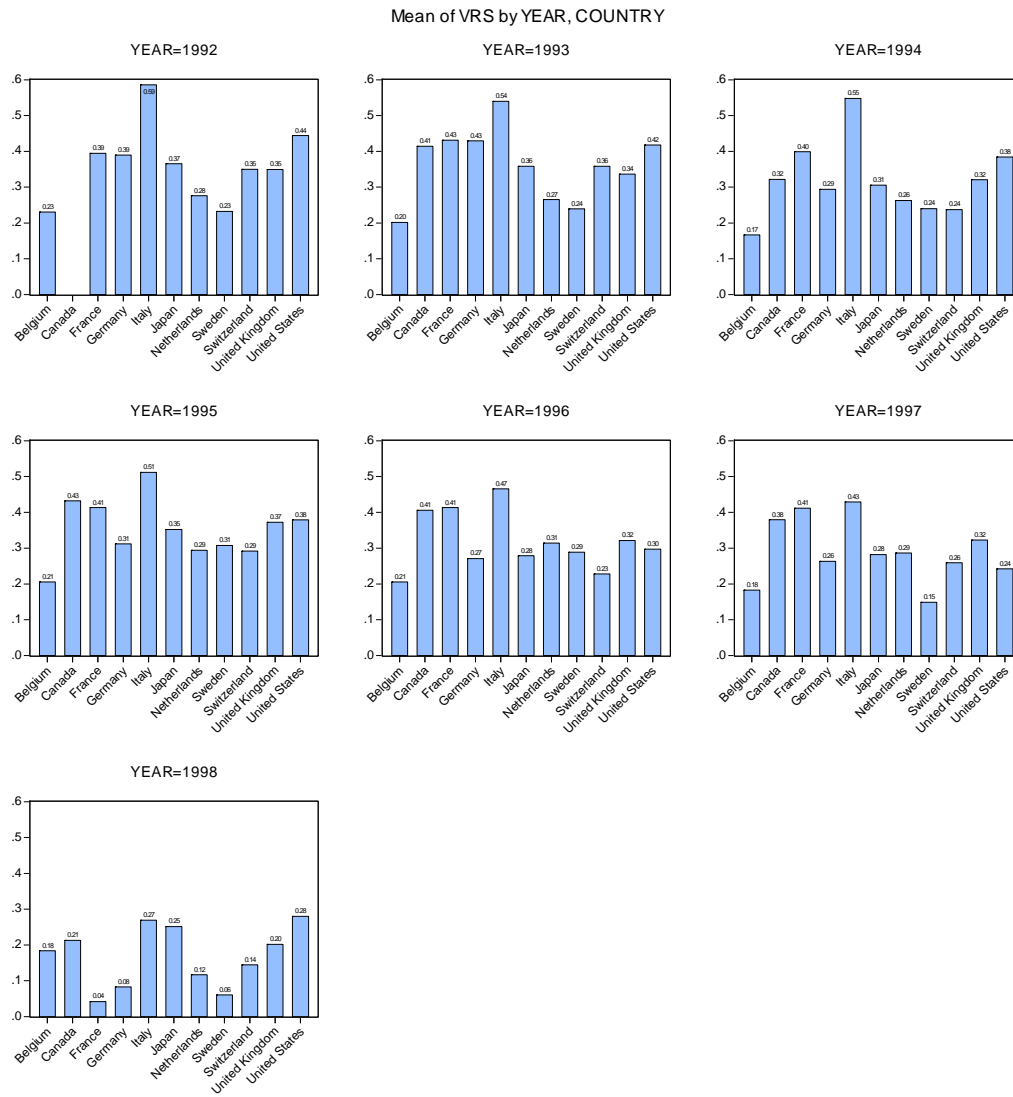
**Figure 20** Average DEA Score by Year by Country (CRS Model excluding OBSA)



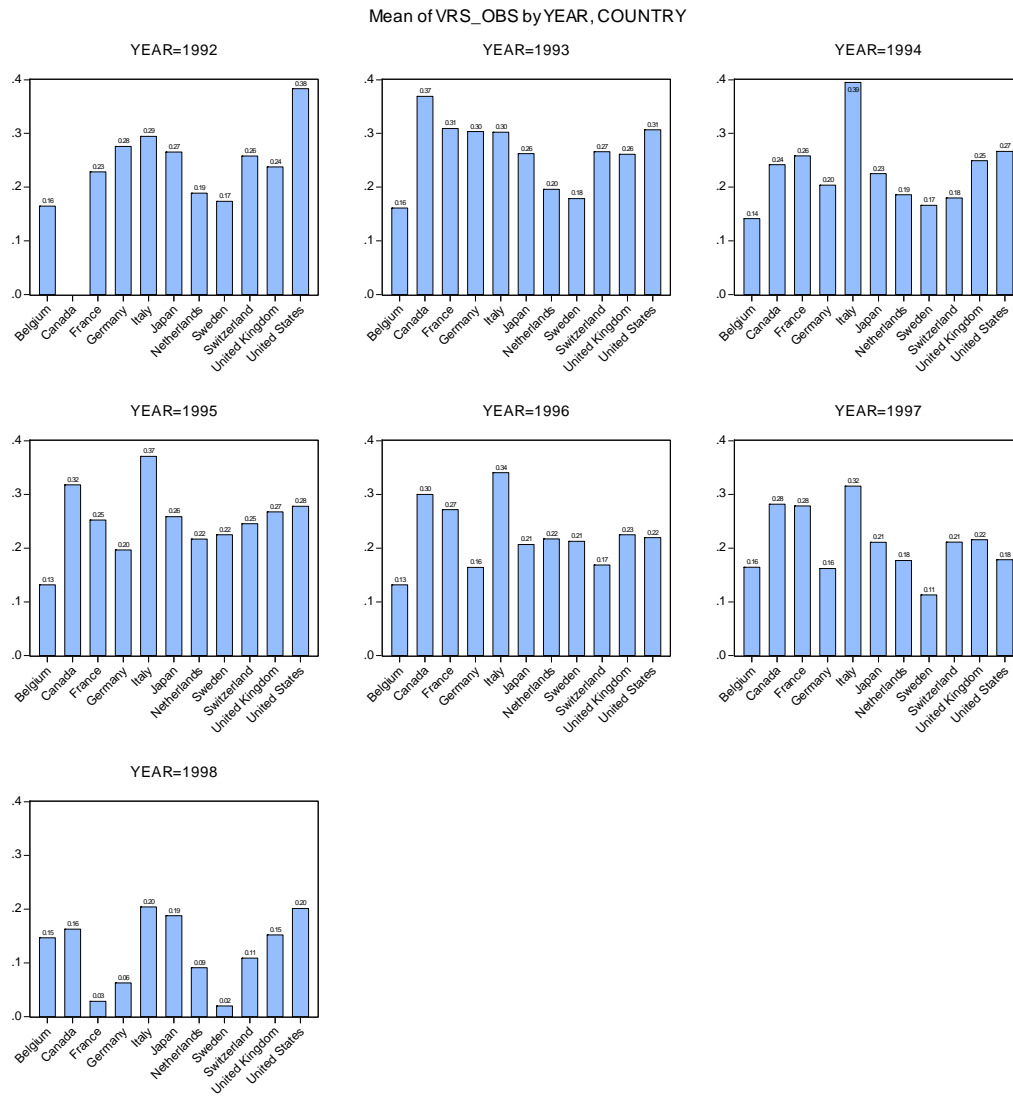
**Figure 21** Average DEA Score by Year by Country (CRS Model including OBSA)



**Figure 22** Average DEA Score by Year by Country (VRS Model excluding OBSA)



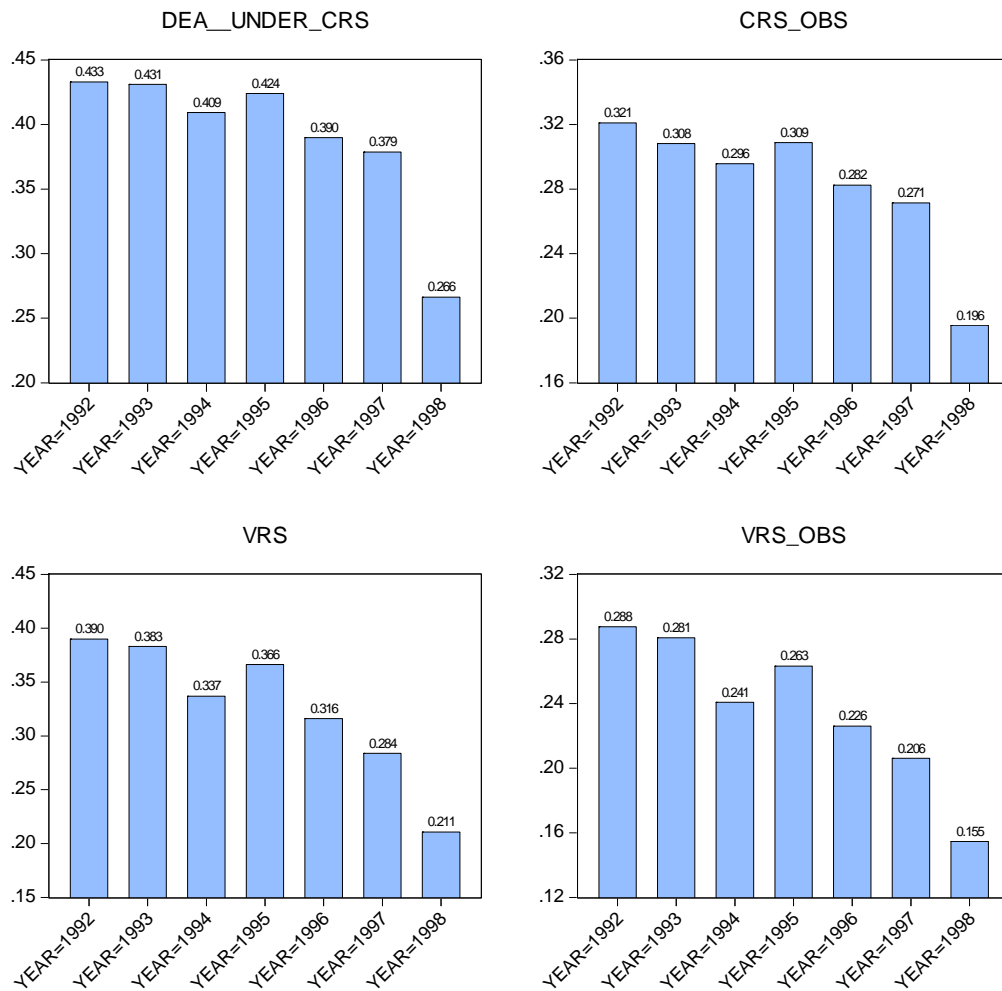
**Figure 23** Average DEA Score by Year by Country (VRS Model including OBSA)



**Figure 24** *Total Sample Results*

	Inefficiency		Inefficiency		Inefficiency					
	<u>DEA</u>	<u>UNDER CRS</u>	<u>CRS</u>	<u>OBS</u>	<u>VRS</u>	<u>VRS_OBS</u>	<u>GDP</u>	<u>CPI</u>	<u>INDP</u>	<u>UNE</u>
Mean	0.39	0.28	0.33	0.24	2.36	1.85	0.68	6.65	-0.004	
Median	0.41	0.30	0.34	0.25	2.53	1.74	0.47	6.10	-0.001	
Maximum	0.83	0.57	0.82	0.56	15.53	6.63	13.02	12.08	0.349	
Minimum	0.00	0.00	0.00	0.00	-2.08	-2.31	-6.87	2.15	-0.339	
Std. Dev.	0.17	0.12	0.19	0.14	1.84	1.45	3.10	2.93	0.066	
Skewness	-0.47	-0.61	-0.07	-0.18	0.98	0.40	-0.08	0.31	-0.653	
Kurtosis	3.34	3.31	2.62	2.35	12.29	4.42	5.37	1.89	7.587	
Jarque-Bera	20.93	33.57	3.50	11.69	1920.62	56.65	120.49	34.56	484.210	
Probability	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.000	
Sum	198.95	144.35	166.31	120.64	1206.01	946.67	346.21	3399.03	-1.836	
Sum Sq. Dev.	14.66	7.47	17.88	9.81	1732.82	1075.42	4900.58	4392.89	2.205	
Observations	511	511	511	511	511	511	511	511	511	

Means by YEAR



**Table 29** Tests for Equality of Means: CRS model with and without OBS activity

Test for Equality of Means Between Series	df	Value	Probability
t-test	1020	11.594	0.00
Satterthwaite-Welch t-test*	922.6155	11.594	0.00
Anova F-test	(1, 1020)	134.422	0.00
Welch F-test*	(1, 922.616)	134.422	0.00
*Test allows for unequal cell variances			
Analysis of Variance			
Source of Variation	df	Sum of Sq.	Mean Sq.
Between	1	2.917	2.917
Within	1020	22.137	0.022
Total	1021	25.054	0.025
Variable	Count	Mean	Std. Dev.
DEA_UNDER_CRIS	511	0.38934	0.169568
CRS_OBS	511	0.282486	0.121044
All	1022	0.335913	0.156648
			Std. Err. of Mean
			0.007501
			0.005355
			0.0049

**Table 30** Tests for Equality of Means: VRS model with and without OBS activity

Test for Equality of Means Between Series	df	Value	Probability
t-test	1020	8.669	0
Satterthwaite-Welch t-test*	940.2346	8.669	0
Anova F-test	(1, 1020)	75.148	0
Welch F-test*	(1, 940.235)	75.148	0
*Test allows for unequal cell variances			
Analysis of Variance			
Source of Variation	df	Sum of Sq.	Mean Sq.
Between	1	2.041	2.041
Within	1020	27.697	0.027
Total	1021	29.737	0.029
Variable	Count	Mean	Std. Dev.
VRS	511	0.325458	0.187251
VRS_OBS	511	0.23609	0.138726
All	1022	0.280774	0.170663
			Std. Err. of Mean
			0.008283
			0.006137
			0.005338

**Table 31** *Stock Performance and Bank Efficiency Regression Results*

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	-0.007065	0.007295	-0.96838	0.333
DEA_UNDER_CRIS	0.008919	0.017182	0.519063	0.604
R-squared	0.000529	Mean dependent var		-0.004
Adjusted R-squared	-0.001435	S.D. dependent var		0.066
S.E. of regression	0.065796	Akaike info criterion		-2.601
Sum squared resid	2.203534	Schwarz criterion		-2.584
Log likelihood	666.4538	Hannan-Quinn criter.		-2.594
F-statistic	0.269427	Durbin-Watson stat		1.116
Prob(F-statistic)	0.603942			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	-0.007144	0.007669	-0.93147	0.35
DEA_UNDER_CRIS	0.00923	0.015545	0.593773	0.55
AR(1)	0.442045	0.039863	11.08918	0.00
R-squared	0.195772	Mean dependent var		0.00
Adjusted R-squared	0.192599	S.D. dependent var		0.07
S.E. of regression	0.059137	Akaike info criterion		-2.81
Sum squared resid	1.773072	Schwarz criterion		-2.79
Log likelihood	720.0741	Hannan-Quinn criter.		-2.80
F-statistic	61.70906	Durbin-Watson stat		2.01
Prob(F-statistic)	0			
Inverted AR Roots	0.44			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	-0.009144	0.007393	-1.23677	0.217
CRS_OBS	0.019652	0.02406	0.816776	0.414
R-squared	0.001309	Mean dependent var		-0.004
Adjusted R-squared	-0.000653	S.D. dependent var		0.066
S.E. of regression	0.065771	Akaike info criterion		-2.601
Sum squared resid	2.201815	Schwarz criterion		-2.585
Log likelihood	666.6533	Hannan-Quinn criter.		-2.595
F-statistic	0.667123	Durbin-Watson stat		1.116
Prob(F-statistic)	0.414438			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	-0.008561	0.007661	-1.11745	0.26
CRS_OBS	0.01774	0.021411	0.828566	0.41
AR(1)	0.441945	0.039869	11.08502	0.00
R-squared	0.196302	Mean dependent var		0.00
Adjusted R-squared	0.193131	S.D. dependent var		0.07
S.E. of regression	0.059118	Akaike info criterion		-2.81
Sum squared resid	1.771904	Schwarz criterion		-2.79
Log likelihood	720.2421	Hannan-Quinn criter.		-2.80
F-statistic	61.91682	Durbin-Watson stat		2.01
Prob(F-statistic)	0			
Inverted AR Roots	0.44			



**Table 32** *Tobit Regression Results. CRS and CRS\_OBS Model Results. Total Sample*

<b>Dependent Variable: DEA_UNDER_CRIS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.394922	0.026532	14.88487	0.000
GDP	-0.000783	0.004315	-0.181475	0.856
CPI	0.011087	0.005145	2.154837	0.031
INDP	-0.004597	0.002567	-1.790873	0.073
UNE	0.002297	0.002636	0.871223	0.384
VAR	0.449658	0.313341	1.435042	0.151
MRA	-0.075961	0.017189	-4.419158	0.000
Error Distribution				
SCALE:C(8)	0.161736	0.005059	31.96874	0.000
Mean dependent var	0.38934	S.D. dependent var		0.170
S.E. of regression	0.163017	Akaike info criterion		-0.774
Sum squared resid	13.36696	Schwarz criterion		-0.708
Log likelihood	205.8579	Hannan-Quinn criter.		-0.748
Avg. log likelihood	0.402853			
Left censored obs	0	Right censored obs		0
Uncensored obs	511	Total obs		511

<b>Dependent Variable: CRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.279244	0.018873	14.79593	0.000
GDP	0.00019	0.003069	0.061797	0.951
CPI	0.010385	0.00366	2.837664	0.005
INDP	-0.003008	0.001826	-1.647525	0.100
UNE	0.001455	0.001875	0.775845	0.438
VAR	0.226302	0.222891	1.015303	0.310
MRA	-0.057428	0.012227	-4.696735	0.000
Error Distribution				
SCALE:C(8)	0.115049	0.003599	31.96874	0.000
Mean dependent var	0.282486	S.D. dependent var		0.121
S.E. of regression	0.11596	Akaike info criterion		-1.456
Sum squared resid	6.763689	Schwarz criterion		-1.389
Log likelihood	379.9091	Hannan-Quinn criter.		-1.430
Avg. log likelihood	0.743462			
Left censored obs	0	Right censored obs		0
Uncensored obs	511	Total obs		511

**Table 33** *Tobit Regression Results. VRS and VRS\_OBS Model Results. Total Sample*

<b>Dependent Variable: VRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.326348	0.028966	11.26657	0.000
GDP	-0.001865	0.004711	-0.395962	0.692
CPI	0.012489	0.005617	2.223458	0.026
INDP	-0.005359	0.002802	-1.912272	0.056
UNE	0.004753	0.002878	1.651316	0.099
VAR	0.740484	0.34209	2.164588	0.030
MRA	-0.0837	0.018766	-4.460191	0.000
Error Distribution				
SCALE:C(8)	0.176575	0.005523	31.96874	0.000
Mean dependent var	0.325458	S.D. dependent var		0.187
S.E. of regression	0.177973	Akaike info criterion		-0.599
Sum squared resid	15.9323	Schwarz criterion		-0.533
Log likelihood	161.0018	Hannan-Quinn criter.		-0.573
Avg. log likelihood	0.315072			
Left censored obs	0	Right censored obs		0
Uncensored obs	511	Total obs		511

<b>Dependent Variable: VRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.239531	0.021511	11.13526	0.000
GDP	0.000377	0.003498	0.10775	0.914
CPI	0.012287	0.004171	2.945613	0.003
INDP	-0.003642	0.002081	-1.749924	0.080
UNE	0.001443	0.002137	0.675065	0.500
VAR	0.540575	0.254046	2.127858	0.033
MRA	-0.05933	0.013936	-4.257221	0.000
Error Distribution				
SCALE:C(8)	0.13113	0.004102	31.96874	0.000
Mean dependent var	0.23609	S.D. dependent var		0.139
S.E. of regression	0.132169	Akaike info criterion		-1.194
Sum squared resid	8.78667	Schwarz criterion		-1.128
Log likelihood	313.0531	Hannan-Quinn criter.		-1.168
Avg. log likelihood	0.612628			
Left censored obs	0	Right censored obs		0
Uncensored obs	511	Total obs		511

## *Chapter 5* **CONCLUSION**

This thesis set out to examine the impact of the 1996 Market Risk Amendment (MRA) on the equity returns of commercial bank shareholders within G-10. The changing nature of bank risk and efficiency levels through the period 1992 to 1998 was also considered. Furthermore, the determinants of bank efficiency were evaluated.

The first objective of this thesis was to evaluate the 4 key announcements made by the Basle Committee that ultimately led to the passage of the MRA. This was achieved via measuring the impact on equity returns using event-study analysis.

The first announcement suggested that banks use a standardized VaR approach to allocate market risk capital. However, this method appeared restrictive and dated when compared with the risk measurement systems already utilized by the majority of large successful banks. The findings for the reaction to the first announcement period show that equity returns in Germany and the US were significantly negatively affected. At this point, US banks had the largest derivative exposure in addition to the most sophisticated risk management systems, therefore, a negative reaction was to be expected because a standardized approach would result in increased capital allocation and lessen their competitive edge in risk measurement. On the other hand, the Japanese bank sample showed a significant positive reaction to the first announcement. A possible reason for this is that the Japanese financial system was in a state of crisis at the time due to a series of bad debts and inflationary pressures. The MRA would likely increase the transparency and safety of these banks, hence their

positive reaction. There were no other notable reactions following the first announcement.

The second announcement allowed banks to use their own internal models approach to calculate market risk. The results of the analysis show that banks responded favourably to this announcement, as would be expected due to the freedom and flexibility such a proposal would provide. Commercial banks in France, Italy, Switzerland, and the United States experienced the most significant positive cumulative abnormal returns around this event.

The third announcement was a joint proposal by Basle and IOSCO that aimed to increase the level of transparency within the financial industry by providing a series of mechanisms for measuring and reporting market risk. This time the overall reaction was mixed with banks in Germany, Japan, Sweden, and the United States showing significant positive returns over the even period. Significant negative returns were noted for the sample of banks in Canada, France, and Italy. The positive trend continued for Japan where regulatory changes that served to increase overall transparency and allocate additional capital were needed and consequently, well received.

The fourth announcement was the final proposal that led to the implementation of the MRA. It allowed banks to use their own internal risk models to calculate market risk, but applied strict rules for calculating market risk, and required a somewhat arbitrary multiplication factor of three, to take into account event risk. Once again the results were conflicting, with significant negative returns for commercial banks in Canada,

Sweden, the United Kingdom, and the United States, whereas the sample of banks in Germany, France, and Japan experienced significant positive abnormal returns over the last event period. Again, there appears to be a common theme, whereby banks within the US and Canada experience significant negative abnormal returns as reaction to potentially more restrictive regulation, whereas Japan consistently reacted in a positive manner to the prospect of market risk regulation.

Based on the findings above, this study differs from existing literature in several ways: First, it considers a sample of large commercial banks in eleven developed countries as opposed to being limited to one specific country. Second, it examines four major announcements leading up to the formation of the 1996 MRA. Third, this thesis examines the financial impact of a key change in bank capital regulation, which enhances our understanding of the potential impact of future regulatory changes.

The second objective of this thesis was to investigate the risk profile of G-10 commercial banks. This objective was achieved by employing a three-factor multi-index model and then applying the factor coefficients to four different VaR methodologies. The analysis covered the period 1992 to 1998 and results highlight the extent to which market risk, interest and foreign exchange rate changes impact bank VaR.

In order to mitigate some of the weaknesses inherent in VaR, this study employed four VaR methodologies to estimate each bank's average weekly VaR. The four approaches were parametric, historical simulation (HS), Monte Carlo (MC), and Extreme Value Theory (EVT). The results indicate that the parametric and HS

approaches consistently underestimate VaR as compared to MC and EVT. This result is consistent with previous literature. The VaR results were displayed in weekly average VaR as a percentage of equity at risk, enabling comparisons to be made across countries. For the entire sample, the average Monte Carlo (MC) VaR through the period 1992 to 1996 was -2.52%. However, 1997 saw a significant increase in risk up to an overall average weekly VaR of -4.31%. The VaR results for 1998 continued to increase and moved up to -4.67%. In terms of ranking the countries by risk level, the sample of Japanese banks ranked highest. The second highest risk rating was Sweden, particularly during the years 1993, 1994 and 1995. The US by far had the lowest risk ranking, and Sweden ranked second lowest. The sample of banks in France and Germany also held relatively low risk. Consistent with the hypothesis that the movement by banks into non-traditional activities would result in increased risk, the results show that risk increased throughout the study period and peaked in the years 1997 and 1998. However, this period also coincided with a time of high financial volatility, which may also have impacted risk levels. In addition, the results showed that the equity values of banks were less dependent on interest rate and foreign exchange rate volatility than at the start of the study period, again supporting the hypothesis that banks have become less dependent on traditional methods for achieving returns.

In sum, the key contribution of this thesis in regard to measuring risk is that the analysis employed four different VaR methodologies to measure risk. This allowed for comparisons to be made across time, country and bank if required. However, the results highlight the fact that comparison of risk cannot be made across institutions unless there is a common approach to measurement of VaR.

Given the more competitive banking environment and volatility within financial markets, there has been an incentive for banks to focus on improving efficiency in addition to rigorously monitoring their risk profile and exposure. This third objective of this thesis was to estimate commercial bank efficiency by applying Data Envelopment Analysis (DEA) to bank-level data for commercial banks in G-10 countries. This study also examines the impact of off-balance-sheet activities (OBS) and estimates efficiency levels with and without this variable.

The analysis was carried out over the period 1992 to 1998. Results indicate that the mean technical inefficiency under the Constant Returns to Scale (CRS) and (VRS) is 39% and 33% respectively: a result that is broadly in line with the main literature on bank efficiency, where the average inefficiency score is 0.30 (Goddard et al., 2007). Inefficiency results are significantly lower when an OBS variable is incorporated, with a CRS\_OBS and VRS\_OBS inefficiency score of 0.28 and 0.24 respectively; with the mean differences for both CRS and VRS models significantly different with the inclusion of the OBS output variable. The results indicate efficiency models that do not incorporate an OBS output variable will result in an underestimation of bank efficiency levels.

Finally, the last objective of the thesis was to explain the variation in calculated efficiency scores by considering explanatory variables such as macro-economic indicators, VaR, and regulatory change through a Tobit regression approach. The overall sample results show that inflation (CPI) is positively related with inefficiency. Industrial production has a negative, but weak, statistical relationship with inefficiency and is consistent with the findings of Kasman and Yildirim (2006). One

key finding is the positive impact of the MRA dummy variable on efficiency. This result is consistent with the findings of previous studies on bank performance and efficiency in terms of regulation enhancing private monitoring and subsequently technical efficiency (Barth et al, 2004, Levine, 2004). This study finds that VaR is negatively correlated with inefficiency, indicating that inefficient banks appear to take on less risk. It is apparent that there are large differences in risk and efficiency within the commercial banks of the US, Japan, Canada and the EU.

This study adds to the efficiency literature by evaluating bank efficiency levels in commercial banks within G-10 while taking into account OBS activity. Furthermore, this thesis attempts to expand the established literature on the determinants of bank efficiency by considering macro-economic variables, each bank's VaR, in addition to incorporating a dummy variable for the 1996 Market Risk Amendment. The Tobit regression results show that inflation, VaR, and bank capital regulation are key determinants of bank efficiency. These results suggest the need to incorporate similar explanatory variables when attempting to evaluate the determinants of efficiency scores.

Understanding the impact of bank capital regulation, the changing risk profile of banks and the determinants of efficiency should assist investors and regulators when monitoring future changes in the banking industry. In terms of direction for future research, it would be interesting to examine the changes in banks' market risk since the inception of the MRA. Furthermore, a future study might consider the VaR of specific banks that have certain levels of capitalisation, large derivative exposure and how this relates to bank efficiency levels.



This findings of this thesis have been significant regarding the relationships between bank capital regulation, risk and bank efficiency. However, it is important to note the limitations of the US bank sample that are likely to have implications for the analysis. Whereby the analysis may suffer from sample-selection bias resulting from the fact that some of the banks are poorly represented, specifically within the US bank sample with many of these banks falling under the ‘commercial bank’ category, but some of which operate as trading or investment banks.

By acknowledging the presence of the problems the aim is to provide a strong framework for analyzing bank efficiency and risk by, among other analysis, determining potential problems as the results are analysed. With these caveats in mind the results of the US bank sample are concerning and may be due to the following and would be worthy of future research. The level of capital held in US banks was relatively high in the early 1990s and as a result places less risk on both the shareholders and the government safety net. Furthermore, (Hansel and Krahn, 2007) find that countries, such as the US, that are considered to be market-based economies, the systematic risk may be significantly smaller and as a result have a material impact on the VaR calculations.

## *APPENDICES*

### **Appendix I Event-Study Interest Rate Coefficients**

#### **Bank Interest-Rate Sensitivity Over the Estimation Period Prior to Each Event**

Interest-rate sensitivities over each estimation period using the methodology described in equation (1) of Chapter 3.

For each announcement, each bank's interest-rate sensitivity is calculated as the coefficient from a two-factor model of returns. The below states the mean for the country specific sample

	1st Event	2nd Event	3rd Event	4th Event
Belgium	-0.024	-0.027	0.052	-0.007
Canada	-0.128	-0.261	-0.448	-0.279
France	-0.052	-0.084	-0.044	-0.082
Germany	-0.399	0.045	-0.029	0.005
Italy	-0.036	-0.124	-0.156	-0.131
Japan	-0.023	0.036	-0.007	-0.002
Netherlands	0.002	-0.219	-0.034	-0.198
Sweden	-0.127	-1.172	-1.224	-1.308
Switzerland	-0.036	-0.047	-0.048	-0.021
United Kingdom	0.021	-0.079	0.006	0.008
United States	0.0288	0.0829	0.0219	0.0527

## Appendix II Three Factor Betas: United States Sample Coefficients

Estimation of Three Factor Capital Asset Pricing Model

$$R_{it} = \alpha_{it} + \beta_{mi} R_{mjt} + \beta_{ri} R_{rjt} + \beta_{xi} R_{xjt} + u_{it}$$

Factor Betas by Bank by Year	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
1992						
Associated Bank	<b>0.243</b>	1.77	<b>0.074</b>	0.53	<b>-0.098</b>	-0.70
Bancorp South	<b>-0.075</b>	-0.53	<b>0.405</b>	3.13**	<b>-0.102</b>	-0.73
Bank of America	<b>0.143</b>	1.02	<b>0.126</b>	0.90	<b>-0.245</b>	-1.79
Bank of New York	<b>0.010</b>	0.07	<b>-0.086</b>	-0.61	<b>-0.111</b>	-0.79
BB&T	<b>-0.052</b>	-0.37	<b>-0.015</b>	-0.11	<b>0.121</b>	0.86
BOK Financial	<b>0.000</b>	0.00	<b>0.000</b>	0.00	<b>0.000</b>	0.00
Charles Schwab	<b>0.109</b>	0.77	<b>-0.031</b>	-0.22	<b>-0.025</b>	-0.17
Colonial Bancorp	<b>-0.062</b>	-0.44	<b>-0.152</b>	-1.08	<b>-0.105</b>	-0.75
Comerica	<b>0.152</b>	1.09	<b>-0.068</b>	-0.48	<b>0.077</b>	0.55
Commerce Bancorp	<b>-0.022</b>	-0.15	<b>0.168</b>	1.21	<b>-0.124</b>	-0.88
Commerce Bankshares	<b>-0.015</b>	-0.11	<b>0.163</b>	1.17	<b>-0.093</b>	-0.66
Compass Bankshares	<b>0.039</b>	0.28	<b>0.068</b>	0.48	<b>-0.025</b>	-0.17
Countrywide	<b>0.197</b>	1.42	<b>0.049</b>	0.35	<b>-0.089</b>	-0.63
Downey Financial	<b>0.032</b>	0.23	<b>0.020</b>	0.14	<b>0.107</b>	0.76
Fifth Third	<b>0.205</b>	1.48	<b>-0.115</b>	-0.82	<b>0.102</b>	0.72
First Horizon	<b>-0.093</b>	-0.66	<b>0.119</b>	0.85	<b>-0.140</b>	-1.00
Fulton Financial	<b>-0.142</b>	-1.02	<b>0.010</b>	0.07	<b>-0.020</b>	-0.14
Huntington Bankshares	<b>-0.150</b>	-1.07	<b>-0.146</b>	-1.05	<b>0.087</b>	0.62
Keycorp Financial	<b>0.044</b>	0.31	<b>0.043</b>	0.31	<b>-0.002</b>	-0.01
Marshall and Isley	<b>0.051</b>	0.36	<b>-0.053</b>	-0.38	<b>0.115</b>	0.82
Merrill Lynch	<b>-0.092</b>	-0.65	<b>-0.120</b>	-0.85	<b>-0.119</b>	-0.85
National City	<b>0.111</b>	0.79	<b>0.034</b>	0.24	<b>-0.059</b>	-0.42
Northern Trust	<b>0.069</b>	0.49	<b>0.042</b>	0.30	<b>0.016</b>	0.12
PnC FinServices	<b>-0.110</b>	-0.78	<b>0.058</b>	0.41	<b>0.132</b>	0.94
Popular Inc	<b>0.071</b>	0.50	<b>0.181</b>	1.30	<b>-0.099</b>	-0.71
Regions Financial	<b>0.071</b>	0.50	<b>-0.196</b>	-1.41	<b>-0.110</b>	-0.78
Sovereign Bancorp	<b>0.223</b>	1.62	<b>0.100</b>	0.71	<b>-0.315</b>	-2.35**
State Street	<b>0.028</b>	0.20	<b>0.036</b>	0.25	<b>-0.064</b>	-0.46
Suntrust Bank	<b>0.185</b>	1.33	<b>-0.060</b>	-0.42	<b>0.209</b>	1.51
Synovus Bank	<b>-0.185</b>	-1.33	<b>-0.048</b>	-0.34	<b>-0.168</b>	-1.20
TCF Financial	<b>0.027</b>	0.19	<b>-0.136</b>	-0.97	<b>0.144</b>	1.03
US Bancorp	<b>0.249</b>	1.81	<b>-0.077</b>	-0.55	<b>0.016</b>	0.11
Wachovia	<b>0.193</b>	1.39	<b>0.174</b>	1.25	<b>-0.107</b>	-0.76
Washington Mutual	<b>-0.082</b>	-0.58	<b>-0.040</b>	-0.28	<b>0.003</b>	0.02
Wells Fargo	<b>0.206</b>	1.49	<b>0.152</b>	1.09	<b>-0.248</b>	-1.81
Zion Corp	<b>0.139</b>	0.99	<b>0.084</b>	0.60	<b>0.046</b>	0.33

3 Factor Betas: United States Bank Sample (cont.)

1993	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
Associated Bank	<b>-0.196</b>	-1.42	<b>0.070</b>	0.49	<b>-0.247</b>	-1.81
Bancorp South	<b>0.043</b>	0.30	<b>0.018</b>	0.13	<b>-0.070</b>	-0.50
Bank of America	<b>0.180</b>	1.29	<b>-0.052</b>	-0.37	<b>-0.180</b>	-1.29
Bank of New York	<b>-0.078</b>	-0.55	<b>-0.028</b>	-0.20	<b>0.054</b>	0.38
BB&T	<b>-0.047</b>	-0.33	<b>0.114</b>	0.81	<b>-0.219</b>	-1.59
BOK Financial	<b>0.000</b>	0.00	<b>0.000</b>	0.00	<b>0.000</b>	0.00
Charles Schwab	<b>0.140</b>	1.00	<b>-0.174</b>	-1.25	<b>-0.099</b>	-0.70
Colonial Bancorp	<b>-0.084</b>	-0.60	<b>-0.012</b>	-0.08	<b>-0.226</b>	-1.64
Comerica	<b>0.028</b>	0.20	<b>0.036</b>	0.25	<b>-0.153</b>	-1.10
Commerce Bancorp	<b>-0.061</b>	-0.43	<b>-0.229</b>	-1.66	<b>-0.046</b>	-0.33
Commerce Bankshares	<b>0.261</b>	1.91	<b>0.031</b>	0.22	<b>-0.114</b>	-0.81
Compass Bankshares	<b>-0.081</b>	-0.57	<b>0.000</b>	0.00	<b>0.001</b>	0.01
Countrywide	<b>0.305</b>	2.26**	<b>-0.247</b>	-1.80	<b>0.054</b>	0.38
Downey Financial	<b>-0.007</b>	-0.05	<b>-0.046</b>	-0.32	<b>-0.012</b>	-0.08
Fifth Third	<b>-0.218</b>	-1.58	<b>0.160</b>	1.15	<b>-0.300</b>	-2.22**
First Horizon	<b>-0.037</b>	-0.26	<b>-0.010</b>	-0.07	<b>0.054</b>	0.38
Fulton Financial	<b>0.184</b>	1.32	<b>-0.132</b>	-0.94	<b>0.025</b>	0.18
Huntington Bankshares	<b>-0.111</b>	-0.79	<b>-0.034</b>	-0.24	<b>0.087</b>	0.62
Keycorp Financial	<b>-0.225</b>	-1.64	<b>0.010</b>	0.07	<b>-0.033</b>	-0.23
Marshall and Isley	<b>0.082</b>	0.58	<b>-0.191</b>	-1.38	<b>-0.104</b>	-0.74
Merrill Lynch	<b>-0.106</b>	-0.75	<b>-0.136</b>	-0.97	<b>0.050</b>	0.36
National City	<b>0.009</b>	0.06	<b>0.144</b>	1.03	<b>0.010</b>	0.07
Northern Trust	<b>0.126</b>	0.90	<b>0.028</b>	0.20	<b>-0.263</b>	-1.93
PnC FinServices	<b>-0.085</b>	-0.61	<b>0.072</b>	0.51	<b>-0.158</b>	-1.13
Popular Inc	<b>-0.065</b>	-0.46	<b>0.058</b>	0.41	<b>-0.096</b>	-0.68
Regions Financial	<b>0.180</b>	1.29	<b>0.209</b>	1.51	<b>-0.194</b>	-1.40
Sovereign Bancorp	<b>0.054</b>	0.38	<b>-0.110</b>	-0.78	<b>-0.047</b>	-0.34
State Street	<b>0.042</b>	0.30	<b>0.125</b>	0.89	<b>-0.156</b>	-1.11
Suntrust Bank	<b>0.111</b>	0.79	<b>0.010</b>	0.07	<b>-0.074</b>	-0.53
Synovus Bank	<b>-0.120</b>	-0.86	<b>-0.159</b>	-1.14	<b>0.042</b>	0.30
TCF Financial	<b>0.060</b>	0.42	<b>-0.034</b>	-0.24	<b>0.059</b>	0.42
US Bancorp	<b>0.143</b>	1.03	<b>0.004</b>	0.03	<b>-0.200</b>	-1.44
Wachovia	<b>0.297</b>	2.20**	<b>-0.034</b>	-0.24	<b>-0.379</b>	-2.90**
Washington Mutual	<b>0.069</b>	0.49	<b>0.061</b>	0.43	<b>-0.023</b>	-0.16
Wells Fargo	<b>-0.150</b>	-1.08	<b>-0.170</b>	-1.22	<b>-0.234</b>	-1.71
Zion Corp	<b>0.227</b>	1.65	<b>-0.161</b>	-1.16	<b>-0.070</b>	-0.50

3 Factor Betas: United States Bank Sample (cont.)

1994	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
Associated Bank	<b>0.119</b>	0.85	<b>0.100</b>	0.71	<b>0.063</b>	0.45
Bancorp South	<b>-0.134</b>	-0.95	<b>-0.039</b>	-0.28	<b>-0.046</b>	-0.33
Bank of America	<b>-0.158</b>	-1.13	<b>0.217</b>	1.57	<b>-0.034</b>	-0.24
Bank of New York	<b>-0.021</b>	-0.15	<b>-0.172</b>	-1.23	<b>0.011</b>	0.08
BB&T	<b>0.087</b>	0.62	<b>0.073</b>	0.52	<b>-0.181</b>	-1.30
BOK Financial	<b>-0.092</b>	-0.65	<b>0.110</b>	0.78	<b>0.028</b>	0.20
Charles Schwab	<b>-0.283</b>	-2.09**	<b>0.286</b>	2.11**	<b>-0.103</b>	-0.73
Colonial Bancorp	<b>-0.120</b>	-0.86	<b>0.127</b>	0.90	<b>-0.008</b>	-0.06
Comerica	<b>0.218</b>	1.58	<b>0.071</b>	0.50	<b>0.001</b>	0.01
Commerce Bancorp	<b>0.198</b>	1.43	<b>-0.175</b>	-1.26	<b>-0.063</b>	-0.45
Commerce Bankshares	<b>-0.176</b>	-1.26	<b>0.062</b>	0.44	<b>0.123</b>	0.88
Compass Bankshares	<b>-0.041</b>	-0.29	<b>-0.106</b>	-0.76	<b>-0.054</b>	-0.38
Countrywide	<b>-0.246</b>	-1.79	<b>0.003</b>	0.02	<b>-0.154</b>	-1.10
Downey Financial	<b>0.302</b>	2.24**	<b>-0.123</b>	-0.88	<b>-0.242</b>	-1.76
Fifth Third	<b>0.047</b>	0.33	<b>-0.093</b>	-0.66	<b>0.135</b>	0.96
First Horizon	<b>0.331</b>	2.48**	<b>-0.074</b>	-0.52	<b>0.194</b>	1.40
Fulton Financial	<b>-0.160</b>	-1.15	<b>0.147</b>	1.05	<b>-0.240</b>	-1.75
Huntington Bankshares	<b>0.183</b>	1.31	<b>-0.088</b>	-0.62	<b>-0.277</b>	-2.04**
Keycorp Financial	<b>0.070</b>	0.50	<b>0.082</b>	0.58	<b>-0.009</b>	-0.06
Marshall and Isley	<b>-0.125</b>	-0.89	<b>0.107</b>	0.76	<b>-0.094</b>	-0.67
Merrill Lynch	<b>0.227</b>	1.65	<b>-0.086</b>	-0.61	<b>-0.144</b>	-1.03
National City	<b>-0.307</b>	-2.28**	<b>0.235</b>	1.71	<b>-0.208</b>	-1.51
Northern Trust	<b>0.204</b>	1.47	<b>-0.080</b>	-0.57	<b>-0.124</b>	-0.89
PnC FinServices	<b>0.043</b>	0.30	<b>0.040</b>	0.28	<b>-0.159</b>	-1.14
Popular Inc	<b>-0.257</b>	-1.88	<b>0.111</b>	0.79	<b>0.002</b>	0.01
Regions Financial	<b>-0.153</b>	-1.09	<b>0.104</b>	0.74	<b>-0.113</b>	-0.80
Sovereign Bancorp	<b>-0.258</b>	-1.89	<b>0.217</b>	1.57	<b>-0.147</b>	-1.05
State Street	<b>0.021</b>	0.15	<b>-0.030</b>	-0.21	<b>-0.038</b>	-0.27
Suntrust Bank	<b>0.061</b>	0.43	<b>-0.023</b>	-0.16	<b>0.173</b>	1.24
Synovus Bank	<b>-0.048</b>	-0.34	<b>0.101</b>	0.72	<b>0.163</b>	1.17
TCF Financial	<b>0.025</b>	0.18	<b>0.054</b>	0.38	<b>0.133</b>	0.95
US Bancorp	<b>-0.240</b>	-1.75	<b>0.200</b>	1.45	<b>-0.236</b>	-1.72
Wachovia	<b>-0.173</b>	-1.24	<b>0.225</b>	1.63	<b>-0.191</b>	-1.37
Washington Mutual	<b>0.056</b>	0.39	<b>-0.065</b>	-0.46	<b>-0.213</b>	-1.54
Wells Fargo	<b>-0.153</b>	-1.10	<b>0.334</b>	2.51**	<b>-0.126</b>	-0.90
Zion Corp	<b>-0.265</b>	-1.95	<b>0.079</b>	0.56	<b>-0.157</b>	-1.13

### 3 Factor Betas: United States Bank Sample (cont.)

1995	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
Associated Bank	<b>0.212</b>	1.53	<b>0.015</b>	0.11	<b>-0.042</b>	-0.29
Bancorp South	<b>0.109</b>	0.77	<b>-0.214</b>	-1.55	<b>-0.278</b>	-2.05**
Bank of America	<b>0.178</b>	1.28	<b>-0.090</b>	-0.64	<b>-0.117</b>	-0.83
Bank of New York	<b>0.160</b>	1.15	<b>0.005</b>	0.04	<b>-0.160</b>	-1.14
BB&T	<b>0.127</b>	0.91	<b>-0.048</b>	-0.34	<b>-0.186</b>	-1.34
BOK Financial	<b>0.043</b>	0.30	<b>0.026</b>	0.18	<b>0.045</b>	0.32
Charles Schwab	<b>-0.242</b>	-1.77	<b>0.076</b>	0.54	<b>0.115</b>	0.82
Colonial Bancorp	<b>0.089</b>	0.63	<b>-0.336</b>	-2.52**	<b>-0.269</b>	-1.98
Comerica	<b>0.032</b>	0.22	<b>-0.115</b>	-0.82	<b>-0.061</b>	-0.43
Commerce Bancorp	<b>-0.184</b>	-1.33	<b>0.232</b>	1.68	<b>-0.219</b>	-1.59
Commerce Bankshares	<b>0.009</b>	0.06	<b>-0.090</b>	-0.64	<b>-0.082</b>	-0.58
Compass Bankshares	<b>-0.096</b>	-0.68	<b>0.071</b>	0.50	<b>-0.124</b>	-0.89
Countrywide	<b>0.040</b>	0.29	<b>-0.204</b>	-1.47	<b>0.007</b>	0.05
Downey Financial	<b>0.096</b>	0.68	<b>-0.192</b>	-1.38	<b>-0.009</b>	-0.06
Fifth Third	<b>-0.042</b>	-0.30	<b>-0.020</b>	-0.14	<b>0.121</b>	0.86
First Horizon	<b>0.126</b>	0.90	<b>0.013</b>	0.09	<b>-0.042</b>	-0.30
Fulton Financial	<b>-0.156</b>	-1.12	<b>0.220</b>	1.60	<b>-0.131</b>	-0.93
Huntington Bankshares	<b>-0.164</b>	-1.17	<b>-0.005</b>	-0.04	<b>-0.090</b>	-0.64
Keycorp Financial	<b>-0.115</b>	-0.82	<b>0.168</b>	1.21	<b>-0.073</b>	-0.52
Marshall and Isley	<b>0.036</b>	0.26	<b>0.163</b>	1.17	<b>-0.107</b>	-0.76
Merrill Lynch	<b>0.256</b>	1.88	<b>-0.061</b>	-0.43	<b>-0.240</b>	-1.75
National City	<b>0.104</b>	0.74	<b>-0.098</b>	-0.69	<b>0.130</b>	0.93
Northern Trust	<b>-0.173</b>	-1.24	<b>-0.004</b>	-0.03	<b>0.062</b>	0.44
PnC FinServices	<b>0.030</b>	0.21	<b>0.054</b>	0.38	<b>-0.195</b>	-1.41
Popular Inc	<b>-0.136</b>	-0.97	<b>0.184</b>	1.32	<b>-0.199</b>	-1.43
Regions Financial	<b>0.103</b>	0.74	<b>-0.028</b>	-0.20	<b>-0.134</b>	-0.96
Sovereign Bancorp	<b>0.155</b>	1.11	<b>-0.030</b>	-0.21	<b>-0.245</b>	-1.79
State Street	<b>0.012</b>	0.08	<b>0.090</b>	0.64	<b>-0.163</b>	-1.16
Suntrust Bank	<b>-0.116</b>	-0.82	<b>0.062</b>	0.44	<b>-0.064</b>	-0.46
Synovus Bank	<b>0.147</b>	1.05	<b>-0.113</b>	-0.80	<b>-0.172</b>	-1.23
TCF Financial	<b>0.113</b>	0.80	<b>0.117</b>	0.83	<b>-0.071</b>	-0.50
US Bancorp	<b>-0.041</b>	-0.29	<b>0.158</b>	1.13	<b>-0.130</b>	-0.93
Wachovia	<b>-0.132</b>	-0.94	<b>0.171</b>	1.23	<b>0.002</b>	0.01
Washington Mutual	<b>0.120</b>	0.85	<b>-0.125</b>	-0.89	<b>-0.025</b>	-0.18
Wells Fargo	<b>0.030</b>	0.21	<b>0.062</b>	0.44	<b>-0.085</b>	-0.60
Zion Corp	<b>-0.001</b>	-0.01	<b>0.088</b>	0.63	<b>0.135</b>	0.96

3 Factor Betas: United States Bank Sample (cont.)

1996	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
Associated Bank	<b>0.220</b>	1.59	<b>-0.151</b>	-1.08	<b>-0.301</b>	-2.23**
Bancorp South	<b>-0.020</b>	-0.14	<b>-0.074</b>	-0.53	<b>-0.162</b>	-1.16
Bank of America	<b>0.149</b>	1.06	<b>-0.128</b>	-0.91	<b>-0.170</b>	-1.22
Bank of New York	<b>0.014</b>	0.10	<b>0.022</b>	0.15	<b>0.086</b>	0.61
BB&T	<b>0.119</b>	0.85	<b>0.056</b>	0.40	<b>0.061</b>	0.43
BOK Financial	<b>0.279</b>	2.05**	<b>-0.053</b>	-0.38	<b>0.020</b>	0.14
Charles Schwab	<b>0.106</b>	0.75	<b>-0.177</b>	-1.27	<b>0.001</b>	0.00
Colonial Bancorp	<b>0.161</b>	1.16	<b>-0.138</b>	-0.98	<b>0.420</b>	3.27**
Comerica	<b>0.092</b>	0.65	<b>0.027</b>	0.19	<b>0.032</b>	0.22
Commerce Bancorp	<b>0.022</b>	0.16	<b>0.049</b>	0.34	<b>-0.106</b>	-0.75
Commerce Bankshares	<b>0.005</b>	0.04	<b>-0.161</b>	-1.15	<b>0.221</b>	1.60
Compass Bankshares	<b>0.083</b>	0.59	<b>0.078</b>	0.55	<b>-0.060</b>	-0.42
Countrywide	<b>-0.173</b>	-1.25	<b>0.008</b>	0.06	<b>-0.004</b>	-0.03
Downey Financial	<b>0.035</b>	0.25	<b>-0.034</b>	-0.24	<b>-0.149</b>	-1.07
Fifth Third	<b>0.068</b>	0.48	<b>0.062</b>	0.44	<b>0.049</b>	0.35
First Horizon	<b>-0.143</b>	-1.02	<b>0.143</b>	1.02	<b>0.029</b>	0.21
Fulton Financial	<b>0.308</b>	2.29**	<b>-0.281</b>	-2.07**	<b>0.252</b>	1.84
Huntington Bankshares	<b>0.078</b>	0.55	<b>0.015</b>	0.11	<b>-0.305</b>	-2.27**
Keycorp Financial	<b>-0.039</b>	-0.27	<b>0.168</b>	1.20	<b>-0.157</b>	-1.13
Marshall and Isley	<b>0.062</b>	0.44	<b>-0.064</b>	-0.45	<b>0.113</b>	0.80
Merrill Lynch	<b>-0.044</b>	-0.31	<b>0.189</b>	1.36	<b>-0.093</b>	-0.66
National City	<b>-0.077</b>	-0.54	<b>-0.180</b>	-1.30	<b>0.000</b>	0.00
Northern Trust	<b>-0.116</b>	-0.83	<b>0.206</b>	1.49	<b>0.063</b>	0.45
PnC FinServices	<b>-0.018</b>	-0.13	<b>0.181</b>	1.30	<b>-0.056</b>	-0.40
Popular Inc	<b>-0.108</b>	-0.77	<b>-0.004</b>	-0.03	<b>-0.015</b>	-0.11
Regions Financial	<b>0.059</b>	0.42	<b>-0.163</b>	-1.17	<b>0.084</b>	0.60
Sovereign Bancorp	<b>0.001</b>	0.01	<b>-0.173</b>	-1.24	<b>-0.005</b>	-0.04
State Street	<b>-0.128</b>	-0.92	<b>0.106</b>	0.75	<b>-0.066</b>	-0.47
Suntrust Bank	<b>-0.088</b>	-0.62	<b>0.175</b>	1.26	<b>-0.089</b>	-0.63
Synovus Bank	<b>-0.256</b>	-1.87	<b>0.043</b>	0.31	<b>-0.238</b>	-1.73
TCF Financial	<b>0.063</b>	0.45	<b>0.105</b>	0.75	<b>-0.014</b>	-0.10
US Bancorp	<b>0.005</b>	0.04	<b>-0.068</b>	-0.48	<b>-0.043</b>	-0.30
Wachovia	<b>0.101</b>	0.72	<b>-0.194</b>	-1.40	<b>-0.013</b>	-0.09
Washington Mutual	<b>0.235</b>	1.71	<b>-0.072</b>	-0.51	<b>-0.063</b>	-0.45
Wells Fargo	<b>0.058</b>	0.41	<b>-0.331</b>	-2.48**	<b>-0.136</b>	-0.97
Zion Corp	<b>0.020</b>	0.14	<b>0.063</b>	0.45	<b>0.090</b>	0.64

### 3 Factor Betas: United States Bank Sample (cont.)

1997	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
Associated Bank	<b>0.063</b>	0.45	<b>-0.143</b>	-1.02	<b>0.048</b>	0.34
Bancorp South	<b>-0.095</b>	-0.68	<b>-0.146</b>	-1.04	<b>0.059</b>	0.42
Bank of America	<b>-0.099</b>	-0.70	<b>0.010</b>	0.07	<b>0.053</b>	0.38
Bank of New York	<b>-0.100</b>	-0.71	<b>-0.284</b>	-2.10**	<b>0.129</b>	0.92
BB&T	<b>0.059</b>	0.42	<b>-0.387</b>	-2.97**	<b>0.030</b>	0.21
BOK Financial	<b>0.169</b>	1.21	<b>-0.004</b>	-0.03	<b>-0.008</b>	-0.06
Charles Schwab	<b>0.010</b>	0.07	<b>0.050</b>	0.35	<b>-0.190</b>	-1.37
Colonial Bancorp	<b>-0.013</b>	-0.09	<b>-0.262</b>	-1.92	<b>0.173</b>	1.24
Comerica	<b>-0.167</b>	-1.20	<b>-0.190</b>	-1.37	<b>0.154</b>	1.10
Commerce Bancorp	<b>-0.204</b>	-1.47	<b>-0.181</b>	-1.30	<b>0.129</b>	0.92
Commerce Bankshares	<b>-0.191</b>	-1.38	<b>-0.084</b>	-0.60	<b>-0.103</b>	-0.73
Compass Bankshares	<b>-0.163</b>	-1.17	<b>-0.111</b>	-0.79	<b>0.079</b>	0.56
Countrywide	<b>-0.140</b>	-1.00	<b>0.115</b>	0.82	<b>0.176</b>	1.27
Downey Financial	<b>-0.261</b>	-1.91	<b>-0.159</b>	-1.14	<b>0.025</b>	0.17
Fifth Third	<b>-0.229</b>	-1.66	<b>-0.003</b>	-0.02	<b>0.051</b>	0.36
First Horizon	<b>-0.082</b>	-0.58	<b>-0.147</b>	-1.05	<b>0.036</b>	0.26
Fulton Financial	<b>-0.179</b>	-1.29	<b>-0.017</b>	-0.12	<b>0.093</b>	0.66
Huntington Bankshares	<b>-0.016</b>	-0.11	<b>-0.286</b>	-2.11**	<b>0.194</b>	1.40
Keycorp Financial	<b>0.137</b>	0.98	<b>0.083</b>	0.59	<b>0.168</b>	1.20
Marshall and Isley	<b>0.104</b>	0.74	<b>-0.070</b>	-0.50	<b>0.002</b>	0.02
Merrill Lynch	<b>0.202</b>	1.46	<b>-0.352</b>	-2.66**	<b>0.154</b>	1.10
National City	<b>-0.010</b>	-0.07	<b>-0.073</b>	-0.52	<b>0.069</b>	0.49
Northern Trust	<b>0.121</b>	0.86	<b>-0.290</b>	-2.14**	<b>0.174</b>	1.25
PnC FinServices	<b>0.045</b>	0.32	<b>-0.427</b>	-3.34**	<b>0.055</b>	0.39
Popular Inc	<b>-0.062</b>	-0.44	<b>0.081</b>	0.58	<b>0.109</b>	0.77
Regions Financial	<b>0.056</b>	0.40	<b>-0.054</b>	-0.38	<b>-0.119</b>	-0.85
Sovereign Bancorp	<b>-0.090</b>	-0.64	<b>-0.096</b>	-0.68	<b>-0.103</b>	-0.73
State Street	<b>0.188</b>	1.35	<b>-0.328</b>	-2.45**	<b>0.163</b>	1.17
Suntrust Bank	<b>0.046</b>	0.33	<b>-0.333</b>	-2.50**	<b>0.169</b>	1.21
Synovus Bank	<b>0.080</b>	0.57	<b>-0.187</b>	-1.34	<b>0.163</b>	1.17
TCF Financial	<b>-0.065</b>	-0.46	<b>0.132</b>	0.94	<b>0.099</b>	0.70
US Bancorp	<b>-0.061</b>	-0.43	<b>-0.103</b>	-0.73	<b>0.096</b>	0.68
Wachovia	<b>-0.031</b>	-0.22	<b>-0.040</b>	-0.28	<b>0.026</b>	0.19
Washington Mutual	<b>-0.207</b>	-1.50	<b>-0.058</b>	-0.41	<b>0.152</b>	1.08
Wells Fargo	<b>-0.014</b>	-0.10	<b>0.112</b>	0.80	<b>0.024</b>	0.17
Zion Corp	<b>0.177</b>	1.27	<b>-0.343</b>	-2.58**	<b>0.171</b>	1.23



### 3 Factor Betas: United States Bank Sample (cont.)

1998	Market Beta		Interest Rate Beta		Foreign Exchange Beta	
Associated Bank	<b>-0.041</b>	-0.24	<b>0.125</b>	0.75	<b>-0.169</b>	-1.02
Bancorp South	<b>-0.073</b>	-0.43	<b>0.063</b>	0.37	<b>0.318</b>	1.99
Bank of America	<b>0.311</b>	1.93	<b>0.149</b>	0.89	<b>-0.126</b>	-0.75
Bank of New York	<b>0.039</b>	0.23	<b>-0.001</b>	0.00	<b>0.093</b>	0.55
BB&T	<b>-0.094</b>	-0.56	<b>0.149</b>	0.89	<b>0.178</b>	1.07
BOK Financial	<b>-0.065</b>	-0.39	<b>0.109</b>	0.65	<b>-0.082</b>	-0.49
Charles Schwab	<b>0.144</b>	0.86	<b>0.203</b>	1.22	<b>0.042</b>	0.25
Colonial Bancorp	<b>0.034</b>	0.20	<b>-0.038</b>	-0.22	<b>-0.020</b>	-0.12
Comerica	<b>0.030</b>	0.17	<b>0.246</b>	1.50	<b>0.102</b>	0.61
Commerce Bancorp	<b>0.109</b>	0.65	<b>-0.258</b>	-1.58	<b>0.096</b>	0.57
Commerce Bankshares	<b>-0.052</b>	-0.31	<b>0.228</b>	1.38	<b>-0.080</b>	-0.48
Compass Bankshares	<b>-0.060</b>	-0.36	<b>0.099</b>	0.59	<b>0.159</b>	0.95
Countrywide	<b>0.311</b>	1.93	<b>0.106</b>	0.63	<b>-0.083</b>	-0.49
Downey Financial	<b>-0.054</b>	-0.32	<b>0.030</b>	0.17	<b>0.314</b>	1.95
Fifth Third	<b>-0.007</b>	-0.04	<b>-0.242</b>	-1.48	<b>0.218</b>	1.32
First Horizon	<b>0.074</b>	0.44	<b>0.015</b>	0.09	<b>0.109</b>	0.65
Fulton Financial	<b>-0.021</b>	-0.12	<b>-0.097</b>	-0.58	<b>0.120</b>	0.72
Huntington Bankshares	<b>0.018</b>	0.11	<b>-0.005</b>	-0.03	<b>0.246</b>	1.50
Keycorp Financial	<b>0.034</b>	0.20	<b>-0.088</b>	-0.52	<b>0.205</b>	1.24
Marshall and Iisley	<b>-0.014</b>	-0.08	<b>-0.004</b>	-0.02	<b>-0.109</b>	-0.65
Merrill Lynch	<b>-0.111</b>	-0.66	<b>-0.121</b>	-0.72	<b>0.108</b>	0.64
National City	<b>0.127</b>	0.76	<b>-0.084</b>	-0.50	<b>-0.152</b>	-0.91
Northern Trust	<b>0.124</b>	0.74	<b>-0.150</b>	-0.90	<b>0.176</b>	1.06
PnC FinServices	<b>0.009</b>	0.05	<b>-0.088</b>	-0.52	<b>0.345</b>	2.18**
Popular Inc	<b>0.032</b>	0.19	<b>0.021</b>	0.12	<b>-0.052</b>	-0.31
Regions Financial	<b>0.198</b>	1.19	<b>0.067</b>	0.40	<b>-0.178</b>	-1.07
Sovereign Bancorp	<b>0.041</b>	0.24	<b>-0.081</b>	-0.48	<b>-0.211</b>	-1.28
State Street	<b>0.039</b>	0.23	<b>-0.074</b>	-0.44	<b>0.172</b>	1.03
Suntrust Bank	<b>0.048</b>	0.28	<b>-0.064</b>	-0.38	<b>0.324</b>	2.03**
Synovus Bank	<b>0.040</b>	0.24	<b>-0.265</b>	-1.63	<b>0.001</b>	0.01
TCF Financial	<b>-0.183</b>	-1.10	<b>-0.078</b>	-0.46	<b>0.092</b>	0.55
US Bancorp	<b>-0.023</b>	-0.13	<b>0.107</b>	0.63	<b>-0.145</b>	-0.87
Wachovia	<b>0.018</b>	0.11	<b>0.031</b>	0.18	<b>-0.119</b>	-0.71
Washington Mutual	<b>-0.008</b>	-0.04	<b>0.192</b>	1.15	<b>0.129</b>	0.77
Wells Fargo	<b>0.077</b>	0.46	<b>-0.082</b>	-0.49	<b>-0.011</b>	-0.06
Zion Corp	<b>0.160</b>	0.96	<b>-0.118</b>	-0.70	<b>-0.026</b>	-0.16

\*\* sig at the 95% confidence interval

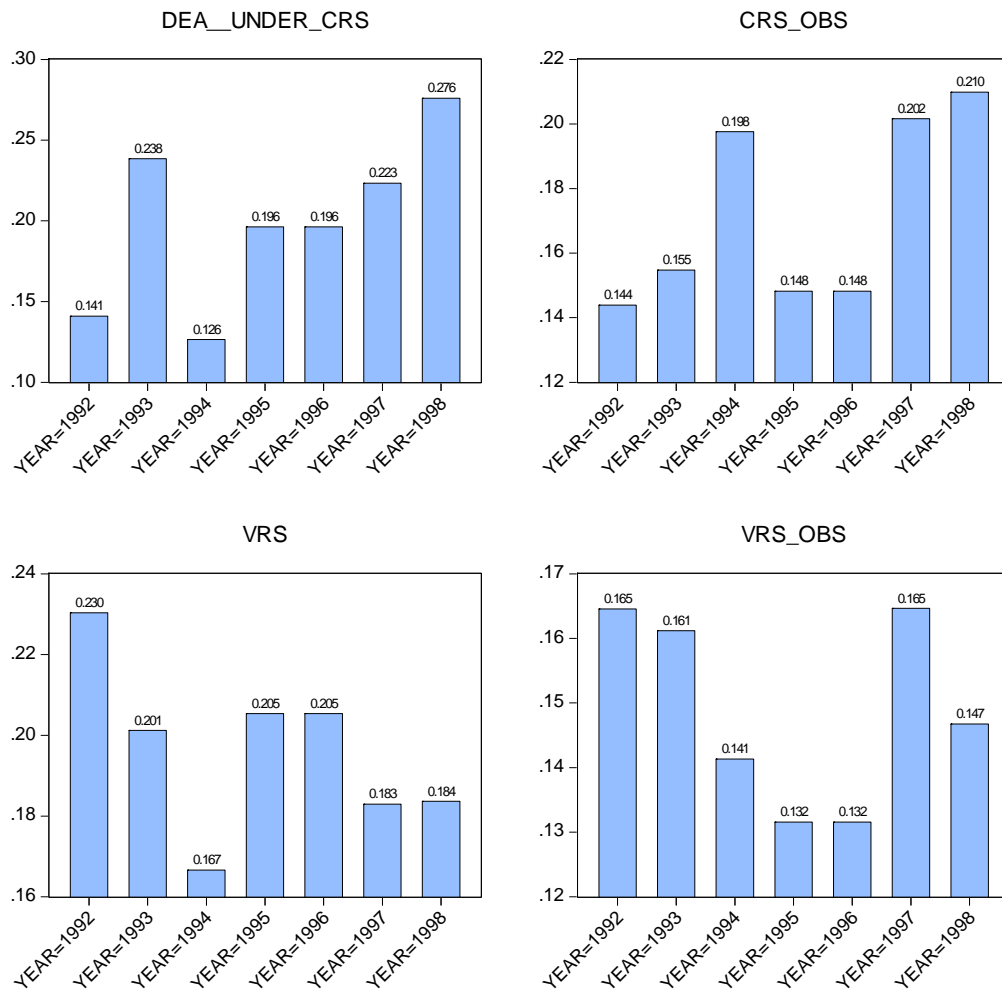
\*\*\* sig. at the 99% confidence interval

$R_{it}$  is the return on bank stock  $i$  during time period  $t$   
 $B_{mi} R_{mjt}$  is the market beta and the return on the market index in country  $j$  at time  $t$   
 $B_{ri} R_{rjt}$  is the interest rate beta and the return on short-term government securities in country  $j$  at time  $t$   
 $B_{fi} R_{fjt}$  is the foreign exchange beta and the return on a foreign exchange index for country  $j$  at time  $t$   
 $\alpha_{it}, u_{it}$  is the bank specific constant and random error terms, respectively

### Appendix III Efficiency Results: Belgium

	Inefficiency			Inefficiency			Inefficiency						
	<u>DEA</u>	<u>UNDER</u>	<u>CRS</u>	<u>CRS</u>	<u>OBS</u>	<u>VRS</u>	<u>VRS</u>	<u>OBS</u>	<u>GDP</u>	<u>CPI</u>	<u>INDP</u>	<u>UNE</u>	<u>STOCK</u>
Mean	0.20		0.17	0.17		0.20	0.15		3.18	0.15	1.53	8.98	0.008
Median	0.20		0.18	0.18		0.19	0.14		1.70	0.15	1.97	9.34	0.015
Maximum	0.33		0.25	0.25		0.30	0.22		15.53	0.22	6.81	9.76	0.080
Minimum	0.12		0.09	0.09		0.12	0.08		-1.00	0.05	-5.11	7.09	-0.123
Std. Dev.	0.07		0.04	0.04		0.05	0.04		4.59	0.06	3.68	0.92	0.043
Skewness	0.32		-0.23	-0.23		0.47	-0.12		2.06	-0.31	-0.54	-1.30	-1.313
Kurtosis	1.70		2.49	2.49		2.31	2.25		6.24	1.71	2.50	3.32	5.831
Jarque-Bera	1.68		0.38	0.38		1.09	0.49		21.77	1.62	1.14	5.47	11.804
Probability	0.43		0.83	0.83		0.58	0.78		0.00	0.44	0.57	0.06	0.003
Sum	3.80		3.32	3.32		3.72	2.86		60.48	2.82	29.01	170.57	0.149
Sum Sq. Dev.	0.08		0.03	0.03		0.05	0.03		379.88	0.07	243.21	15.09	0.033
Observations	19		19	19		19	19		19	19	19	19	19

Means by YEAR



## Stock Performance and Bank Efficiency Regression Results: Belgium

Dependent Variable: STOCK_PERF				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.031611	0.031718	0.996615	0.333
DEA_UNDER_CRS	-0.118721	0.150512	-0.78878	0.441
R-squared	0.035306	Mean dependent var		0.008
Adjusted R-squared	-0.02144	S.D. dependent var		0.043
S.E. of regression	0.043523	Akaike info criterion		-3.332
Sum squared resid	0.032202	Schwarz criterion		-3.232
Log likelihood	33.65169	Hannan-Quinn criter.		-3.315
F-statistic	0.622172	Durbin-Watson stat		2.102
Prob(F-statistic)	0.441103			

Dependent Variable: STOCK_PERF				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.035469	0.03473	1.021298	0.32
DEA_UNDER_CRS	-0.132541	0.163289	-0.8117	0.43
AR(1)	-0.072385	0.262865	-0.27537	0.79
R-squared	0.050366	Mean dependent var		0.01
Adjusted R-squared	-0.076252	S.D. dependent var		0.04
S.E. of regression	0.045806	Akaike info criterion		-3.18
Sum squared resid	0.031472	Schwarz criterion		-3.03
Log likelihood	31.60024	Hannan-Quinn criter.		-3.16
F-statistic	0.397782	Durbin-Watson stat		1.87
Prob(F-statistic)	0.678689			
Inverted AR Roots	-0.07			

Dependent Variable: STOCK_PERF				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.043437	0.043366	1.001635	0.331
CRS_OBS	-0.20383	0.241843	-0.84282	0.411
R-squared	0.040109	Mean dependent var		0.008
Adjusted R-squared	-0.016355	S.D. dependent var		0.043
S.E. of regression	0.043414	Akaike info criterion		-3.337
Sum squared resid	0.032042	Schwarz criterion		-3.237
Log likelihood	33.69911	Hannan-Quinn criter.		-3.320
F-statistic	0.710348	Durbin-Watson stat		2.284
Prob(F-statistic)	0.41103			

Dependent Variable: STOCK_PERF				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.054814	0.04341	1.262715	0.23
CRS_OBS	-0.265492	0.242912	-1.09295	0.29
AR(1)	-0.183875	0.257467	-0.71417	0.49
R-squared	0.072969	Mean dependent var		0.01
Adjusted R-squared	-0.050635	S.D. dependent var		0.04
S.E. of regression	0.045257	Akaike info criterion		-3.20
Sum squared resid	0.030723	Schwarz criterion		-3.05
Log likelihood	31.81705	Hannan-Quinn criter.		-3.18
F-statistic	0.590348	Durbin-Watson stat		2.01
Prob(F-statistic)	0.566507			
Inverted AR Roots	-0.18			

Tobit Regression Results. CRS Model Results. Belgium

<b>Dependent Variable: DEA_UNDER_CRIS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.088502	0.169738	0.521401	0.602
GDP	0.011042	0.004751	2.324003	0.020
CPI	0.040703	0.489515	0.083149	0.934
INDP	-0.020175	0.007179	-2.810171	0.005
UNE	0.012476	0.012743	0.979035	0.328
VAR	2.953433	1.289197	2.290908	0.022
MRA	0.237039	0.065873	3.598413	0.000
Error Distribution				
SCALE:C(8)	0.041249	0.006691	6.164414	0.000
Mean dependent var	0.20002	S.D. dependent var		0.068
S.E. of regression	0.054212	Akaike info criterion		-2.696
Sum squared resid	0.032328	Schwarz criterion		-2.299
Log likelihood	33.61463	Hannan-Quinn criter.		-2.629
Avg. log likelihood	1.769191			
Left censored obs	0	Right censored obs		0
Uncensored obs	19	Total obs		19

<b>Dependent Variable: CRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.221608	0.123176	1.799118	0.072
GDP	-0.004914	0.003448	-1.425174	0.154
CPI	-0.407473	0.355232	-1.147063	0.251
INDP	0.003047	0.00521	0.584799	0.559
UNE	0.006955	0.009248	0.752127	0.452
VAR	1.583223	0.935546	1.692299	0.091
MRA	0.024811	0.047803	0.519023	0.604
Error Distribution				
SCALE:C(8)	0.029934	0.004856	6.164414	0.000
Mean dependent var	0.174522	S.D. dependent var		0.042
S.E. of regression	0.03934	Akaike info criterion		-3.338
Sum squared resid	0.017024	Schwarz criterion		-2.940
Log likelihood	39.70689	Hannan-Quinn criter.		-3.270
Avg. log likelihood	2.089836			
Left censored obs	0	Right censored obs		0
Uncensored obs	19	Total obs		19

Tobit Regression Results. VRS Model Results. Belgium

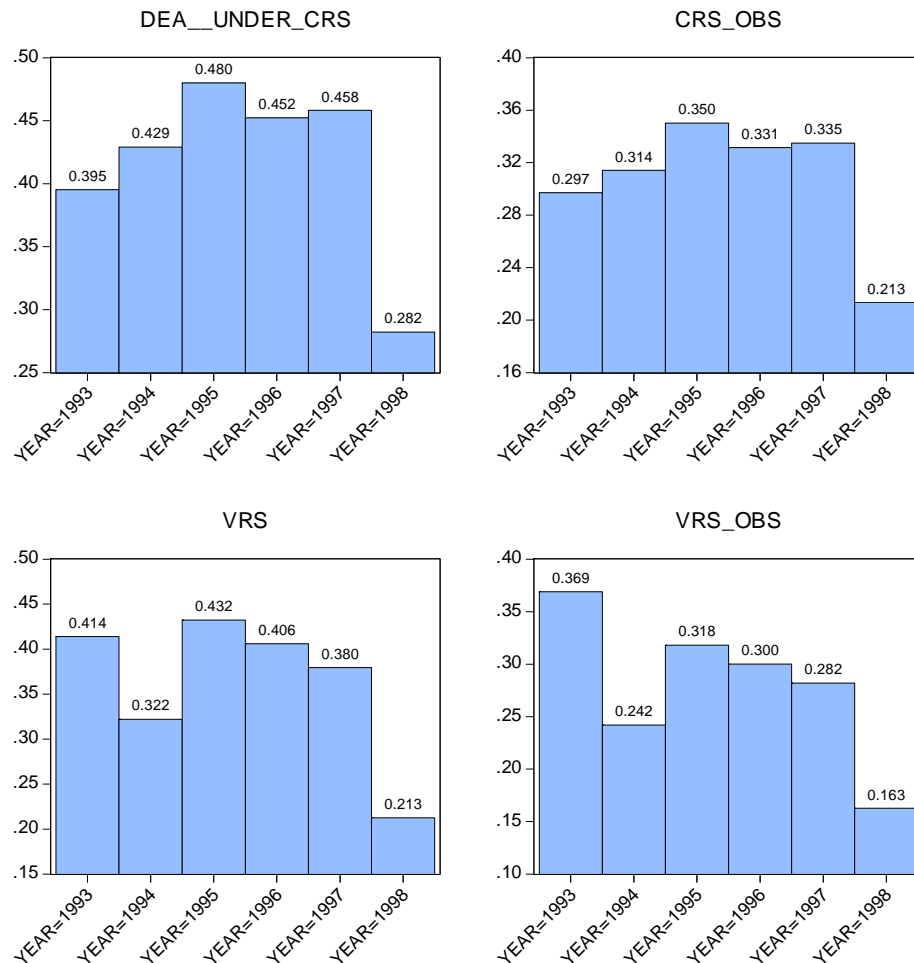
<b>Dependent Variable: VRS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	0.336777	0.19233	1.751041	0.080
GDP	0.002239	0.005384	0.415891	0.678
CPI	0.224352	0.554667	0.404481	0.686
INDP	0.000514	0.008135	0.063177	0.950
UNE	-0.018655	0.01444	-1.291966	0.196
VAR	0.963135	1.460783	0.659328	0.510
MRA	0.041305	0.074641	0.55339	0.580
Error Distribution				
SCALE:C(8)	0.046739	0.007582	6.164414	0.000
Mean dependent var	0.195575	S.D. dependent var		0.052
S.E. of regression	0.061427	Akaike info criterion		-2.446
Sum squared resid	0.041506	Schwarz criterion		-2.049
Log likelihood	31.24053	Hannan-Quinn criter.		-2.379
Avg. log likelihood	1.644239			
Left censored obs	0	Right censored obs		0
Uncensored obs	19	Total obs		19

<b>Dependent Variable: VRS_OBS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	0.165869	0.151134	1.097494	0.272
GDP	0.001236	0.00423	0.292078	0.770
CPI	0.115537	0.435863	0.265078	0.791
INDP	-0.002453	0.006392	-0.383739	0.701
UNE	-0.007206	0.011347	-0.635055	0.525
VAR	-1.050179	1.147897	-0.914872	0.360
MRA	0.005165	0.058653	0.088059	0.930
Error Distribution				
SCALE:C(8)	0.036728	0.005958	6.164414	0.000
Mean dependent var	0.150612	S.D. dependent var		0.040
S.E. of regression	0.04827	Akaike info criterion		-2.928
Sum squared resid	0.02563	Schwarz criterion		-2.531
Log likelihood	35.8203	Hannan-Quinn criter.		-2.861
Avg. log likelihood	1.885279			
Left censored obs	0	Right censored obs		0
Uncensored obs	19	Total obs		19

## Appendix IV Efficiency Results: Canada

	Inefficiency		Inefficiency		Inefficiency		GDP	CPI	INDP	UNE	STOCK_PERF
	DEA	UNDER CRS	CRS_OBS	VRS	VRS_OBS						
Mean	0.42		0.31	0.36	0.28	4.57	1.40	0.23	9.72	0.024	
Median	0.44		0.32	0.37	0.29	4.45	1.61	0.17	9.57	0.033	
Maximum	0.51		0.40	0.50	0.43	6.00	2.15	0.66	11.38	0.106	
Minimum	0.24		0.19	0.14	0.11	3.30	0.16	-0.01	8.30	-0.061	
Std. Dev.	0.07		0.05	0.09	0.07	1.03	0.67	0.24	0.99	0.046	
Skewness	-1.08		-0.88	-0.76	-0.53	0.12	-0.85	0.72	0.33	-0.200	
Kurtosis	3.20		3.05	2.88	3.12	1.35	2.50	2.22	2.25	1.982	
Jarque-Bera	5.92		3.92	2.89	1.44	3.46	3.92	3.34	1.23	1.495	
Probability	0.05		0.14	0.24	0.49	0.18	0.14	0.19	0.54	0.474	
Sum	12.48		9.21	10.83	8.37	137.00	42.04	6.78	291.46	0.715	
Sum Sq. Dev.	0.16		0.08	0.26	0.16	30.77	12.91	1.64	28.19	0.060	
Observations	30		30	30	30	30	30	30	30	30	

Means by YEAR



## Stock Performance and Bank Efficiency Regression Results: Canada

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.095216	0.043382	-2.19484	0.037
DEA_UNDER_CRS	0.286067	0.102682	2.785965	0.010
R-squared	0.217037	Mean dependent var		0.024
Adjusted R-squared	0.189074	S.D. dependent var		0.046
S.E. of regression	0.041053	Akaike info criterion		-3.484
Sum squared resid	0.04719	Schwarz criterion		-3.390
Log likelihood	54.25342	Hannan-Quinn criter.		-3.454
F-statistic	7.7616	Durbin-Watson stat		0.657
Prob(F-statistic)	0.00947			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.083968	0.042055	-1.99663	0.06
DEA_UNDER_CRS	0.258623	0.095447	2.709614	0.01
AR(1)	0.674168	0.145051	4.647809	0.00
R-squared	0.569782	Mean dependent var		0.02
Adjusted R-squared	0.536688	S.D. dependent var		0.05
S.E. of regression	0.031516	Akaike info criterion		-3.98
Sum squared resid	0.025825	Schwarz criterion		-3.84
Log likelihood	60.69453	Hannan-Quinn criter.		-3.93
F-statistic	17.21721	Durbin-Watson stat		1.87
Prob(F-statistic)	0.000017			
Inverted AR Roots	0.67			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.097917	0.043932	-2.22881	0.034
CRS_OBS	0.396716	0.141069	2.812213	0.009
R-squared	0.220241	Mean dependent var		0.024
Adjusted R-squared	0.192393	S.D. dependent var		0.046
S.E. of regression	0.040969	Akaike info criterion		-3.488
Sum squared resid	0.046997	Schwarz criterion		-3.394
Log likelihood	54.31493	Hannan-Quinn criter.		-3.458
F-statistic	7.90854	Durbin-Watson stat		0.471
Prob(F-statistic)	0.008889			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.143552	0.039371	-3.64613	0.00
CRS_OBS	0.522059	0.110962	4.704842	0.00
AR(1)	0.747348	0.119852	6.235597	0.00
R-squared	0.699617	Mean dependent var		0.02
Adjusted R-squared	0.67651	S.D. dependent var		0.05
S.E. of regression	0.026335	Akaike info criterion		-4.34
Sum squared resid	0.018031	Schwarz criterion		-4.20
Log likelihood	65.90341	Hannan-Quinn criter.		-4.29
F-statistic	30.27803	Durbin-Watson stat		1.95
Prob(F-statistic)	0			
Inverted AR Roots	0.75			

Tobit Regression Results. CRS Model Results. Canada

<b>Dependent Variable: DEA_UNDER_CRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	-0.117751	0.257898	-0.456581	0.648
GDP	0.11378	0.025458	4.46934	0.000
CPI	0.012539	0.014632	0.856957	0.392
INDP	-0.496115	0.126513	-3.921467	0.000
UNE	0.014977	0.014363	1.042802	0.297
VAR	-1.135262	1.958132	-0.579768	0.562
MRA	-0.2162	0.063061	-3.428453	0.001
Error Distribution				
SCALE:C(8)	0.0321	0.004144	7.746102	0.000
Mean dependent var	0.416136	S.D. dependent var	0.074	
S.E. of regression	0.037485	Akaike info criterion	-3.507	
Sum squared resid	0.030913	Schwarz criterion	-3.133	
Log likelihood	60.59844	Hannan-Quinn criter.	-3.387	
Avg. log likelihood	2.019948			
Left censored obs	0	Right censored obs	0	
Uncensored obs	30	Total obs	30	

<b>Dependent Variable: CRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.017918	0.225455	0.079473	0.937
GDP	0.067497	0.022255	3.032814	0.002
CPI	0.007119	0.012791	0.556565	0.578
INDP	-0.294735	0.110598	-2.664931	0.008
UNE	0.008106	0.012556	0.645578	0.519
VAR	0.025433	1.711805	0.014858	0.988
MRA	-0.121692	0.055128	-2.20746	0.027
Error Distribution				
SCALE:C(8)	0.028062	0.003623	7.746102	0.000
Mean dependent var	0.306878	S.D. dependent var	0.054	
S.E. of regression	0.03277	Akaike info criterion	-3.775	
Sum squared resid	0.023625	Schwarz criterion	-3.402	
Log likelihood	64.63171	Hannan-Quinn criter.	-3.656	
Avg. log likelihood	2.15439			
Left censored obs	0	Right censored obs	0	
Uncensored obs	30	Total obs	30	



Tobit Regression Results. VRS Model Results. Canada

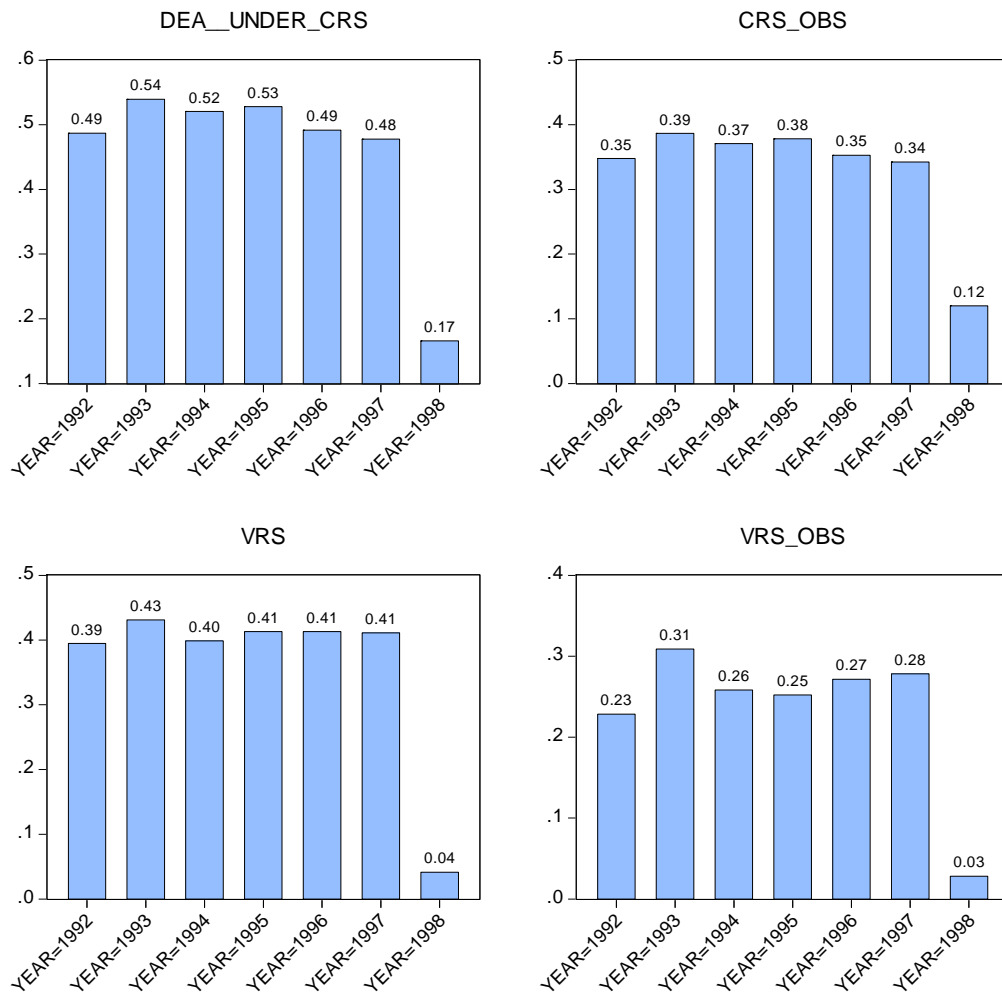
<b>Dependent Variable: VRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	-0.161339	0.43575	-0.370255	0.711
GDP	0.063929	0.043014	1.48623	0.137
CPI	0.047802	0.024722	1.933565	0.053
INDP	-0.315059	0.213758	-1.473902	0.141
UNE	0.02986	0.024268	1.230436	0.219
VAR	0.394249	3.308503	0.119162	0.905
MRA	-0.129056	0.106548	-1.211239	0.226
Error Distribution				
SCALE:C(8)	0.054238	0.007002	7.746102	0.000
Mean dependent var	0.361121	S.D. dependent var	0.094	
S.E. of regression	0.063336	Akaike info criterion	-2.458	
Sum squared resid	0.088251	Schwarz criterion	-2.084	
Log likelihood	44.86328	Hannan-Quinn criter.	-2.338	
Avg. log likelihood	1.495443			
Left censored obs	0	Right censored obs	0	
Uncensored obs	30	Total obs	30	

<b>Dependent Variable: VRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	-0.292899	0.267699	-1.094135	0.274
GDP	0.024579	0.026425	0.930119	0.352
CPI	0.047442	0.015188	3.123685	0.002
INDP	-0.134561	0.13132	-1.024674	0.306
UNE	0.046461	0.014909	3.116383	0.002
VAR	0.505273	2.032547	0.248591	0.804
MRA	-0.036145	0.065457	-0.55219	0.581
Error Distribution				
SCALE:C(8)	0.03332	0.004302	7.746102	0.000
Mean dependent var	0.278957	S.D. dependent var	0.074	
S.E. of regression	0.03891	Akaike info criterion	-3.432	
Sum squared resid	0.033307	Schwarz criterion	-3.058	
Log likelihood	59.47947	Hannan-Quinn criter.	-3.312	
Avg. log likelihood	1.982649			
Left censored obs	0	Right censored obs	0	
Uncensored obs	30	Total obs	30	

## Appendix V Efficiency Results: France

	Inefficiency			Inefficiency						
	<u>DEA</u>	<u>UNDER CRS</u>	<u>CRS OBS</u>	<u>VRS</u>	<u>VRS OBS</u>	<u>GDP</u>	<u>CPI</u>	<u>INDP</u>	<u>UNE</u>	<u>STOCK PERF</u>
Mean	0.46		0.33	0.36	0.23	1.69	1.68	1.27	11.57	-0.005
Median	0.50		0.36	0.37	0.23	2.23	1.78	2.26	11.59	-0.005
Maximum	0.73		0.51	0.72	0.50	3.53	2.38	4.52	12.08	0.132
Minimum	0.00		0.00	0.00	0.00	-0.80	0.63	-4.03	10.27	-0.160
Std. Dev.	0.21		0.15	0.26	0.19	1.27	0.56	3.10	0.61	0.062
Skewness	-0.66		-0.77	-0.11	0.08	-0.66	-0.65	-0.48	-1.23	-0.128
Kurtosis	2.55		2.69	1.70	1.54	2.90	2.32	1.77	3.46	3.155
Jarque-Bera	3.44		4.28	3.03	3.76	3.04	3.80	4.23	10.98	0.157
Probability	0.18		0.12	0.22	0.15	0.22	0.15	0.12	0.00	0.925
Sum	19.26		13.80	15.02	9.76	71.10	70.35	53.15	486.05	-0.190
Sum Sq. Dev.	1.79		0.88	2.71	1.47	66.18	12.97	394.48	15.04	0.155
Observations	42		42	42	42	42	42	42	42	42

Means by YEAR



## Stock Performance and Bank Inefficiency Regression Results: France

<b>Dependent Variable: STOCK_PERF</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	0.010987	0.023246	0.472645	0.639
DEA__UNDER_CRS	-0.033804	0.04622	-0.73138	0.469
R-squared	0.013196	Mean dependent var		-0.005
Adjusted R-squared	-0.011474	S.D. dependent var		0.062
S.E. of regression	0.061913	Akaike info criterion		-2.680
Sum squared resid	0.15333	Schwarz criterion		-2.597
Log likelihood	58.27408	Hannan-Quinn criter.		-2.649
F-statistic	0.534915	Durbin-Watson stat		1.326
Prob(F-statistic)	0.468811			

<b>Dependent Variable: STOCK_PERF</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	0.009148	0.025745	0.35535	0.72
DEA__UNDER_CRS	-0.026817	0.046084	-0.58192	0.56
AR(1)	0.335131	0.152755	2.193911	0.03
R-squared	0.12956	Mean dependent var		0.00
Adjusted R-squared	0.083748	S.D. dependent var		0.06
S.E. of regression	0.059511	Akaike info criterion		-2.73
Sum squared resid	0.134581	Schwarz criterion		-2.61
Log likelihood	59.06627	Hannan-Quinn criter.		-2.69
F-statistic	2.82805	Durbin-Watson stat		2.07
Prob(F-statistic)	0.07162			
Inverted AR Roots	0.34			

<b>Dependent Variable: STOCK_PERF</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	0.012397	0.023694	0.523195	0.604
CRS_OBS	-0.05148	0.066026	-0.7797	0.440
R-squared	0.014971	Mean dependent var		-0.005
Adjusted R-squared	-0.009655	S.D. dependent var		0.062
S.E. of regression	0.061858	Akaike info criterion		-2.682
Sum squared resid	0.153054	Schwarz criterion		-2.599
Log likelihood	58.31188	Hannan-Quinn criter.		-2.651
F-statistic	0.60793	Durbin-Watson stat		1.329
Prob(F-statistic)	0.440158			

<b>Dependent Variable: STOCK_PERF</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	0.010574	0.026444	0.399864	0.69
CRS_OBS	-0.041681	0.06688	-0.62322	0.54
AR(1)	0.333261	0.152863	2.18013	0.04
R-squared	0.130654	Mean dependent var		0.00
Adjusted R-squared	0.084899	S.D. dependent var		0.06
S.E. of regression	0.059474	Akaike info criterion		-2.74
Sum squared resid	0.134412	Schwarz criterion		-2.61
Log likelihood	59.09205	Hannan-Quinn criter.		-2.69
F-statistic	2.855517	Durbin-Watson stat		2.07
Prob(F-statistic)	0.069929			
Inverted AR Roots	0.33			

Tobit Regression Results. CRS Model. France

<b>Dependent Variable: DEA_UNDER_CRIS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.533094	1.443474	0.369313	0.712
GDP	-0.112911	0.08375	-1.348196	0.178
CPI	0.186017	0.178725	1.0408	0.298
INDP	0.055123	0.030376	1.814723	0.070
UNE	-0.02079	0.094509	-0.219985	0.826
VAR	1.029269	2.53144	0.406594	0.684
MRA	0.006771	0.150524	0.044986	0.964
Error Distribution				
SCALE:C(8)	0.169235	0.018465	9.16531	0.000
Mean dependent var	0.458512	S.D. dependent var		0.209
S.E. of regression	0.188085	Akaike info criterion		-0.334
Sum squared resid	1.202789	Schwarz criterion		-0.003
Log likelihood	15.01623	Hannan-Quinn criter.		-0.213
Avg. log likelihood	0.357529			
Left censored obs	0	Right censored obs		0
Uncensored obs	42	Total obs		42

<b>Dependent Variable: CRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.370733	1.001167	0.3703	0.711
GDP	-0.079597	0.058087	-1.3703	0.171
CPI	0.133084	0.12396	1.073603	0.283
INDP	0.038784	0.021068	1.840908	0.066
UNE	-0.013999	0.06555	-0.213563	0.831
VAR	0.765159	1.75576	0.435799	0.663
MRA	0.006634	0.104401	0.063543	0.949
Error Distribution				
SCALE:C(8)	0.117378	0.012807	9.16531	0.000
Mean dependent var	0.328463	S.D. dependent var		0.146
S.E. of regression	0.130459	Akaike info criterion		-1.066
Sum squared resid	0.578661	Schwarz criterion		-0.735
Log likelihood	30.38345	Hannan-Quinn criter.		-0.945
Avg. log likelihood	0.723415			
Left censored obs	0	Right censored obs		0
Uncensored obs	42	Total obs		42

Tobit Regression Results. VRS Model. France

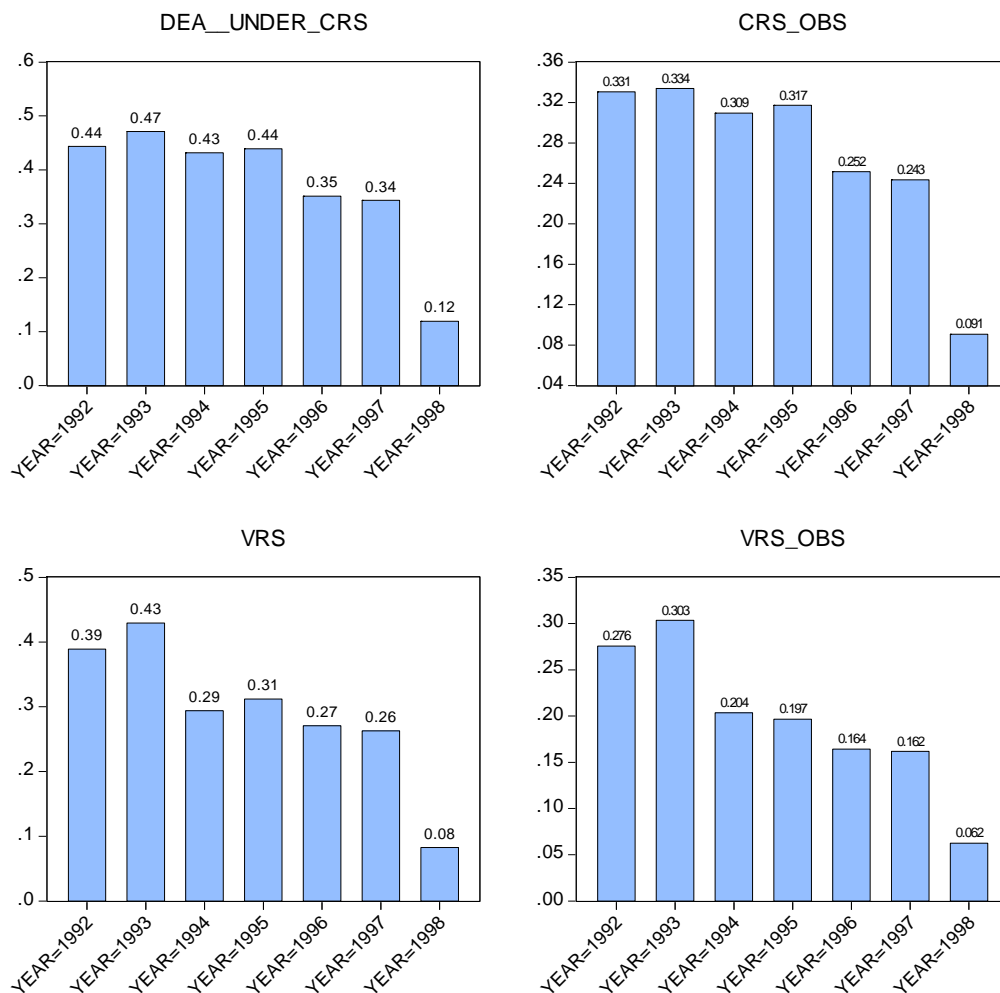
<b>Dependent Variable: VRS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	-0.9727	1.853644	-0.52475	0.600
GDP	-0.088207	0.107548	-0.820161	0.412
CPI	0.356566	0.229511	1.553594	0.120
INDP	0.048486	0.039007	1.24301	0.214
UNE	0.061575	0.121364	0.507358	0.612
VAR	-3.521527	3.250761	-1.083293	0.279
MRA	0.067112	0.193296	0.347197	0.728
Error Distribution				
SCALE:C(8)	0.217324	0.023712	9.16531	0.000
Mean dependent var	0.357674	S.D. dependent var		0.257
S.E. of regression	0.241545	Akaike info criterion		0.166
Sum squared resid	1.983688	Schwarz criterion		0.497
Log likelihood	4.511994	Hannan-Quinn criter.		0.287
Avg. log likelihood	0.107428			
Left censored obs	0	Right censored obs		0
Uncensored obs	42	Total obs		42

<b>Dependent Variable: VRS_OBS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	-0.67687	1.407143	-0.481024	0.631
GDP	-0.075781	0.081642	-0.928216	0.353
CPI	0.19983	0.174227	1.146954	0.251
INDP	0.032038	0.029611	1.081974	0.279
UNE	0.050732	0.09213	0.550653	0.582
VAR	-2.526898	2.467726	-1.023979	0.306
MRA	0.038383	0.146735	0.261582	0.794
Error Distribution				
SCALE:C(8)	0.164975	0.018	9.16531	0.000
Mean dependent var	0.232268	S.D. dependent var		0.189
S.E. of regression	0.18336	Akaike info criterion		-0.385
Sum squared resid	1.143109	Schwarz criterion		-0.054
Log likelihood	16.08686	Hannan-Quinn criter.		-0.264
Avg. log likelihood	0.38302			
Left censored obs	0	Right censored obs		0
Uncensored obs	42	Total obs		42

## Appendix VI Efficiency Results: Germany

	Inefficiency		Inefficiency		Inefficiency		Inefficiency		GDP	CPI	INDP	UNE	STOCK_PERF
	DEA	UNDER CRS	CRS_OBS	VRS	VRS_OBS								
Mean	0.37		0.27	0.29	0.20	1.49	2.61	0.18	9.81	0.004			
Median	0.35		0.33	0.19	0.10	1.85	1.91	0.33	9.60	-0.003			
Maximum	0.83		0.57	0.78	0.54	2.70	5.08	3.66	11.48	0.094			
Minimum	0.00		0.00	0.00	0.00	-0.80	0.94	-6.61	7.72	-0.077			
Std. Dev.	0.27		0.19	0.29	0.21	1.05	1.48	3.31	1.21	0.045			
Skewness	0.17		0.06	0.51	0.48	-1.29	0.65	-0.98	-0.25	0.515			
Kurtosis	1.69		1.65	1.71	1.56	3.67	1.87	3.01	2.10	2.567			
Jarque-Bera	2.67		2.69	3.95	4.39	10.42	4.33	5.58	1.54	1.823			
Probability	0.26		0.26	0.14	0.11	0.01	0.11	0.06	0.46	0.402			
Sum	13.00		9.39	10.20	6.84	52.25	91.29	6.29	343.25	0.127			
Sum Sq. Dev.	2.53		1.20	2.86	1.50	37.75	74.43	371.83	50.10	0.069			
Observations	35		35	35	35	35	35	35	35	35			

Means by YEAR



## Stock Performance and Bank Inefficiency Regression Results: Germany

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	0.010939	0.013049	0.838303	0.408
DEA_UNDER_CRS	-0.019721	0.028462	-0.69289	0.493
R-squared	0.01434	Mean dependent var		0.004
Adjusted R-squared	-0.015529	S.D. dependent var		0.045
S.E. of regression	0.045273	Akaike info criterion		-3.297
Sum squared resid	0.067639	Schwarz criterion		-3.208
Log likelihood	59.69318	Hannan-Quinn criter.		-3.266
F-statistic	0.4801	Durbin-Watson stat		0.877
Prob(F-statistic)	0.493225			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	0.009778	0.017126	0.570947	0.57
DEA_UNDER_CRS	-0.010564	0.023846	-0.44301	0.66
AR(1)	0.558875	0.147574	3.787088	0.00
R-squared	0.322054	Mean dependent var		0.00
Adjusted R-squared	0.278316	S.D. dependent var		0.05
S.E. of regression	0.038423	Akaike info criterion		-3.60
Sum squared resid	0.045767	Schwarz criterion		-3.46
Log likelihood	64.13557	Hannan-Quinn criter.		-3.55
F-statistic	7.363181	Durbin-Watson stat		1.82
Prob(F-statistic)	0.002418			
Inverted AR Roots	0.56			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	0.013175	0.013398	0.98336	0.333
CRS_OBS	-0.035647	0.041089	-0.86756	0.392
R-squared	0.022299	Mean dependent var		0.004
Adjusted R-squared	-0.007328	S.D. dependent var		0.045
S.E. of regression	0.04509	Akaike info criterion		-3.305
Sum squared resid	0.067093	Schwarz criterion		-3.216
Log likelihood	59.83507	Hannan-Quinn criter.		-3.274
F-statistic	0.752659	Durbin-Watson stat		0.874
Prob(F-statistic)	0.391901			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	0.012113	0.017326	0.69911	0.49
CRS_OBS	-0.023756	0.034661	-0.68538	0.50
AR(1)	0.560143	0.147561	3.796011	0.00
R-squared	0.327945	Mean dependent var		0.00
Adjusted R-squared	0.284586	S.D. dependent var		0.05
S.E. of regression	0.038256	Akaike info criterion		-3.60
Sum squared resid	0.045369	Schwarz criterion		-3.47
Log likelihood	64.28393	Hannan-Quinn criter.		-3.56
F-statistic	7.56358	Durbin-Watson stat		1.81
Prob(F-statistic)	0.002112			
Inverted AR Roots	0.56			

Tobit Regression Results. CRS Model. Germany

<b>Dependent Variable: DEA_UNDER_CRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	-1.763499	1.70672	-1.033267	0.302
GDP	0.239074	0.224309	1.065825	0.287
CPI	0.072705	0.071637	1.014914	0.310
INDP	-0.084132	0.085729	-0.981372	0.326
UNE	0.170332	0.14017	1.21518	0.224
VAR	-0.122554	4.253668	-0.028811	0.977
MRA	-0.245288	0.194361	-1.262021	0.207
Error Distribution				
SCALE:C(8)	0.245597	0.029352	8.367211	0.000
Mean dependent var	0.371347	S.D. dependent var	0.273	
S.E. of regression	0.279624	Akaike info criterion	0.487	
Sum squared resid	2.111113	Schwarz criterion	0.842	
Log likelihood	-0.520623	Hannan-Quinn criter.	0.610	
Avg. log likelihood	-0.014875			
Left censored obs	0	Right censored obs	0	
Uncensored obs	35	Total obs	35	

<b>Dependent Variable: CRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	-1.083447	1.167745	-0.927812	0.354
GDP	0.162741	0.153473	1.060388	0.289
CPI	0.048824	0.049014	0.996132	0.319
INDP	-0.056135	0.058656	-0.957012	0.339
UNE	0.107014	0.095905	1.115833	0.265
VAR	0.610957	2.910377	0.209924	0.834
MRA	-0.150286	0.132983	-1.130116	0.258
Error Distribution				
SCALE:C(8)	0.168038	0.020083	8.367211	0.000
Mean dependent var	0.268163	S.D. dependent var	0.188	
S.E. of regression	0.19132	Akaike info criterion	-0.272	
Sum squared resid	0.988291	Schwarz criterion	0.083	
Log likelihood	12.76185	Hannan-Quinn criter.	-0.149	
Avg. log likelihood	0.364624			
Left censored obs	0	Right censored obs	0	
Uncensored obs	35	Total obs	35	



Tobit Regression Results. VRS Model. Germany

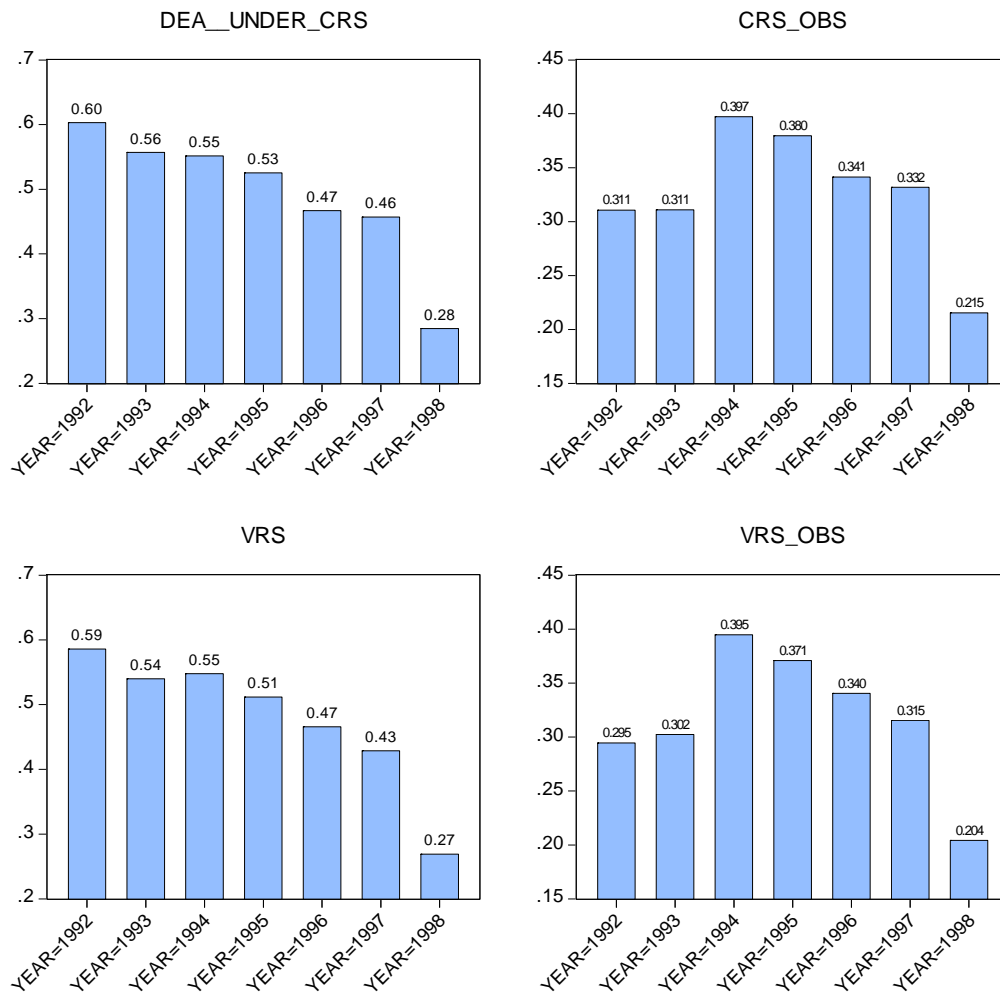
<b>Dependent Variable: VRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	-1.174584	1.853275	-0.633788	0.526
GDP	0.160349	0.24357	0.658329	0.510
CPI	0.066055	0.077788	0.849166	0.396
INDP	-0.063466	0.093091	-0.681768	0.495
UNE	0.115104	0.152206	0.756237	0.450
VAR	1.065128	4.618926	0.230601	0.818
MRA	-0.127836	0.211051	-0.605709	0.545
Error Distribution				
SCALE:C(8)	0.266686	0.031873	8.367211	0.000
Mean dependent var	0.291566	S.D. dependent var		0.290
S.E. of regression	0.303628	Akaike info criterion		0.652
Sum squared resid	2.489134	Schwarz criterion		1.007
Log likelihood	-3.403941	Hannan-Quinn criter.		0.774
Avg. log likelihood	-0.097255			
Left censored obs	0	Right censored obs		0
Uncensored obs	35	Total obs		35

<b>Dependent Variable: VRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	-0.426483	1.34136	-0.317948	0.751
GDP	0.05777	0.17629	0.327699	0.743
CPI	0.047656	0.056301	0.846451	0.397
INDP	-0.023548	0.067377	-0.349501	0.727
UNE	0.047727	0.110164	0.433241	0.665
VAR	1.47846	3.343079	0.442245	0.658
MRA	-0.055287	0.152754	-0.361931	0.717
Error Distribution				
SCALE:C(8)	0.193016	0.02307	8.3666	0.000
Mean dependent var	0.195417	S.D. dependent var		0.210
S.E. of regression	0.219758	Akaike info criterion		0.005
Sum squared resid	1.30393	Schwarz criterion		0.361
Log likelihood	7.91153	Hannan-Quinn criter.		0.128
Avg. log likelihood	0.226044			
Left censored obs	0	Right censored obs		0
Uncensored obs	35	Total obs		35

## Appendix VII Efficiency Results: Italy

	Inefficiency		Inefficiency		Inefficiency		Inefficiency		UNE	STOCK PERF
	DEA	UNDER CRS	CRS OBS	VRS	VRS OBS	GDP	CPI	INDP		
Mean	0.49		0.33	0.48	0.32	1.26	1.81	1.90	10.59	0.006
Median	0.50		0.36	0.49	0.35	1.30	0.98	1.89	11.16	-0.020
Maximum	0.65		0.46	0.65	0.46	2.90	6.63	5.81	11.34	0.222
Minimum	0.24		0.00	0.23	0.00	-0.90	-2.31	-2.00	8.90	-0.098
Std. Dev.	0.11		0.12	0.12	0.12	1.20	3.66	3.02	0.89	0.072
Skewness	-0.67		-1.52	-0.63	-1.41	-0.41	0.21	0.10	-0.98	1.039
Kurtosis	2.63		4.93	2.53	4.64	2.25	1.34	1.46	2.39	4.003
Jarque-Bera	2.24		15.09	2.09	12.45	1.44	3.43	2.83	4.92	6.208
Probability	0.33		0.00	0.35	0.00	0.49	0.18	0.24	0.09	0.045
Sum	13.78		9.15	13.40	8.89	35.40	50.70	53.33	296.64	0.157
Sum Sq. Dev.	0.35		0.38	0.36	0.37	39.17	361.46	245.96	21.20	0.141
Observations	28		28	28	28	28	28	28	28	28

Means by YEAR



## Stock Performance and Bank Inefficiency Regression Results: Italy

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	0.160268	0.054888	2.91989	0.007
DEA_UNDER_CRS	-0.31418	0.108756	-2.88887	0.008
R-squared	0.242988	Mean dependent var		0.006
Adjusted R-squared	0.213872	S.D. dependent var		0.072
S.E. of regression	0.06396	Akaike info criterion		-2.592
Sum squared resid	0.106362	Schwarz criterion		-2.497
Log likelihood	38.29323	Hannan-Quinn criter.		-2.563
F-statistic	8.345539	Durbin-Watson stat		1.496
Prob(F-statistic)	0.007695			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	-0.029658	0.072588	-0.40858	0.69
DEA_UNDER_CRS	0.106638	0.139259	0.765751	0.45
AR(1)	0.71318	0.161616	4.412812	0.00
R-squared	0.384808	Mean dependent var		0.01
Adjusted R-squared	0.333542	S.D. dependent var		0.07
S.E. of regression	0.059607	Akaike info criterion		-2.70
Sum squared resid	0.085273	Schwarz criterion		-2.55
Log likelihood	39.41803	Hannan-Quinn criter.		-2.65
F-statistic	7.506091	Durbin-Watson stat		2.15
Prob(F-statistic)	0.002939			
Inverted AR Roots	0.71			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	0.018386	0.041524	0.442789	0.662
CRS_OBS	-0.039148	0.119796	-0.32679	0.746
R-squared	0.004091	Mean dependent var		0.006
Adjusted R-squared	-0.034214	S.D. dependent var		0.072
S.E. of regression	0.073361	Akaike info criterion		-2.318
Sum squared resid	0.139928	Schwarz criterion		-2.223
Log likelihood	34.45335	Hannan-Quinn criter.		-2.289
F-statistic	0.10679	Durbin-Watson stat		0.821
Prob(F-statistic)	0.746445			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic Prob.</u>	
C	-0.015154	0.042506	-0.3565	0.72
CRS_OBS	0.1062	0.074455	1.426363	0.17
AR(1)	0.687315	0.158003	4.350024	0.00
R-squared	0.421796	Mean dependent var		0.01
Adjusted R-squared	0.373613	S.D. dependent var		0.07
S.E. of regression	0.057788	Akaike info criterion		-2.76
Sum squared resid	0.080146	Schwarz criterion		-2.62
Log likelihood	40.25515	Hannan-Quinn criter.		-2.72
F-statistic	8.753932	Durbin-Watson stat		2.20
Prob(F-statistic)	0.001396			
Inverted AR Roots	0.69			

Tobit Regression Results. CRS Model. Italy

<b>Dependent Variable: DEA_UNDER_CRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	1.405991	0.168874	8.325704	0.000
GDP	0.059414	0.032476	1.829444	0.067
CPI	0.077275	0.029457	2.623353	0.009
INDP	-0.105166	0.042488	-2.475211	0.013
UNE	-0.082516	0.016461	-5.012715	0.000
VAR	1.451525	0.881434	1.646776	0.100
MRA	-0.065982	0.03224	-2.046569	0.041
Error Distribution				
SCALE:C(8)	0.051785	0.00692	7.483327	0.000
Mean dependent var	0.492304	S.D. dependent var	0.113	
S.E. of regression	0.061273	Akaike info criterion	-2.512	
Sum squared resid	0.075087	Schwarz criterion	-2.131	
Log likelihood	43.16819	Hannan-Quinn criter.	-2.396	
Avg. log likelihood	1.541721			
Left censored obs	0	Right censored obs	0	
Uncensored obs	28	Total obs	28	

<b>Dependent Variable: CRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.24191	0.330729	0.731444	0.465
GDP	0.055778	0.063603	0.876963	0.381
CPI	0.090881	0.057689	1.575359	0.115
INDP	-0.119065	0.08321	-1.430896	0.153
UNE	0.007513	0.032238	0.233032	0.816
VAR	-1.100692	1.726235	-0.637626	0.524
MRA	-0.104554	0.06314	-1.655893	0.098
Error Distribution				
SCALE:C(8)	0.101417	0.013552	7.483327	0.000
Mean dependent var	0.32673	S.D. dependent var	0.118	
S.E. of regression	0.119999	Akaike info criterion	-1.168	
Sum squared resid	0.287993	Schwarz criterion	-0.787	
Log likelihood	24.34805	Hannan-Quinn criter.	-1.051	
Avg. log likelihood	0.869573			
Left censored obs	0	Right censored obs	0	
Uncensored obs	28	Total obs	28	

Tobit Regression Result. VRS Model. Italy

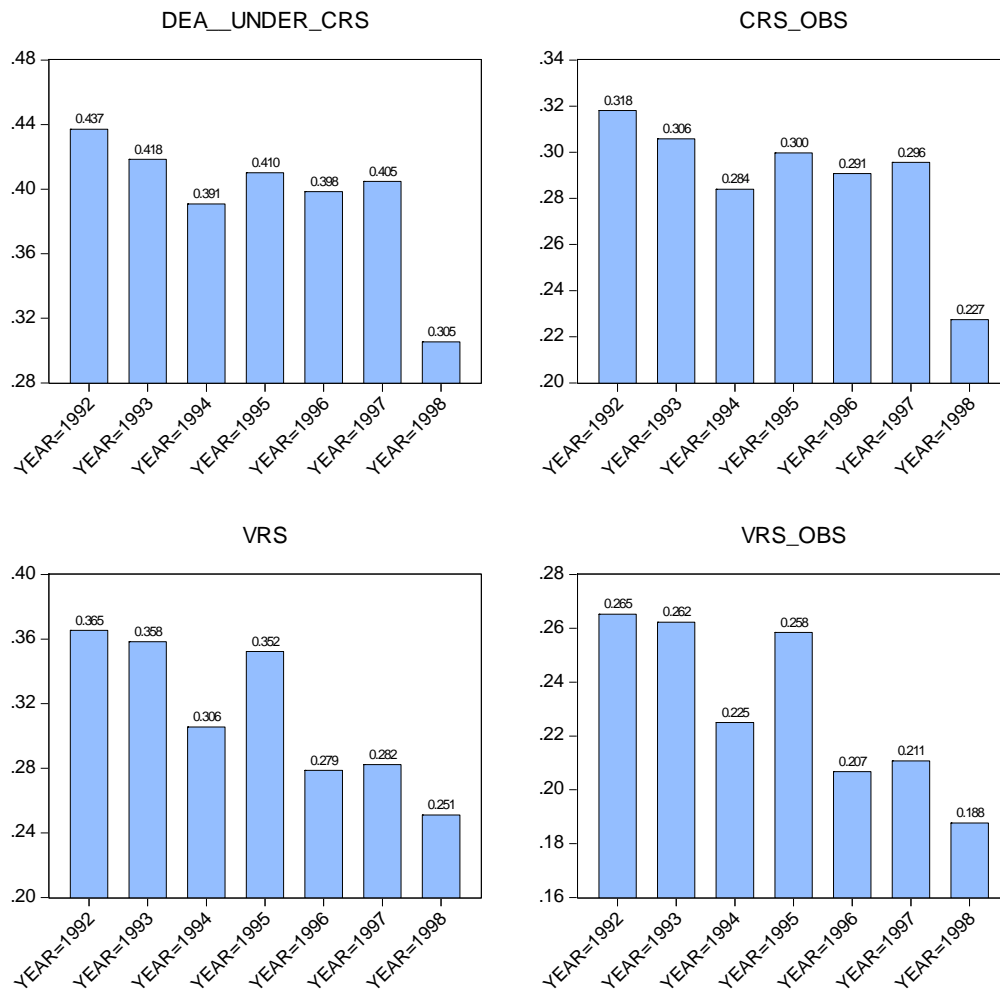
<b>Dependent Variable: VRS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	1.314604	0.174351	7.539979	0.000
GDP	0.055652	0.03353	1.659759	0.097
CPI	0.071584	0.030412	2.353804	0.019
INDP	-0.097403	0.043866	-2.220463	0.026
UNE	-0.074831	0.016995	-4.403034	0.000
VAR	1.355655	0.910024	1.489691	0.136
MRA	-0.086876	0.033286	-2.610012	0.009
Error Distribution				
SCALE:C(8)	0.053464	0.007144	7.483327	0.000
Mean dependent var	0.478428	S.D. dependent var		0.115
S.E. of regression	0.06326	Akaike info criterion		-2.448
Sum squared resid	0.080036	Schwarz criterion		-2.068
Log likelihood	42.2744	Hannan-Quinn criter.		-2.332
Avg. log likelihood	1.5098			
Left censored obs	0	Right censored obs		0
Uncensored obs	28	Total obs		28

<b>Dependent Variable: VRS_OBS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	0.161781	0.321873	0.502624	0.615
GDP	0.051007	0.0619	0.824017	0.410
CPI	0.090469	0.056144	1.611367	0.107
INDP	-0.117311	0.080982	-1.448615	0.147
UNE	0.014701	0.031375	0.468569	0.639
VAR	-1.190603	1.680011	-0.708688	0.479
MRA	-0.118573	0.06145	-1.929598	0.054
Error Distribution				
SCALE:C(8)	0.098702	0.01319	7.483327	0.000
Mean dependent var	0.317509	S.D. dependent var		0.117
S.E. of regression	0.116785	Akaike info criterion		-1.222
Sum squared resid	0.272776	Schwarz criterion		-0.841
Log likelihood	25.10804	Hannan-Quinn criter.		-1.106
Avg. log likelihood	0.896716			
Left censored obs	0	Right censored obs		0
Uncensored obs	28	Total obs		28

## Appendix VIII Efficiency Results: Japan

	Inefficiency		Inefficiency		Inefficiency							
	DEA	UNDER CRS	CRS	OBS	VRS	VRS	OBS	GDP	CPI	INDP	UNE	STOCK_PERF
Mean	0.39		0.29		0.31		0.23	1.14	0.86	-0.90	3.09	-0.004
Median	0.43		0.31		0.33		0.25	1.63	0.68	0.95	3.15	-0.001
Maximum	0.67		0.47		0.65		0.46	2.73	1.74	3.67	4.10	0.092
Minimum	0.00		0.00		0.00		0.00	-2.08	-0.08	-6.87	2.15	-0.223
Std. Dev.	0.16		0.12		0.19		0.14	1.54	0.67	4.22	0.59	0.057
Skewness	-1.11		-1.23		-0.33		-0.43	-1.04	0.02	-0.32	0.07	-1.065
Kurtosis	3.60		3.83		1.98		2.02	3.08	1.58	1.35	2.28	5.084
Jarque-Bera	24.55		31.00		6.83		7.84	20.14	9.36	14.48	2.50	41.093
Probability	0.00		0.00		0.03		0.02	0.00	0.01	0.00	0.29	0.000
Sum	43.81		32.03		34.74		25.59	126.04	95.86	-99.99	342.78	-0.477
Sum Sq. Dev.	2.97		1.51		4.12		2.13	260.08	49.55	1959.64	38.59	0.360
Observations	111		111		111		111	111	111	111	111	111

Means by YEAR



## Stock Performance and Bank Inefficiency Regression Results: Japan.

Dependent Variable: STOCK_PERF				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.040178	0.013757	-2.92064	0.004
DEA__UNDER_CRS	0.090906	0.032203	2.822935	0.006
R-squared	0.068129	Mean dependent var		-0.004
Adjusted R-squared	0.05958	S.D. dependent var		0.057
S.E. of regression	0.055475	Akaike info criterion		-2.928
Sum squared resid	0.335445	Schwarz criterion		-2.879
Log likelihood	164.4992	Hannan-Quinn criter.		-2.908
F-statistic	7.968964	Durbin-Watson stat		0.976
Prob(F-statistic)	0.005658			

Dependent Variable: STOCK_PERF				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.037809	0.014626	-2.58494	0.01
DEA__UNDER_CRS	0.081944	0.028787	2.846614	0.01
AR(1)	0.510728	0.083113	6.144968	0.00
R-squared	0.307787	Mean dependent var		0.00
Adjusted R-squared	0.294848	S.D. dependent var		0.06
S.E. of regression	0.048028	Akaike info criterion		-3.21
Sum squared resid	0.24682	Schwarz criterion		-3.13
Log likelihood	179.3934	Hannan-Quinn criter.		-3.18
F-statistic	23.78832	Durbin-Watson stat		2.20
Prob(F-statistic)	0			
Inverted AR Roots	0.51			

Dependent Variable: STOCK_PERF				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.041279	0.014059	-2.93614	0.004
CRS_OBS	0.128158	0.045182	2.8365	0.005
R-squared	0.06874	Mean dependent var		-0.004
Adjusted R-squared	0.060196	S.D. dependent var		0.057
S.E. of regression	0.055457	Akaike info criterion		-2.929
Sum squared resid	0.335225	Schwarz criterion		-2.880
Log likelihood	164.5356	Hannan-Quinn criter.		-2.909
F-statistic	8.045729	Durbin-Watson stat		0.974
Prob(F-statistic)	0.005439			

Dependent Variable: STOCK_PERF				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.038734	0.01477	-2.62247	0.01
CRS_OBS	0.115226	0.039982	2.881952	0.00
AR(1)	0.511424	0.083072	6.15642	0.00
R-squared	0.308992	Mean dependent var		0.00
Adjusted R-squared	0.296076	S.D. dependent var		0.06
S.E. of regression	0.047987	Akaike info criterion		-3.21
Sum squared resid	0.246391	Schwarz criterion		-3.14
Log likelihood	179.4892	Hannan-Quinn criter.		-3.18
F-statistic	23.92317	Durbin-Watson stat		2.20
Prob(F-statistic)	0			
Inverted AR Roots	0.51			

Tobit Regression Results. CRS Model. Japan.

<b>Dependent Variable: DEA_UNDER_CRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.546567	0.465879	1.173194	0.241
GDP	0.03535	0.017079	2.069766	0.039
CPI	0.02782	0.095259	0.292045	0.770
INDP	0.002446	0.005048	0.484475	0.628
UNE	-0.043499	0.141785	-0.306792	0.759
VAR	2.203177	0.469825	4.689356	0.000
MRA	0.143519	0.180727	0.794118	0.427
Error Distribution				
SCALE:C(8)	0.145116	0.009739	14.90043	0.000
Mean dependent var	0.394657	S.D. dependent var		0.164
S.E. of regression	0.150645	Akaike info criterion		-0.878
Sum squared resid	2.337474	Schwarz criterion		-0.683
Log likelihood	56.75262	Hannan-Quinn criter.		-0.799
Avg. log likelihood	0.511285			
Left censored obs	0	Right censored obs		0
Uncensored obs	111	Total obs		111

<b>Dependent Variable: CRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.403804	0.331707	1.217353	0.224
GDP	0.025675	0.01216	2.111395	0.035
CPI	0.01758	0.067825	0.259194	0.796
INDP	0.001517	0.003594	0.42217	0.673
UNE	-0.033069	0.100952	-0.327575	0.743
VAR	1.593454	0.334517	4.763452	0.000
MRA	0.108677	0.128678	0.844564	0.398
Error Distribution				
SCALE:C(8)	0.103323	0.006934	14.90043	0.000
Mean dependent var	0.288528	S.D. dependent var		0.117
S.E. of regression	0.10726	Akaike info criterion		-1.558
Sum squared resid	1.184991	Schwarz criterion		-1.362
Log likelihood	94.45644	Hannan-Quinn criter.		-1.479
Avg. log likelihood	0.850959			
Left censored obs	0	Right censored obs		0
Uncensored obs	111	Total obs		111



Tobit Regression Results. VRS Model. Japan

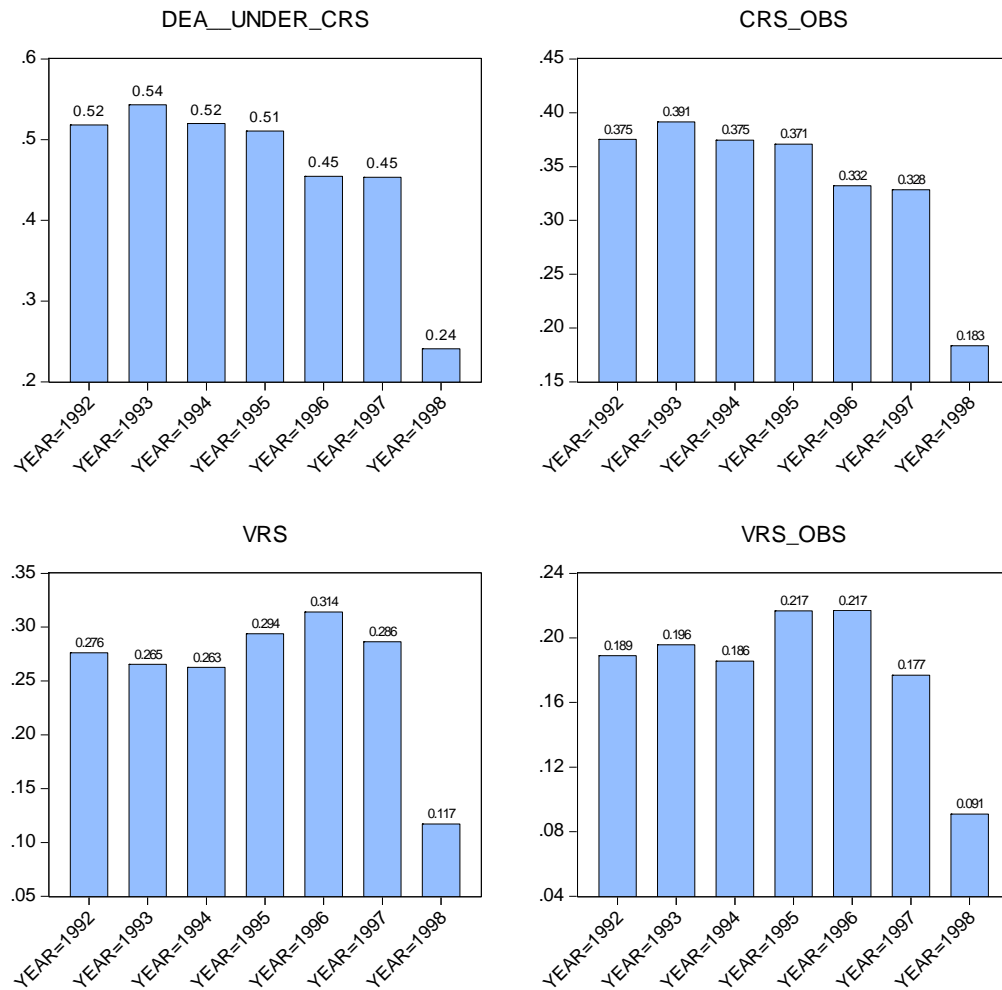
<b>Dependent Variable: VRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	1.013571	0.556801	1.820346	0.069
GDP	0.030732	0.020412	1.505579	0.132
CPI	-0.077608	0.11385	-0.681674	0.495
INDP	-0.001095	0.006033	-0.181415	0.856
UNE	-0.203314	0.169457	-1.199801	0.230
VAR	2.499094	0.561517	4.450608	0.000
MRA	0.331371	0.215998	1.53414	0.125
Error Distribution				
SCALE:C(8)	0.173437	0.01164	14.90043	0.000
Mean dependent var	0.312943	S.D. dependent var		0.194
S.E. of regression	0.180046	Akaike info criterion		-0.522
Sum squared resid	3.338908	Schwarz criterion		-0.327
Log likelihood	36.9633	Hannan-Quinn criter.		-0.443
Avg. log likelihood	0.333003			
Left censored obs	0	Right censored obs		0
Uncensored obs	111	Total obs		111

<b>Dependent Variable: VRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.717111	0.399843	1.79348	0.073
GDP	0.022356	0.014658	1.525126	0.127
CPI	-0.052394	0.081756	-0.64085	0.522
INDP	-0.000572	0.004333	-0.131987	0.895
UNE	-0.140664	0.121688	-1.15594	0.248
VAR	1.842591	0.40323	4.569576	0.000
MRA	0.23703	0.15511	1.528143	0.127
Error Distribution				
SCALE:C(8)	0.124546	0.008359	14.90043	0.000
Mean dependent var	0.230581	S.D. dependent var		0.139
S.E. of regression	0.129293	Akaike info criterion		-1.184
Sum squared resid	1.721812	Schwarz criterion		-0.989
Log likelihood	73.7193	Hannan-Quinn criter.		-1.105
Avg. log likelihood	0.664138			
Left censored obs	0	Right censored obs		0
Uncensored obs	111	Total obs		111

## Appendix IX Efficiency Results: the Netherlands

	Inefficiency		Inefficiency		Inefficiency					
	<u>DEA</u>	<u>UNDER CRS</u>	<u>CRS OBS</u>	<u>VRS</u>	<u>VRS OBS</u>	<u>GDP</u>	<u>CPI</u>	<u>INDP</u>	<u>UNE</u>	<u>STOCK PERF</u>
Mean	0.48		0.35	0.26	0.19	2.63	2.71	1.03	5.12	-0.012
Median	0.48		0.35	0.30	0.21	2.94	2.69	0.08	5.24	-0.006
Maximum	0.61		0.44	0.45	0.33	4.28	6.27	3.48	6.56	0.023
Minimum	0.20		0.15	0.00	0.00	0.65	-0.96	-1.09	3.46	-0.062
Std. Dev.	0.11		0.07	0.13	0.10	1.24	2.65	1.79	1.13	0.021
Skewness	-1.12		-1.19	-0.84	-0.66	-0.41	-0.02	0.39	-0.17	-0.735
Kurtosis	4.26		4.40	2.77	2.65	1.89	1.51	1.49	1.71	3.342
Jarque-Bera	4.98		5.75	2.18	1.40	1.44	1.68	2.17	1.33	1.707
Probability	0.08		0.06	0.34	0.50	0.49	0.43	0.34	0.52	0.426
Sum	8.57		6.22	4.73	3.33	47.33	48.79	18.50	92.12	-0.208
Sum Sq. Dev.	0.19		0.09	0.30	0.15	26.24	118.94	54.36	21.79	0.008
Observations	18		18	18	18	18	18	18	18	18

Means by YEAR



Stock Performance and Bank Inefficiency Regression Results. Netherlands.

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.032672	0.023849	-1.36993	0.190
DEA_UNDER_CRS	0.044319	0.04895	0.905396	0.379
R-squared	0.048737	Mean dependent var		-0.012
Adjusted R-squared	-0.010717	S.D. dependent var		0.021
S.E. of regression	0.021238	Akaike info criterion		-4.762
Sum squared resid	0.007217	Schwarz criterion		-4.663
Log likelihood	44.85461	Hannan-Quinn criter.		-4.748
F-statistic	0.819743	Durbin-Watson stat		2.062
Prob(F-statistic)	0.378688			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.024112	0.022925	-1.05182	0.31
DEA_UNDER_CRS	0.022692	0.047648	0.476251	0.64
AR(1)	-0.119923	0.246529	-0.48645	0.63
R-squared	0.031729	Mean dependent var		-0.01
Adjusted R-squared	-0.106596	S.D. dependent var		0.02
S.E. of regression	0.020907	Akaike info criterion		-4.74
Sum squared resid	0.00612	Schwarz criterion		-4.59
Log likelihood	43.27848	Hannan-Quinn criter.		-4.72
F-statistic	0.229379	Durbin-Watson stat		2.21
Prob(F-statistic)	0.797956			
Inverted AR Roots	-0.12			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.033593	0.025252	-1.33034	0.202
CRS_OBS	0.063719	0.071575	0.890246	0.387
R-squared	0.047196	Mean dependent var		-0.012
Adjusted R-squared	-0.012354	S.D. dependent var		0.021
S.E. of regression	0.021255	Akaike info criterion		-4.760
Sum squared resid	0.007228	Schwarz criterion		-4.661
Log likelihood	44.84004	Hannan-Quinn criter.		-4.746
F-statistic	0.792538	Durbin-Watson stat		2.060
Prob(F-statistic)	0.386524			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.02455	0.024207	-1.01416	0.33
CRS_OBS	0.032512	0.069405	0.46844	0.65
AR(1)	-0.119542	0.246372	-0.48521	0.64
R-squared	0.031228	Mean dependent var		-0.01
Adjusted R-squared	-0.107168	S.D. dependent var		0.02
S.E. of regression	0.020913	Akaike info criterion		-4.74
Sum squared resid	0.006123	Schwarz criterion		-4.59
Log likelihood	43.27408	Hannan-Quinn criter.		-4.72
F-statistic	0.22564	Durbin-Watson stat		2.21
Prob(F-statistic)	0.800852			
Inverted AR Roots	-0.12			

Tobit Regression Results. CRS Model. Netherlands

<b>Dependent Variable: DEA_UNDER_CRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.518749	0.127464	4.069757	0.000
GDP	-0.059095	0.048278	-1.224043	0.221
CPI	0.006526	0.015202	0.429307	0.668
INDP	-0.017396	0.015864	-1.096611	0.273
UNE	0.038445	0.041296	0.930963	0.352
VAR	3.199075	2.657176	1.203938	0.229
MRA	0.082739	0.166893	0.49576	0.620
Error Distribution				
SCALE:C(8)	0.070088	0.011681	6.000001	0.000
Mean dependent var	0.476362	S.D. dependent var	0.105	
S.E. of regression	0.094034	Akaike info criterion	-1.589	
Sum squared resid	0.088423	Schwarz criterion	-1.194	
Log likelihood	22.30304	Hannan-Quinn criter.	-1.535	
Avg. log likelihood	1.239058			
Left censored obs	0	Right censored obs	0	
Uncensored obs	18	Total obs	18	

<b>Dependent Variable: CRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.377906	0.085943	4.397172	0.000
GDP	-0.040847	0.032552	-1.25484	0.210
CPI	0.004931	0.01025	0.481125	0.630
INDP	-0.011642	0.010696	-1.088392	0.276
UNE	0.025947	0.027844	0.931884	0.351
VAR	2.235245	1.791605	1.247622	0.212
MRA	0.055462	0.112528	0.492871	0.622
Error Distribution				
SCALE:C(8)	0.047257	0.007876	6.000001	0.000
Mean dependent var	0.345786	S.D. dependent var	0.072	
S.E. of regression	0.063402	Akaike info criterion	-2.378	
Sum squared resid	0.040199	Schwarz criterion	-1.982	
Log likelihood	29.39778	Hannan-Quinn criter.	-2.323	
Avg. log likelihood	1.63321			
Left censored obs	0	Right censored obs	0	
Uncensored obs	18	Total obs	18	

Tobit Regression Results. VRS Model. Netherlands.

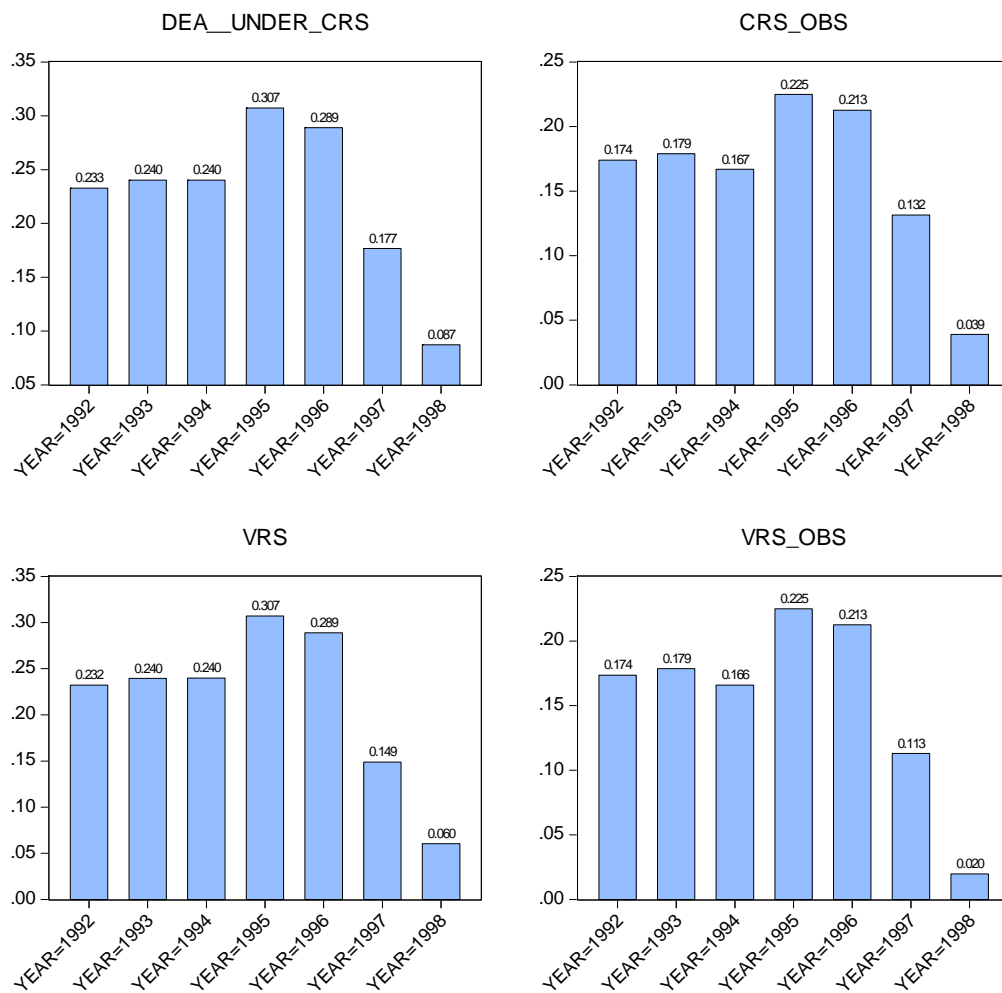
<b>Dependent Variable: VRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.215351	0.210065	1.025163	0.305
GDP	-0.010269	0.079564	-0.129062	0.897
CPI	0.021414	0.025053	0.854723	0.393
INDP	-0.008549	0.026144	-0.326997	0.744
UNE	-0.014896	0.068057	-0.218868	0.827
VAR	-5.427366	4.379105	-1.239378	0.215
MRA	-0.322398	0.275044	-1.172169	0.241
Error Distribution				
SCALE:C(8)	0.115508	0.019251	6.000001	0.000
Mean dependent var	0.262709	S.D. dependent var		0.132
S.E. of regression	0.15497	Akaike info criterion		-0.590
Sum squared resid	0.240158	Schwarz criterion		-0.194
Log likelihood	13.31059	Hannan-Quinn criter.		-0.536
Avg. log likelihood	0.739477			
Left censored obs	0	Right censored obs		0
Uncensored obs	18	Total obs		18

<b>Dependent Variable: VRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.14284	0.155365	0.919383	0.358
GDP	-0.013923	0.058846	-0.236595	0.813
CPI	0.010411	0.018529	0.56187	0.574
INDP	-0.002878	0.019336	-0.148822	0.882
UNE	0.002272	0.050335	0.045134	0.964
VAR	-2.479546	3.238812	-0.765573	0.444
MRA	-0.166935	0.203424	-0.820624	0.412
Error Distribution				
SCALE:C(8)	0.08543	0.014238	6.000001	0.000
Mean dependent var	0.185052	S.D. dependent var		0.095
S.E. of regression	0.114617	Akaike info criterion		-1.193
Sum squared resid	0.13137	Schwarz criterion		-0.798
Log likelihood	18.74007	Hannan-Quinn criter.		-1.139
Avg. log likelihood	1.041115			
Left censored obs	0	Right censored obs		0
Uncensored obs	18	Total obs		18

## Appendix X Efficiency Results: Sweden

	Inefficiency		Inefficiency		Inefficiency					
	<u>DEA</u>	<u>UNDER CRS</u>	<u>CRS OBS</u>	<u>VRS</u>	<u>VRS OBS</u>	<u>GDP</u>	<u>CPI</u>	<u>INDP</u>	<u>UNE</u>	<u>STOCK PERF</u>
Mean	0.22		0.16	0.22	0.16	0.86	1.79	5.19	7.39	0.006
Median	0.32		0.21	0.32	0.21	0.53	2.20	4.43	7.97	0.014
Maximum	0.47		0.35	0.47	0.35	2.83	4.65	13.02	8.23	0.349
Minimum	0.00		0.00	0.00	0.00	-0.23	-0.13	-0.07	5.29	-0.339
Std. Dev.	0.19		0.14	0.19	0.14	1.04	1.56	5.13	1.03	0.145
Skewness	-0.13		-0.11	-0.05	-0.02	0.90	0.51	0.52	-1.21	-0.193
Kurtosis	1.33		1.28	1.27	1.23	2.43	2.31	1.71	2.92	4.377
Jarque-Bera	2.50		2.62	2.64	2.74	3.14	1.32	2.40	5.13	1.789
Probability	0.29		0.27	0.27	0.25	0.21	0.52	0.30	0.08	0.409
Sum	4.72		3.38	4.55	3.27	18.12	37.61	109.07	155.23	0.126
Sum Sq. Dev.	0.70		0.40	0.72	0.40	21.49	48.58	526.79	21.27	0.421
Observations	21		21	21	21	21	21	21	21	21

Means by YEAR



Stock Performance and Bank Inefficiency Regression Results. Sweden.

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.003844	0.051441	-0.07473	0.941
DEA__UNDER_CRS	0.043895	0.17764	0.247102	0.808
R-squared	0.003203	Mean dependent var		0.006
Adjusted R-squared	-0.04926	S.D. dependent var		0.145
S.E. of regression	0.148624	Akaike info criterion		-0.884
Sum squared resid	0.419691	Schwarz criterion		-0.785
Log likelihood	11.28627	Hannan-Quinn criter.		-0.863
F-statistic	0.061059	Durbin-Watson stat		0.827
Prob(F-statistic)	0.80748			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	0.032565	0.06802	0.478763	0.64
DEA__UNDER_CRS	-0.023488	0.116661	-0.20133	0.84
AR(1)	0.554986	0.188817	2.939274	0.01
R-squared	0.337563	Mean dependent var		0.02
Adjusted R-squared	0.259629	S.D. dependent var		0.14
S.E. of regression	0.122715	Akaike info criterion		-1.22
Sum squared resid	0.256002	Schwarz criterion		-1.07
Log likelihood	15.20426	Hannan-Quinn criter.		-1.19
F-statistic	4.331411	Durbin-Watson stat		1.30
Prob(F-statistic)	0.030181			
Inverted AR Roots	0.55			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.00082	0.049995	-0.01641	0.987
CRS_OBS	0.042456	0.235927	0.179953	0.859
R-squared	0.001701	Mean dependent var		0.006
Adjusted R-squared	-0.050841	S.D. dependent var		0.145
S.E. of regression	0.148736	Akaike info criterion		-0.883
Sum squared resid	0.420323	Schwarz criterion		-0.783
Log likelihood	11.27046	Hannan-Quinn criter.		-0.861
F-statistic	0.032383	Durbin-Watson stat		0.824
Prob(F-statistic)	0.859095			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	0.035072	0.067534	0.519321	0.61
CRS_OBS	-0.047379	0.155667	-0.30436	0.76
AR(1)	0.555632	0.188407	2.949103	0.01
R-squared	0.339586	Mean dependent var		0.02
Adjusted R-squared	0.26189	S.D. dependent var		0.14
S.E. of regression	0.122527	Akaike info criterion		-1.22
Sum squared resid	0.25522	Schwarz criterion		-1.07
Log likelihood	15.23484	Hannan-Quinn criter.		-1.19
F-statistic	4.370711	Durbin-Watson stat		1.30
Prob(F-statistic)	0.029406			
Inverted AR Roots	0.56			

Tobit Regression Results. CRS Model. Sweden.

<b>Dependent Variable: DEA_UNDER_CRS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	0.977274	0.554442	1.762627	0.078
GDP	-0.064312	0.150467	-0.427418	0.669
CPI	-0.022225	0.042786	-0.519451	0.603
INDP	0.00562	0.009059	0.620413	0.535
UNE	-0.064645	0.062349	-1.036822	0.300
VAR	7.492246	4.652517	1.610364	0.107
MRA	0.129648	0.277582	0.467064	0.641
Error Distribution				
SCALE:C(8)	0.160427	0.024754	6.480931	0.000
Mean dependent var	0.224778	S.D. dependent var		0.187
S.E. of regression	0.203899	Akaike info criterion		-0.060
Sum squared resid	0.540471	Schwarz criterion		0.338
Log likelihood	8.630577	Hannan-Quinn criter.		0.026
Avg. log likelihood	0.41098			
Left censored obs	0	Right censored obs		0
Uncensored obs	21	Total obs		21

<b>Dependent Variable: CRS_OBS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	0.795652	0.40344	1.972166	0.049
GDP	-0.074257	0.109488	-0.678224	0.498
CPI	-0.020599	0.031133	-0.661644	0.508
INDP	0.004605	0.006592	0.69863	0.485
UNE	-0.053669	0.045368	-1.182954	0.237
VAR	6.184071	3.385409	1.826683	0.068
MRA	0.14698	0.201983	0.727686	0.467
Error Distribution				
SCALE:C(8)	0.116735	0.018012	6.480931	0.000
Mean dependent var	0.161181	S.D. dependent var		0.141
S.E. of regression	0.148367	Akaike info criterion		-0.696
Sum squared resid	0.286167	Schwarz criterion		-0.298
Log likelihood	15.30718	Hannan-Quinn criter.		-0.610
Avg. log likelihood	0.728913			
Left censored obs	0	Right censored obs		0
Uncensored obs	21	Total obs		21



Tobit Regression Results. VRS Model. Sweden.

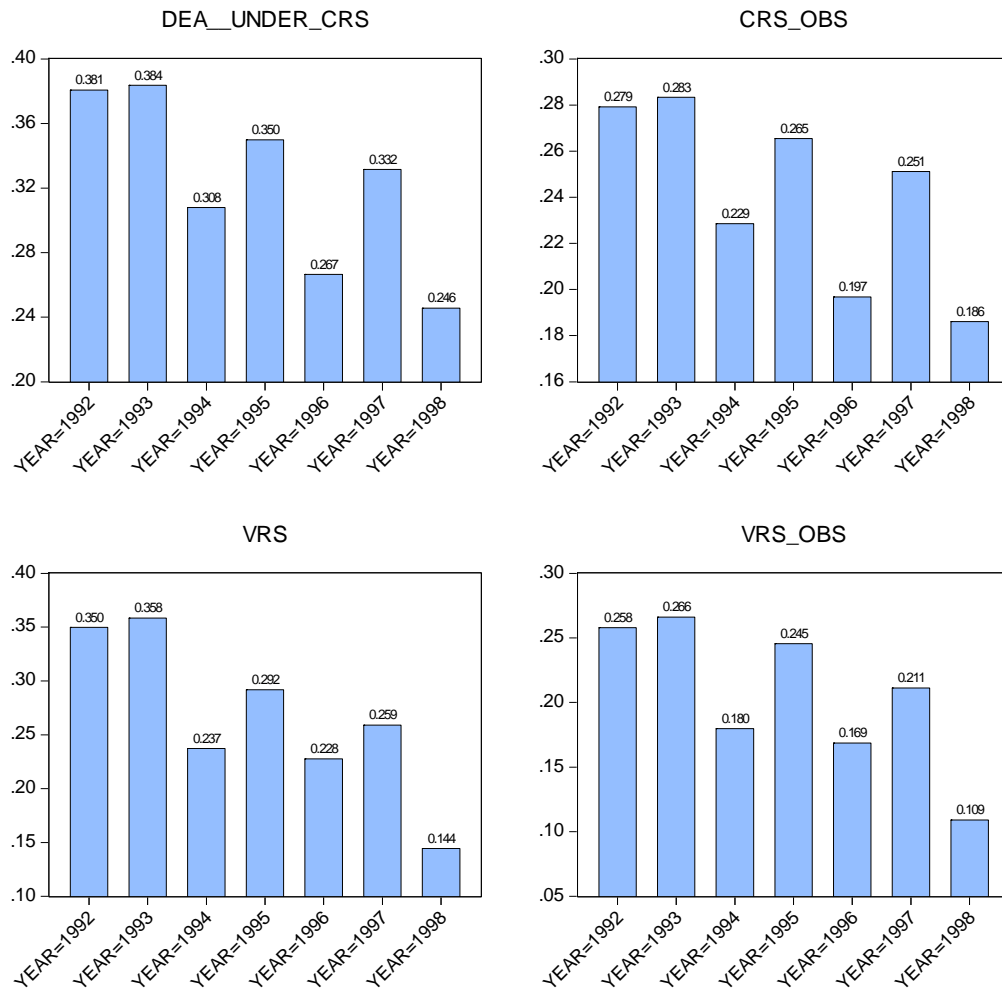
<b>Dependent Variable: VRS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	0.966133	0.54789	1.76337	0.078
GDP	-0.063636	0.148689	-0.427978	0.669
CPI	-0.022224	0.042281	-0.525639	0.599
INDP	0.005568	0.008952	0.621928	0.534
UNE	-0.063535	0.061612	-1.031212	0.302
VAR	7.390504	4.597536	1.607492	0.108
MRA	0.098941	0.274302	0.3607	0.718
Error Distribution				
SCALE:C(8)	0.158531	0.024461	6.480931	0.000
Mean dependent var	0.216711	S.D. dependent var		0.190
S.E. of regression	0.201489	Akaike info criterion		-0.084
Sum squared resid	0.527772	Schwarz criterion		0.314
Log likelihood	8.88022	Hannan-Quinn criter.		0.003
Avg. log likelihood	0.422868			
Left censored obs	0	Right censored obs		0
Uncensored obs	21	Total obs		21

<b>Dependent Variable: VRS_OBS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	0.786985	0.395997	1.987353	0.047
GDP	-0.075635	0.107467	-0.703798	0.482
CPI	-0.020898	0.030559	-0.683854	0.494
INDP	0.004581	0.00647	0.70807	0.479
UNE	-0.052681	0.044531	-1.183019	0.237
VAR	6.100833	3.322947	1.83597	0.066
MRA	0.128809	0.198256	0.64971	0.516
Error Distribution				
SCALE:C(8)	0.114581	0.01768	6.480931	0.000
Mean dependent var	0.155501	S.D. dependent var		0.142
S.E. of regression	0.14563	Akaike info criterion		-0.733
Sum squared resid	0.275704	Schwarz criterion		-0.335
Log likelihood	15.69826	Hannan-Quinn criter.		-0.647
Avg. log likelihood	0.747536			
Left censored obs	0	Right censored obs		0
Uncensored obs	21	Total obs		21

## Appendix XI Efficiency Results: Switzerland

	Inefficiency		Inefficiency		Inefficiency						
	<u>DEA</u>	<u>UNDER CRS</u>	<u>CRS</u>	<u>OBS</u>	<u>VRS</u>	<u>VRS</u>	<u>GDP</u>	<u>CPI</u>	<u>INDP</u>	<u>UNE</u>	<u>STOCK</u>
Mean	0.33		0.25		0.27	0.21	0.96	1.62	1.95	4.27	-0.020
Median	0.37		0.28		0.30	0.26	0.53	0.85	2.20	4.52	-0.021
Maximum	0.53		0.38		0.49	0.36	2.83	4.06	4.55	5.21	0.058
Minimum	0.00		0.00		0.00	0.00	-0.23	0.02	-1.95	2.55	-0.089
Std. Dev.	0.17		0.12		0.17	0.12	1.03	1.41	2.48	0.82	0.040
Skewness	-0.47		-0.58		-0.25	-0.48	0.61	0.65	-0.41	-1.05	0.103
Kurtosis	1.86		1.93		1.65	1.74	2.08	1.97	1.58	3.31	2.450
Jarque-Bera	1.99		2.26		1.90	2.30	2.14	2.55	2.48	4.10	0.316
Probability	0.37		0.32		0.39	0.32	0.34	0.28	0.29	0.13	0.854
Sum	7.21		5.39		5.93	4.60	21.23	35.53	43.00	93.92	-0.439
Sum Sq. Dev.	0.59		0.31		0.60	0.32	22.42	42.03	128.73	14.02	0.033
Observations	22		22		22	22	22	22	22	22	22

Means by YEAR



Stock Performance and Bank Inefficiency Regression Results. Switzerland.

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.021525	0.019348	-1.11251	0.279
DEA_UNDER_CRS	0.004834	0.052758	0.091625	0.928
R-squared	0.00042	Mean dependent var		-0.020
Adjusted R-squared	-0.049559	S.D. dependent var		0.040
S.E. of regression	0.040665	Akaike info criterion		-3.480
Sum squared resid	0.033073	Schwarz criterion		-3.381
Log likelihood	40.28412	Hannan-Quinn criter.		-3.457
F-statistic	0.008395	Durbin-Watson stat		2.423
Prob(F-statistic)	0.927908			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.017433	0.021137	-0.82479	0.42
DEA_UNDER_CRS	-0.004896	0.058912	-0.08312	0.93
AR(1)	-0.24625	0.231816	-1.06227	0.30
R-squared	0.061132	Mean dependent var		-0.02
Adjusted R-squared	-0.043187	S.D. dependent var		0.04
S.E. of regression	0.04093	Akaike info criterion		-3.42
Sum squared resid	0.030155	Schwarz criterion		-3.27
Log likelihood	38.93448	Hannan-Quinn criter.		-3.39
F-statistic	0.586007	Durbin-Watson stat		1.83
Prob(F-statistic)	0.566817			
Inverted AR Roots	-0.25			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.024324	0.019903	-1.22213	0.236
CRS_OBS	0.017887	0.073121	0.24462	0.809
R-squared	0.002983	Mean dependent var		-0.020
Adjusted R-squared	-0.046868	S.D. dependent var		0.040
S.E. of regression	0.040613	Akaike info criterion		-3.483
Sum squared resid	0.032989	Schwarz criterion		-3.384
Log likelihood	40.31237	Hannan-Quinn criter.		-3.460
F-statistic	0.059839	Durbin-Watson stat		2.424
Prob(F-statistic)	0.809243			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.020227	0.02179	-0.92829	0.37
CRS_OBS	0.004564	0.08168	0.055876	0.96
AR(1)	-0.247195	0.231562	-1.06751	0.30
R-squared	0.060927	Mean dependent var		-0.02
Adjusted R-squared	-0.043414	S.D. dependent var		0.04
S.E. of regression	0.040935	Akaike info criterion		-3.42
Sum squared resid	0.030162	Schwarz criterion		-3.27
Log likelihood	38.93219	Hannan-Quinn criter.		-3.39
F-statistic	0.583923	Durbin-Watson stat		1.84
Prob(F-statistic)	0.567927			
Inverted AR Roots	-0.25			

Tobit Regression Results. CRS Model. Switzerland.

<b>Dependent Variable: DEA_UNDER_CRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.149243	0.60113	0.24827	0.804
GDP	-0.082794	0.188344	-0.439589	0.660
CPI	0.041404	0.093821	0.441311	0.659
INDP	0.019399	0.025297	0.76684	0.443
UNE	0.007053	0.087027	0.081047	0.935
VAR	-4.555541	1.91362	-2.380589	0.017
MRA	0.039579	0.230454	0.171741	0.864
Error Distribution				
SCALE:C(8)	0.140453	0.021174	6.63325	0.000
Mean dependent var	0.327856	S.D. dependent var		0.168
S.E. of regression	0.176067	Akaike info criterion		-0.361
Sum squared resid	0.433996	Schwarz criterion		0.036
Log likelihood	11.96673	Hannan-Quinn criter.		-0.267
Avg. log likelihood	0.543942			
Left censored obs	0	Right censored obs		0
Uncensored obs	22	Total obs		22

<b>Dependent Variable: CRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.129099	0.424257	0.304293	0.761
GDP	-0.071218	0.132927	-0.535771	0.592
CPI	0.027237	0.066216	0.411343	0.681
INDP	0.015745	0.017854	0.88191	0.378
UNE	0.002613	0.06142	0.042544	0.966
VAR	-3.534432	1.350566	-2.617	0.009
MRA	0.039778	0.162646	0.244566	0.807
Error Distribution				
SCALE:C(8)	0.099127	0.014944	6.63325	0.000
Mean dependent var	0.245086	S.D. dependent var		0.121
S.E. of regression	0.124262	Akaike info criterion		-1.058
Sum squared resid	0.216176	Schwarz criterion		-0.661
Log likelihood	19.63313	Hannan-Quinn criter.		-0.964
Avg. log likelihood	0.892415			
Left censored obs	0	Right censored obs		0
Uncensored obs	22	Total obs		22

Tobit Regression Results. VRS Model. Switzerland.

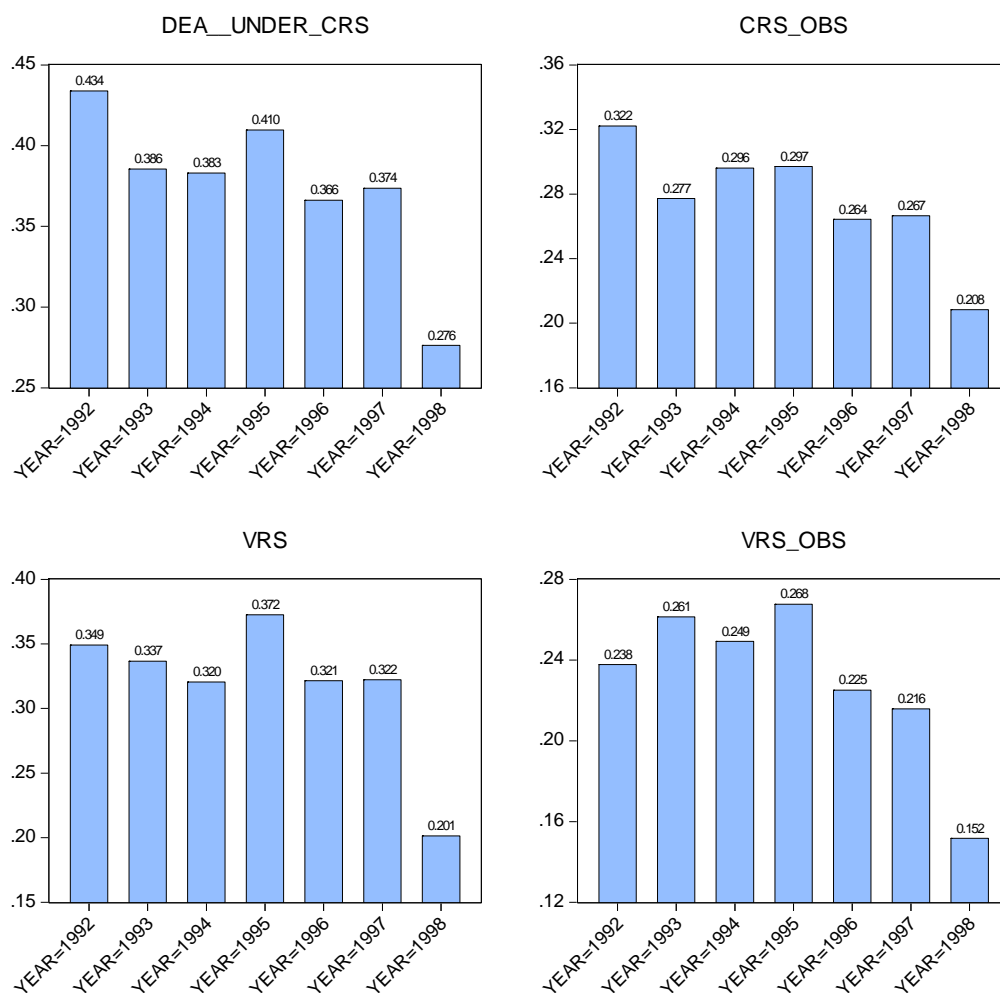
<b>Dependent Variable: VRS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	0.110428	0.572809	0.192783	0.847
GDP	-0.105868	0.179471	-0.589888	0.555
CPI	0.040972	0.089401	0.45829	0.647
INDP	0.015756	0.024105	0.653626	0.513
UNE	0.008779	0.082927	0.105866	0.916
VAR	-4.446588	1.823465	-2.438538	0.015
MRA	0.057857	0.219597	0.263467	0.792
Error Distribution				
SCALE:C(8)	0.133836	0.020177	6.63325	0.000
Mean dependent var	0.26949	S.D. dependent var		0.169
S.E. of regression	0.167772	Akaike info criterion		-0.457
Sum squared resid	0.394066	Schwarz criterion		-0.060
Log likelihood	13.02841	Hannan-Quinn criter.		-0.364
Avg. log likelihood	0.592201			
Left censored obs	0	Right censored obs		0
Uncensored obs	22	Total obs		22

<b>Dependent Variable: VRS_OBS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	0.174831	0.397242	0.440114	0.660
GDP	-0.128168	0.124463	-1.029773	0.303
CPI	0.016247	0.061999	0.262046	0.793
INDP	0.0187	0.016717	1.118599	0.263
UNE	-0.00588	0.057509	-0.102253	0.919
VAR	-3.767484	1.264567	-2.979268	0.003
MRA	0.089644	0.15229	0.588642	0.556
Error Distribution				
SCALE:C(8)	0.092815	0.013992	6.63325	0.000
Mean dependent var	0.209184	S.D. dependent var		0.124
S.E. of regression	0.11635	Akaike info criterion		-1.189
Sum squared resid	0.189521	Schwarz criterion		-0.792
Log likelihood	21.0806	Hannan-Quinn criter.		-1.096
Avg. log likelihood	0.958209			
Left censored obs	0	Right censored obs		0
Uncensored obs	22	Total obs		22

## Appendix XII Efficiency Results: United Kingdom

	Inefficiency		Inefficiency		Inefficiency					
	<u>DEA</u>	<u>UNDER CRS</u>	<u>CRS OBS</u>	<u>VRS</u>	<u>VRS OBS</u>	<u>GDP</u>	<u>CPI</u>	<u>INDP</u>	<u>UNE</u>	<u>STOCK PERF</u>
Mean	0.38		0.28	0.32	0.23	2.76	2.47	2.04	7.57	0.025
Median	0.46		0.34	0.40	0.27	2.95	2.48	1.37	7.62	0.027
Maximum	0.56		0.41	0.55	0.43	4.30	4.31	5.37	9.73	0.120
Minimum	0.00		0.00	0.00	0.00	0.23	1.57	0.39	4.49	-0.058
Std. Dev.	0.19		0.14	0.18	0.14	1.17	0.81	1.58	1.85	0.048
Skewness	-1.23		-1.26	-0.81	-0.58	-0.99	1.30	1.39	-0.46	0.297
Kurtosis	2.97		3.05	2.35	2.05	3.61	3.93	3.64	1.81	2.431
Jarque-Bera	7.76		8.15	3.96	2.91	5.55	9.80	10.52	2.91	0.874
Probability	0.02		0.02	0.14	0.23	0.06	0.01	0.01	0.23	0.646
Sum	11.69		8.60	9.92	7.21	85.53	76.45	63.11	234.53	0.761
Sum Sq. Dev.	1.08		0.57	0.93	0.60	40.78	19.79	74.43	103.18	0.070
Observations	31		31	31	31	31	31	31	31	31

Means by YEAR



Stock Performance and Bank Inefficiency Regression Results. United Kingdom

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	0.019917	0.01986	1.002889	0.324
DEA__UNDER_CRS	0.012284	0.047207	0.260215	0.797
R-squared	0.002329	Mean dependent var		0.025
Adjusted R-squared	-0.032073	S.D. dependent var		0.048
S.E. of regression	0.049012	Akaike info criterion		-3.131
Sum squared resid	0.069664	Schwarz criterion		-3.039
Log likelihood	50.53288	Hannan-Quinn criter.		-3.101
F-statistic	0.067712	Durbin-Watson stat		1.337
Prob(F-statistic)	0.796536			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	0.027321	0.020496	1.333	0.19
DEA__UNDER_CRS	-0.002722	0.043109	-0.06315	0.95
AR(1)	0.326849	0.181108	1.804721	0.08
R-squared	0.107036	Mean dependent var		0.03
Adjusted R-squared	0.040891	S.D. dependent var		0.05
S.E. of regression	0.047286	Akaike info criterion		-3.17
Sum squared resid	0.06037	Schwarz criterion		-3.03
Log likelihood	50.55875	Hannan-Quinn criter.		-3.13
F-statistic	1.618191	Durbin-Watson stat		1.69
Prob(F-statistic)	0.216899			
Inverted AR Roots	0.33			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	0.02258	0.020024	1.12766	0.269
CRS_OBS	0.0071	0.064827	0.109527	0.914
R-squared	0.000413	Mean dependent var		0.025
Adjusted R-squared	-0.034055	S.D. dependent var		0.048
S.E. of regression	0.049059	Akaike info criterion		-3.129
Sum squared resid	0.069797	Schwarz criterion		-3.037
Log likelihood	50.50315	Hannan-Quinn criter.		-3.099
F-statistic	0.011996	Durbin-Watson stat		1.323
Prob(F-statistic)	0.913539			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	0.029164	0.020488	1.423517	0.17
CRS_OBS	-0.010444	0.058337	-0.17903	0.86
AR(1)	0.3307	0.180621	1.830906	0.08
R-squared	0.107933	Mean dependent var		0.03
Adjusted R-squared	0.041854	S.D. dependent var		0.05
S.E. of regression	0.047262	Akaike info criterion		-3.17
Sum squared resid	0.060309	Schwarz criterion		-3.03
Log likelihood	50.57382	Hannan-Quinn criter.		-3.13
F-statistic	1.633391	Durbin-Watson stat		1.69
Prob(F-statistic)	0.213977			
Inverted AR Roots	0.33			

Tobit Regression Results. CRS Model. United Kingdom

<b>Dependent Variable: DEA_UNDER_CRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	-0.387057	2.227416	-0.17377	0.862
GDP	0.079089	0.328236	0.240952	0.810
CPI	0.143065	0.279126	0.512548	0.608
INDP	-0.013973	0.141733	-0.09859	0.922
UNE	0.036684	0.117049	0.31341	0.754
VAR	3.204135	4.447276	0.720472	0.471
MRA	0.222027	0.373827	0.593929	0.553
Error Distribution				
SCALE:C(8)	0.180669	0.022944	7.874273	0.000
Mean dependent var	0.377116	S.D. dependent var	0.190	
S.E. of regression	0.209749	Akaike info criterion	-0.068	
Sum squared resid	1.011879	Schwarz criterion	0.302	
Log likelihood	9.056723	Hannan-Quinn criter.	0.052	
Avg. log likelihood	0.292152			
Left censored obs	0	Right censored obs	0	
Uncensored obs	31	Total obs	31	

<b>Dependent Variable: CRS_OBS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	-0.193242	1.619171	-0.119347	0.905
GDP	0.042012	0.238604	0.176074	0.860
CPI	0.102459	0.202905	0.504963	0.614
INDP	0.003444	0.10303	0.033424	0.973
UNE	0.018283	0.085086	0.214881	0.830
VAR	2.336398	3.23285	0.722705	0.470
MRA	0.152134	0.271746	0.55984	0.576
Error Distribution				
SCALE:C(8)	0.131333	0.016679	7.874273	0.000
Mean dependent var	0.277372	S.D. dependent var	0.138	
S.E. of regression	0.152472	Akaike info criterion	-0.706	
Sum squared resid	0.5347	Schwarz criterion	-0.336	
Log likelihood	18.94348	Hannan-Quinn criter.	-0.585	
Avg. log likelihood	0.61108			
Left censored obs	0	Right censored obs	0	
Uncensored obs	31	Total obs	31	



Tobit Regression Results. VRS Model. United Kingdom.

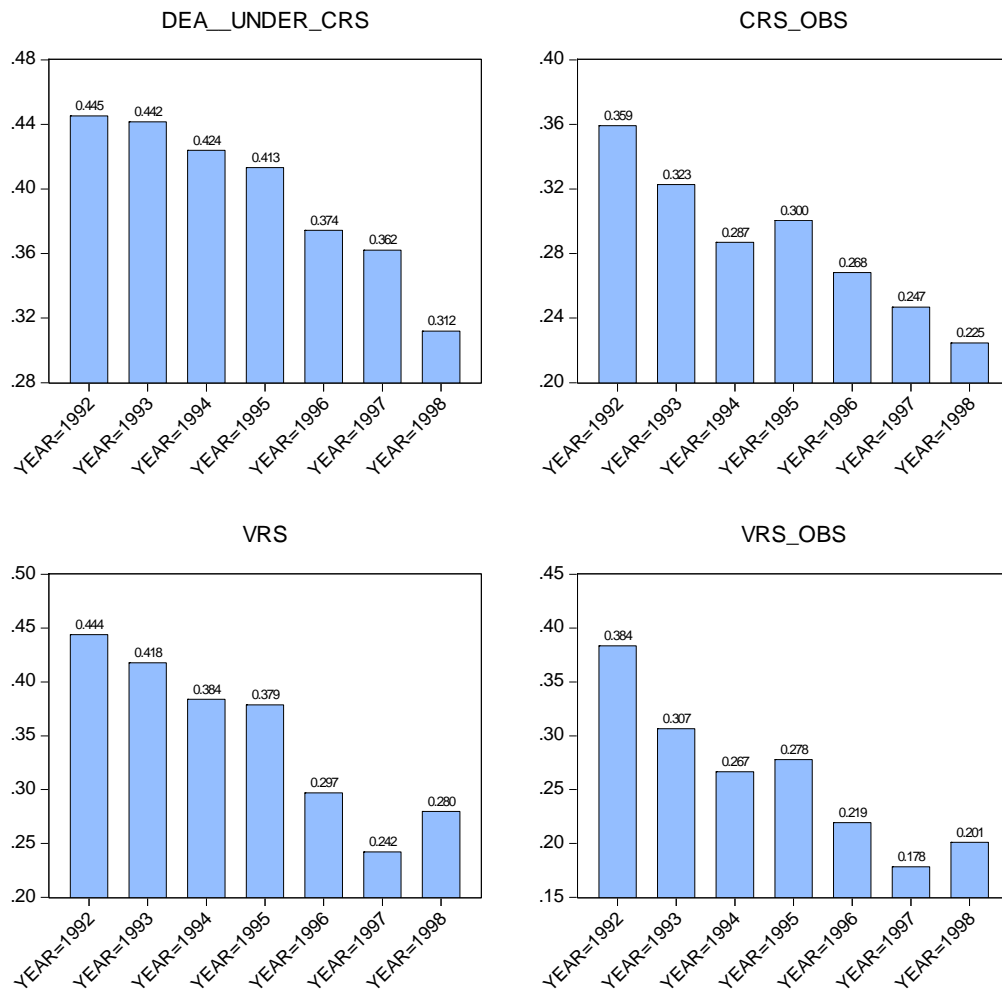
<b>Dependent Variable: VRS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	-0.599503	2.019082	-0.296919	0.767
GDP	0.107659	0.297535	0.361835	0.718
CPI	0.16041	0.253019	0.633982	0.526
INDP	-0.028251	0.128476	-0.219896	0.826
UNE	0.050692	0.106101	0.477771	0.633
VAR	4.913224	4.031316	1.218764	0.223
MRA	0.289266	0.338863	0.853639	0.393
Error Distribution				
SCALE:C(8)	0.16377	0.020798	7.874273	0.000
Mean dependent var	0.320129	S.D. dependent var		0.176
S.E. of regression	0.190131	Akaike info criterion		-0.265
Sum squared resid	0.831444	Schwarz criterion		0.105
Log likelihood	12.10089	Hannan-Quinn criter.		-0.144
Avg. log likelihood	0.390351			
Left censored obs	0	Right censored obs		0
Uncensored obs	31	Total obs		31

<b>Dependent Variable: VRS_OBS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	-0.35135	1.625805	-0.216108	0.829
GDP	0.062289	0.239581	0.259992	0.795
CPI	0.089225	0.203736	0.437942	0.661
INDP	-0.014155	0.103452	-0.136825	0.891
UNE	0.040246	0.085435	0.471075	0.638
VAR	3.901317	3.246096	1.201849	0.229
MRA	0.210548	0.272859	0.771638	0.440
Error Distribution				
SCALE:C(8)	0.131871	0.016747	7.874273	0.000
Mean dependent var	0.232676	S.D. dependent var		0.141
S.E. of regression	0.153097	Akaike info criterion		-0.698
Sum squared resid	0.53909	Schwarz criterion		-0.328
Log likelihood	18.81672	Hannan-Quinn criter.		-0.577
Avg. log likelihood	0.606991			
Left censored obs	0	Right censored obs		0
Uncensored obs	31	Total obs		31

## Appendix XII Efficiency Results: United States

	Inefficiency		Inefficiency		Inefficiency					
	<u>DEA</u>	<u>UNDER CRS</u>	<u>CRS OBS</u>	<u>VRS</u>	<u>VRS OBS</u>	<u>GDP</u>	<u>CPI</u>	<u>INDP</u>	<u>UNE</u>	<u>STOCK PERF</u>
Mean	0.39		0.28	0.35	0.26	3.58	2.57	0.42	5.80	-0.017
Median	0.39		0.28	0.35	0.26	3.70	2.81	0.33	5.59	0.000
Maximum	0.83		0.57	0.82	0.56	4.50	3.03	0.67	7.49	0.117
Minimum	0.00		0.00	0.00	0.00	2.53	1.55	0.23	4.50	-0.256
Std. Dev.	0.12		0.09	0.15	0.11	0.71	0.50	0.15	1.00	0.071
Skewness	0.41		0.21	0.22	0.07	-0.30	-1.13	0.50	0.40	-1.259
Kurtosis	6.68		5.12	4.31	3.40	1.63	2.93	1.80	1.93	4.674
Jarque-Bera	91.14		29.90	12.18	1.12	14.49	32.87	15.70	11.50	58.683
Probability	0.00		0.00	0.00	0.57	0.00	0.00	0.00	0.00	0.000
Sum	60.62		43.87	53.27	39.92	551.55	395.23	63.95	892.50	-2.557
Sum Sq. Dev.	2.21		1.22	3.42	1.95	78.14	38.76	3.58	152.21	0.766
Observations	154		154	154	154	154	154	154	154	154

Means by YEAR



## Stock Performance and Bank Inefficiency Regression Results. United States

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.022383	0.019638	-1.13983	0.256
DEA_UNDER_CRS	0.014683	0.047722	0.307673	0.759
R-squared	0.000622	Mean dependent var		-0.017
Adjusted R-squared	-0.005952	S.D. dependent var		0.071
S.E. of regression	0.070973	Akaike info criterion		-2.440
Sum squared resid	0.765651	Schwarz criterion		-2.401
Log likelihood	189.8901	Hannan-Quinn criter.		-2.424
F-statistic	0.094662	Durbin-Watson stat		1.380
Prob(F-statistic)	0.758753			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.015693	0.018973	-0.82716	0.41
DEA_UNDER_CRS	-0.003114	0.043811	-0.07109	0.94
AR(1)	0.31124	0.077736	4.003787	0.00
R-squared	0.096705	Mean dependent var		-0.02
Adjusted R-squared	0.084661	S.D. dependent var		0.07
S.E. of regression	0.067834	Akaike info criterion		-2.52
Sum squared resid	0.690221	Schwarz criterion		-2.46
Log likelihood	196.0928	Hannan-Quinn criter.		-2.50
F-statistic	8.029342	Durbin-Watson stat		2.05
Prob(F-statistic)	0.000487			
Inverted AR Roots	0.31			

Dependent Variable: STOCK_PERF				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.02243	0.019195	-1.16855	0.244
CRS_OBS	0.020453	0.064317	0.318004	0.751
R-squared	0.000665	Mean dependent var		-0.017
Adjusted R-squared	-0.00591	S.D. dependent var		0.071
S.E. of regression	0.070972	Akaike info criterion		-2.440
Sum squared resid	0.765618	Schwarz criterion		-2.401
Log likelihood	189.8933	Hannan-Quinn criter.		-2.424
F-statistic	0.101126	Durbin-Watson stat		1.381
Prob(F-statistic)	0.750919			

<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>t-Statistic</u>	<u>Prob.</u>
C	-0.013723	0.019052	-0.72032	0.47
CRS_OBS	-0.011254	0.060959	-0.18462	0.85
AR(1)	0.312249	0.077699	4.018717	0.00
R-squared	0.096879	Mean dependent var		-0.02
Adjusted R-squared	0.084837	S.D. dependent var		0.07
S.E. of regression	0.067828	Akaike info criterion		-2.52
Sum squared resid	0.690088	Schwarz criterion		-2.46
Log likelihood	196.1075	Hannan-Quinn criter.		-2.50
F-statistic	8.045307	Durbin-Watson stat		2.05
Prob(F-statistic)	0.00048			
Inverted AR Roots	0.31			

Tobit Regression Results. CRS Model. United States

<b>Dependent Variable: DEA_UNDER_CRS</b>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.366038	0.196011	1.867436	0.062
GDP	-0.058936	0.042368	-1.391028	0.164
CPI	-0.028699	0.057329	-0.500604	0.617
INDP	0.23722	0.163074	1.454673	0.146
UNE	0.032875	0.015698	2.094261	0.036
VAR	-2.060946	1.11063	-1.855655	0.064
MRA	-0.029971	0.044364	-0.675574	0.499
Error Distribution				
SCALE:C(8)	0.109518	0.00624	17.55015	0.000
Mean dependent var	0.393663	S.D. dependent var	0.120	
S.E. of regression	0.112478	Akaike info criterion	-1.482	
Sum squared resid	1.847103	Schwarz criterion	-1.324	
Log likelihood	122.0802	Hannan-Quinn criter.	-1.417	
Avg. log likelihood	0.792729			
Left censored obs	0	Right censored obs	0	
Uncensored obs	154	Total obs	154	

<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>
C	0.033309	0.138161	0.241085	0.810
GDP	-0.004303	0.029864	-0.144091	0.885
CPI	0.026382	0.04041	0.652871	0.514
INDP	-0.033377	0.114946	-0.290372	0.772
UNE	0.032239	0.011065	2.913615	0.004
VAR	-1.520841	0.782846	-1.942709	0.052
MRA	0.00589	0.031271	0.188353	0.851
Error Distribution				
SCALE:C(8)	0.077195	0.004399	17.55015	0.000
Mean dependent var	0.284885	S.D. dependent var	0.089	
S.E. of regression	0.079282	Akaike info criterion	-2.181	
Sum squared resid	0.917708	Schwarz criterion	-2.023	
Log likelihood	175.9413	Hannan-Quinn criter.	-2.117	
Avg. log likelihood	1.142476			
Left censored obs	0	Right censored obs	0	
Uncensored obs	154	Total obs	154	

Tobit Regression Results. VRS Model. United States

<b>Dependent Variable: VRS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	0.377819	0.231712	1.630556	0.103
GDP	-0.050341	0.050085	-1.005113	0.315
CPI	-0.10557	0.067771	-1.557736	0.119
INDP	0.107445	0.192776	0.557358	0.577
UNE	0.062526	0.018557	3.369427	0.001
VAR	-2.616397	1.312917	-1.992812	0.046
MRA	-0.091303	0.052444	-1.740944	0.082
Error Distribution				
SCALE:C(8)	0.129465	0.007377	17.55015	0.000
Mean dependent var	0.345891	S.D. dependent var		0.150
S.E. of regression	0.132965	Akaike info criterion		-1.147
Sum squared resid	2.58123	Schwarz criterion		-0.989
Log likelihood	96.31234	Hannan-Quinn criter.		-1.083
Avg. log likelihood	0.625405			
Left censored obs	0	Right censored obs		0
Uncensored obs	154	Total obs		154

<b>Dependent Variable: VRS_OBS</b>				
<u>Variable</u>	<u>Coefficient</u>	<u>Std. Error</u>	<u>z-Statistic</u>	<u>Prob.</u>
C	-0.097043	0.164462	-0.590059	0.555
GDP	0.022271	0.035549	0.626489	0.531
CPI	0.00017	0.048102	0.003529	0.997
INDP	-0.180041	0.136827	-1.315831	0.188
UNE	0.058027	0.013171	4.405567	0.000
VAR	-1.265811	0.931872	-1.358353	0.174
MRA	-0.017736	0.037224	-0.476476	0.634
Error Distribution				
SCALE:C(8)	0.091891	0.005236	17.55015	0.000
Mean dependent var	0.259226	S.D. dependent var		0.113
S.E. of regression	0.094375	Akaike info criterion		-1.833
Sum squared resid	1.300363	Schwarz criterion		-1.675
Log likelihood	149.1053	Hannan-Quinn criter.		-1.768
Avg. log likelihood	0.968216			
Left censored obs	0	Right censored obs		0
Uncensored obs	154	Total obs		154

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