Bank Capital Regulation:
A Comparison of Risk Measurements Based on The GVAR Model

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A Thesis Submitted in Fulfilment of the Requirements for the
Degree of Doctor of Philosophy of Cardiff University

February 2019

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Acknowledgements

I would like to acknowledge this thesis to my loving parents and husband for their extraordinary support. Many thanks and appreciations to my supervisors Dr Woon Wong and Dr Zhirong Ou who provide expert advice and encouragement throughout the research process. This thesis would have been impossible without the support of Professor Konstantinos Theodoridis, Professor Patrick Minford and Julian Hodge scholarship. Also, I am grateful to all the colleagues in B48 for their excellent collaboration and inspiration.

Abstract

Risk measures are the core indicator of risk management and a proper risk assessment model is essential for successful financial institutions. Value at Risk and Expected Shortfall are the two most popular and acceptable risk measurement methods presently employed to assess risks in the financial market. In the past few years, researchers have attempted to demonstrate that Expected Shortfall performs better against the traditional Value at Risk method. However, the lack of elicitability and difficult backtesting of this method suggest that the popularisation of ES might be gradual. This thesis will present a comparison of these two methods not only from a traditional perspective, such as the measurement of tail risk, but also form the perspective of risk capital requirement. Through Historical Simulation and Filtered Historical Simulation, it concludes that switching from Value at Risk to Expected Shortfall method would reduce risk capital requirement and enhance financial leverage of organisations. Additionally, this research also combines macroeconomic elements, the financial market and central banks, and analyses the influence of a positive leverage shock on the macro-economy through a Global Vector Autoregression model.

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Nomenclature

Acronyms / Abbreviations

BCBS Basel Committee on Banking Supervision

CAR Capital Adequacy Ratio

CES Capital Requirement of Expected Shortfall

RCES Risk Capital of Expected Shortfall

CVaR Capital Requirement of Value at Risk

RCVaR Risk Capital of Value at Risk

DR Deposit Rate

ES Expected Shortfall

EWMA Equally Weighted Moving Average

FHS Filtered Historical Simulation

GHOS Group of Governors and Heads of Supervision

GVAR Global Vector Autoregression

HPI Housing Price Index

HS Historical Simulation

IMA Internal Models-Approach

IPD GDP Deflater

LIR Loan Interest Rate

LTIR Long-term Interest Rate

MCS-GVAR Mixed-Cross-Section Global Vector Autoregression

MCS Monte Carlo Simulation

POD Probability of Default

RMSE RiskMetrics Standard Error

STPR Short-term Policy Rate

SVAR Structural Vector Autoregression

VaR Value at Risk

VC Variance-Covariance

Chapter 1

Introduction

1.1 Motivation

Risk measure is the core indicator of risk management and a proper risk assessment model is essential for successful financial institutions. Value at Risk and Expected Shortfall are the two most popular and acceptable risk measurement methods employed to assess financial market risk now-days. VaR is a traditional risk measure that has been widely accepted and used by financial institutions. While ES is an alternative risk measure that is conceptually superior to VaR in numerous aspects, especially, with regard to its sensitivity towards tail risk. However, it has been criticised for the difficulty it presents in backtesting. Since neither of the methods are perfect, the question arises: if only one method is to be employed to describe the risk in a particular situation, which one of the two presents the best alternative?

Risk management protects individuals from various risks such as credit, market, liquidity and operational risks. This study focuses on market risk measurement and the management of the banking sector. Dionne (2013) indicated that risk management should encompass more than mere control and reduction of the impact of risks, diminishing costs related to various risks and maximisation of firm value. It is vital that effective risk management also enhance a bank's capital structure by accurately forecasting risks.

To improve the stability of the financial market, banks must follow the minimum capital requirement regulation which is stated by the Basel Committee on Banking Supervision (BCBS). The minimum capital requirement, also known as capital adequacy, is the amount of capital banks require to hold in the form of a percentage of risk-weighted assets and is calculated using a risk assessment model. BCBS shifted its quantitative internal risk model from VaR to ES in its 2013 revision which stated that: "some weaknesses have been identified with using VaR for determining regulatory capital requirements, including its inability to capture tail risk" (BCBS, 2013). Although the reform has been proposed, the extensive application of ES will still require a long time due to the difficulty involved in its backtesting. Furthermore, the costs and potential impact of this method on financial institutions may be significant because this reformation requires substantial modifications in the size and distribution of capital requirement. Adequate capital reserves have become a significant concern, in partocular, after the international banking crisis of 2007-2008. Miles et al. (2013) demonstrated that regulators and banks agree that under equal conditions, efficient distribution of capital charges is preferred. The allocation of daily capital charges generally depends on two aspects: (1) the risk measures (ES versus VaR); and (2) the penalty multiplier. Therefore, banks can improve capital liquidity through the precise capturing and forecasting of risks.

In discussing the merits and consequences of VaR and ES I am taking a probabilistic approach to risk – a view that risk can be captured by a probability distribution constructed from historic observations. This is the basis of ES and VaR and also of the treatment of risk in a wide range of contexts in, and, beyond finance. I recognise that this is controversial in some quarters. Keynes, for example, who understood a great deal about financial markets in both theory and practice, famously wrote: By "uncertain" knowledge, let me explain, I do not mean merely to distinguish what is known for certain from what is only probable. The game of roulette is not subject, in this sense, to uncertainty; nor is the prospect of a Victory bond being drawn. Or, again, the expectation of life is only slightly uncertain. Even the weather is only moderately uncertain. The sense in which I am using the term is that in which the prospect of a European war is uncertain, or the price of copper and the rate of interest twenty years hence, or the obsolescence of a new invention, or the position of private wealth-owners in the social system in 1970. About these matters there is no scientific basis on which to form any calculable probability whatever. We simply do not know (Keynes, 1937). Much the same distinction had been made earlier by Knight (1921) and formed a central theme of Shackle's later work (e.g. Shackle, 2017). The argument that the past cannot be used to estimate the likelihood of future events features currently in the work of Paul Davidson (2010) and other Post-Keynesians. However, I am here concerned with the merits of VaR and ES and their application in a context within which a probabilistic approach to risk is widely-accepted.

1.2 Structure and Methodology

An argument has been raised concerning the risk measures that perform better in practice. This thesis presents a comparison between VaR and ES methods through three perspectives.

The background chapter introduces the financial environment of modern risk management that includes the global economic conditions, development and reforms of the Basel Accord and some basic concepts concerning risk management. The background chapter further offers an outline of risk management and emphasises the significance of using proper risk measures.

The comparison starts from the theoretical level in the following chapter. I compare VaR and ES in terms of their numerous mathematical properties such as coherence, robustness and elicitability[1]. Moreover, their capacities for backtesting and sensitivity against tail risk[2] are also examined in this chapter.

To consider the perspective of optimal bank capital, I utilise the data from 25 most representative banks from G7 countries for the year 2017 in chapter 3. An empirical comparison of VaR and ES is subsequently conducted via Historical Simulation and Filtered Historical Simulation. Meanwhile, the backtesting of both measures is tested according to the Basel Accord requirement. Since ES is difficult to backtest, I test the efficiency of ES based on VaR. Furthermore, I compare the capital requirements of VaR and ES using the outcomes of HS and FHS respectively as well as their backtesting counterparts.

In the final chapter, a Global Vector Autoregressive (GVAR) model is applied to link the macro-economy, financial market and central bank together. This chapter also discusses the correlation between risk measures, risk capital requirement and leverage ratio. Theoretically, risk reflects not only through stock prices but also through the leverage ratio. A shift in risk measure could effect a change in leverage ratio. The GVAR model estimates the way in which the change in leverage ratio impacts the macro-economy through the switch between

[1]The definition of coherence, elicitability, and robustness will be explained in Section 3.5 Page 25, 29 and 31 in detail.

[2]The property of tail risk and backtesting will be discussed in Page 28 and 30 respectively.

risk measures, from VaR to ES. I selected the data in G7 countries to produce the estimation and forecasting via the GVAR model. Furthermore, a sign restriction approach is applied to identify the structural shock.

1.3 Contribution

Although several researchers in the past have studied the comparison of VaR and ES, this thesis considers this question from a new perspective. First, previous research works concentrated the comparison of the values of VaR and ES themselves, while I begin with the point of minimum capital requirement. The distribution of capital is crucial in risk management. The Basel Accord makes a clear statement regarding the minimum capital requirement of banks that are based on the risk measurement model. With regard to the values of VaR and ES, ES is conceptually superior to VaR. However, the consequence may be inverse when the risk capital requirements are calculated. It is essential to study the value of capital requirements because setting capital requirement is a major task for regulators, and banks as well as the macroeconomy benefit from an optimal bank capital arrangement.

Moreover, there is rising concern with regard to the association between macroeconomics and financial market, especially after the financial crisis of 2007. Economics constitutes a comprehensive section that comprises both macroeconomics and finance. While macroeconomics refers to behaviours of large segments of markets or countries, finance denotes the specific ways in which money is created and managed. The previous studies focused on the influence of risk measures in relation to the financial market alone, while this thesis links macroeconomics, financial market and central banks together across the GVAR model.

Lastly, I outline the properties of risk measures and summarise the comparison with regard to different features.

Chapter 2

Background

2.1 Global Environment

From the end of 1970, the disorganisation of the Bretton Woods System and the oil price shock caused severe problems for the global economy. Meanwhile, an increasing interaction of goods, services and financial markets stimulated economic expansion and brought about the development of international capital flows and information exchange, exerting an interactive influence on financial markets. In a global market under such conditions, economic agents also become vulnerable to additional financial risks, such as inflation, increasing capital cost, and unstable prices, which slowed down the pace of economic growth. Moreover, the escalating financial risks in different markets raised fluctuations in the global market. This scenario makes stakeholders gradually understand the necessity and urgency required to ensure proper risk management. Furthermore, topics such as financial risk measurement and economic capital have become the core concerns in research.

In the changing financial environment, the current financial market is more complicated compared to the situation of Basel I. The Basel Committee focused on regular cooperation in banking supervision. Basel I regulation initially demonstrated that capital operation brings risks and the risk level of capital always changes. Following this, Basel II regulation offered updated insight, stating that capital adequacy, supervision and inspection of the supervision department and market discipline form the three pillars of risk management. However, the crisis proved that risk management systems are marked by severe limitations.

A supervisory framework for the application of backtesting in conjunction with the internal models approaches and the market risk capital requirements are needed. The BCBS supplemented an incremental risk capital charge with the VaR-based framework, obtaining the default risk and migration risk, for unsecuritized credit products. It is worth mentioning that after Basel III, the Committee changed the internal risk measurement model from VaR to ES.

2.2 The Innovation of Basel Regulation

A banking crisis is defined as “cases where there were runs or other substantial portfolio shifts, collapses of financial firms or massive government intervention. Extensive unsoundness short of crisis is termed significant”(Calomiris, 2009). One possible reason behind bank crisis might be the banking sector’s inherent fragility.

Calomiris (2009) summarised some possible causes behind the occurrence of a banking crisis. First, it can be caused if the increase in asset price turns out to be unstable. Furthermore, credit booms can lead to the creation of a debt burden for the bank. Moreover, marginal loans create systemic risk as well. And lastly, a bank crisis may be caused by the failure of regulation and supervision to keep pace with financial innovation.

As for the reasons provided, especially the last one, it appeared necessary to establish a formal department to supervise market standards. The Basel Committee was established in 1974 by the central bank Governors of the Group of Ten countries and has presently expanded its members to 45 countries. The aim to set up the Basel Committee was to enhance the stability of the financial market via the standardisation and escalation of the global regulation for banking supervision. It was serving as a forum which allows the cooperation between member countries. A series of international regulations have been published by the Committee to standardise banking systems, most remarkable is the publications of the accords concerning capital adequacy referred to as Basel I, Basel II, and Basel III.

2.2.1 Basel I: The Basel Capital Accord

With the opening up of capital flow, capital adequacy became a crucial factor in banking supervision. The debt crisis in the early 1980s in Latin America intensified the Committee's concern that with the increasing global risks, the capital ratios of leading international banks could be deteriorating.

According to the comments on a advisory paper which was published in December 1987, a capital measurement system was approved by the G10 Governors as the Basel Capital Accord and it was released to banks in July 1988.

In this Accord, a base proportion of money was required to perform the possible weighted resources of 8% before the end of 1992. The structure was presented in member nations as well as in practically all countries with active global banks.

Constant planning was done for the Accord's development. It was rectified in November 1991 to all characterise with more unequivocal agreements that the general arrangements or credit savings could be included in the capital sufficiency computation. The BCBS issued another modification in April 1995 which perceives the effect of the two-side mesh of bank's credit exposures. Moreover, the 1995 amendment also extend the network of additional factors. In April 1996, some documents were issued to explain the way in which how the Committee members admit the influence of multilateral netting.

2.2.2 Basel II: The New Capital Framework

The Committee issued a subject for another capital sufficiency structure to replace the 1988 Accord in June 1999. This proposal facilitated the release of a revised capital framework in June 2004. Commonly referred to "Basel II", the revised structure comprised three pillars (BCBS, 2004):

1. minimum capital requirements, which sought to develop and expand the standardised rules proposed in the 1988 Accord;

2. supervisory survey of an institution's capital adequacy and interior evaluation process;

3. effective utilisation of disclosure as a lever to reinforce market discipline and support sound banking practices.

The committee improves the capital adequacy requirement by increasing the core tier 1 capital adequacy ratio and minimum requirements. Capital requirement is the measure of wealth that an organisation, usually those in financial services, require to ensure that the company remains solvent in view of its risk profile. It constitutes the estimation of capital that the firm should possess to arrange support for any risks that it takes; it is measured through the internal model. The revised framework which was issued in June 2004, the Basel Committee concentrates on the development of capital requirement after the original version. The updated structure was intended to strengthen the regulatory capital requirement which could help to meet the financial innovation and challenge during recent years. Those changes target rewarding and encouraging continuous improvement in risk measurement and management.

2.2.3 Basel III: Post-Crisis Regulatory Reforms

Basel III was designed in response to the financial crisis of 2007-2009. The banking system suffered the financial crisis with an excessive and considerable amount of leverage and inadequate liquidity buffers. These deficiencies brought the banks unsufficient administration, risk management as well as motivation structures. The Group of Governors and Heads of Supervision (GHOS) reported higher global minimum capital requirement for commercial banks in September 2010, which followed an assertion agreed to in July with regard to the general outline of the changes in capital and liquidity requirements which is now referred to as "Basel III" (BCBS, 2010). The new capital standards were accepted in the G20 Leaders' Summit in November 2010 and subsequently consensus on it was gained at the December 2010 Basel Committee meeting.

In the Basel III, the reform packages are listed as follows (BCBS, 2010):

- an additional layer of common equity - the capital conservation buffer that when breached, restricts payouts to facilitate satisfying the minimum common equity requirement;

- a countercyclical capital buffer, which places restrictions on participation by banks in system-wide credit booms with the aim to reduce their losses in credit busts;

- a leverage ratio, - a minimum amount of loss-absorbing capital relative to a bank's total assets and off-balance sheet exposures regardless of risk weightage;

- liquidity requirements, - a minimum liquidity ratio, the Liquidity Coverage Ratio (LCR), intended to provide sufficient cash to cover funding requirements over a 30-day period; and a longer-term ratio, the Net Stable Funding Ratio (NSFR), aimed to address maturity discrepancies over the entire balance sheet;

- additional proposals for systemically important banks, including requirements for supplementary capital, augmented contingent capital and strengthened arrangements for cross-border supervision and resolution.

The strengthened definition of capital was phased in over five years. The committee raises the capital requirement for risk exposure on asset securitisation. Meanwhile, the risk measurement requires to be increased, especially under stress. The Basel Committee improves risk capital requirements of trading business such as the over-the-counter derivatives trading and securities financing business of counterparty. Whether they are under the standard method or the internal rating method, risk weightings of securitisation risk exposure have been increased in comparison to the original standard. The Basel Committee recommended that the asset securitisation risk exposure should be calculated according to the accounting standards. Moreover, credit risk introduced the concept of "exposure limitation", which fortified the supervision of securitised debt for securitisation through higher capital requirements.

Chapter 3

Theoretical Comparison of Risk Measures

3.1 Introduction

Risk management represents a crucial capability of financial organisations such as banks, insurance agencies, among others, and thus, the accuracy of risk assessment is essential to the process. Risk can be estimated with regard to probability distributions of possible losses and confidence level of an organisation. Whereas, it is sometimes beneficial to express risk with one number that can be interpreted as a capital amount.

VaR is presently the most popularly accepted and widely employed risk assessment method; it also serves as a formal indicator to calculate the capital requirement for banks in Basel I and II Accords. However, the recent reformation introduced in the Basel III Accord is now altering the financial market. According to some significant deficiency of VaR, the Accord requires banks to communicate daily risk forecasts by applying a new internal model approach "Expected Shortfall" rather than the traditional model - "VaR". However, ES does not present a perfect risk measure either. Therefore, investors are uncertain as to which of the two is a superior risk measurement and whether the reformation have a positive impact on the financial market.

In this chapter, I will attempt a theoretical comparison of VaR and ES, considering their definitions, mathematical properties, backtesting ability, ability to capture tail risks as well as other relevant characteristics.

3.2 Literature Review

Some research works have offered significant comparisons of VaR and ES during the last few years.

Yamai and Yoshiba (2005) compared VaR and ES in a particular case. They concluded that because VaR disregards any loss beyond its level, it could cause a severe problem when the tail risk occurs since incorrect information from VaR measurement could mislead investors. Further, ES presents a better risk assessment method since it yields more accurate estimation, especially under the situation of tail risk, and it could serve more aptly in its place. They also demonstrated that ES requires a larger sample size as compared to VaR to attain the same level of accuracy.

Harmantzis et al. (2006) empirically tested the performance of VaR and ES using models with heavy tails in returns. In the evaluation of VaR measurement, they found that models that can capture rare events tend to estimate risk more accurately as compared to models without fat tails, while for ES measurement, both historical model and fat-tail models can produce precise results.

VaR works as a quantile measure which can provide investors an incorrect sense of security without excessive nonlinearity in the payoff structure, while ES can examine more realistically rare risks in relation to considerable losses (Wong and Copeland, 2008). These researchers applied a portfolio with different derivative assets and employed the saddlepoint technique to backtest ES. Based on the results, they concluded that ES contributes more than VaR, especially in the case of the tail risk, while VaR was consistent in prediction only if the underlying return distribution was well behaved. Moreover, they applied a power function to precisely measure the critical value of ES statistic.

It is commonly known that the backtest of ES is difficult to achieve since it relies on asymptotic test statistics for large samples. Wong (2010) introduced the saddlepoint technique to backtest the trading risk of commercial banks using ES. The Monte Carlo Simulation (MCS) results revealed the asymptotic method to be highly accurate and robust even with small sample sizes.

Emmer et al. (2015) retrospectively studied the risk measurements with regard to the desirable properties and their impact on capital allocation. They drew some conclusions that VaR could be more robust in contrast to ES since it does not cover tail risks. Furthermore, ES satisfies subadditivity and is sensitive to capture tail risk, while ES has been found to be not elicitable and less straightforward to backtest as compared to VaR.

Righi and Ceretta (2015) employed an unconditional, conditional and quantile regression-based model to assess the performance of models by applying the ES backtest and an interspersion truncated through VaR. A MCS indicated that the test is powerful. Meanwhile, VaR estimation was found to be essential for ES measurement with regard to the models that yielded the incorrect violation rates and also presented low p-values for the ES backtests.

It is common knowledge that the BCBS recently published fundamental changes in the regulatory capital requirement of financial organisations. The VaR measurement has been replaced by ES, increasing the capital requirement for heavy tailed risks (Kellner and Rösch, 2016). They empirically tested the risk assessment using daily log-returns for three indices and two exchange rates during January 2001 and January 2015. The result indicated that a higher potential exists for regulatory arbitrage when the ES approach is employed. Moreover, ES is more sensitive to parameter specifications than the VaR method.

3.3 Value-at-Risk

3.3.1 History and Definition of VaR

Since the volatility of financial assets' prices cause financial risks, the focus of risk measurement is estimating the fluctuations in rates. A considerable number of empirical studies have established that volatility comprises the following characteristics: fat tail, volatility clustering, leverage effect, long memory and persistence and co-movement. Fama (1965) observed that price changes did not tend to be independent over time and were rather characterised by tranquil and volatile periods, and the unconditional distributions of price changes were found to be typically fat-tailed or leptokurtic.

Beder (1995) applied eight invariant VaR methods under three portfolios. Based on the consequences, the study indicated that VaR depends heavily on the elements such as the input parameters, assumption, data selection as well as the methodology. Risk managers were surprised by those findings since the risk report can be modified under different assumptions. The study then demonstrated that there is no universal method for the VaR calculation which also illustrated that banks could achieve their purposes through various VaR estimation methods. It concluded that VaR estimation does not provide specific outcomes but the expected results based on certain assumptions.

Berkowitz and O'Brien (2002) collected the sample returns for six large banks and checked the accuracy of VaR estimation and forecasts during financial trading. The study initially presented a comprehensive analysis of the efficiency of models applied by banks in practice.

Furthermore, Bao et al. (2006), considered five Asian countries that suffered the financial crisis from 1997 to 1998. They applied different VaR models on the stock market and revealed that it is more difficult to forecast the risk under crisis as compared to those gained during periods of tranquillity. They demonstrated that most VaR models performed similarly before and after the disaster but differently during the crisis.

As the most popular risk measurement method currently, VaR is defined to measure the maximum loss of a financial institution or a portfolio at a certain period under a given confidence level. For instance, if the confidence level α is 99%, then VaR is the loss that is likely to be exceeded only 1% of the time.

$$VaR_\alpha(X) = inf\{\underset{m \in R}{m} : Pr(L \leq m) \geq 1 - \alpha\} \tag{3.1}$$

where α is the confidence level, m is the largest loss and L is the portfolio loss.

3.3.2 Calculation of VaR

The value of VaR can be calculated from different situations. We apply a parameter estimation under a known probability distribution whereas directly introduced quantile to determine the VaR value under an unknown distribution. According to this, VaR measurement model can be divided into two categories: parametric and non-parametric model. In order to estimate the VaR value, the parameter model assumes that portfolio yields obey a particular distribution, such as RiskMetrics JP Morgan's, GARCH models. The non-parameter model does not require any assumptions regarding the distribution of portfolio yields. It performs analyses and the simulation of existing historical data to estimate VaR value, for instance, Historical Simulation and Monte Carlo Simulation method.

Table 3.1 summaries the classification of VaR calculation approaches according to the probability of distribution.

Table 3.1 VaR classification

	Parametric	Non-Parametric
i.i.d.	Variance-Covariance(VC)	Historical Simulation
Time Dependence	RiskMetrics Method & GARCH	Monte Carlo Simulation

Parametric Method

1. The Variance - Covariance Method

   The variance-covariance method is the most commonly employed method at the current financial market which utilises the historical data of asset returns to estimate the standard deviation and correlation coefficient of assets. This method determines the appropriate value of VaR through the standard deviation of the portfolio based on this variance and covariance under certain distribution assumptions.

   The variance-covariance method is easy to execute because it only requires the assets market price which concerns the latest situation. Another advantage is it can measure almost all kinds of financial risks, especially bank credit risk and operational risk. Based on whether the financial risks are well quantified, this method can also be employed for performance assessment. However, it does entail certain shortcomings.

This approach can mainly be applied to direct investment since it only reflects the influence of the first-order linear combination of risk factors for the entire value of the investment, which does not consider the non-linear relationship.

2. RiskMetrics Method

   JP Morgan proposed the RiskMetrics model in 1994 based on the Equally Weighted Moving Average (EWMA) model, and he put higher weightages on recent data, which reflected the dynamics of volatility and can also quickly reflect market shocks. After the clashes take place, instability exponentially decays with heavyweight decrease. In practice, the RiskMetrics system determines the λ value by minimising the root mean squared error.

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(r_{t+1}^{2}) - \sigma_{t+\frac{1}{t}}^{2}(\lambda)\right)} \tag{3.2}$$

   where $\sigma_{t+\frac{1}{t}}^{2}$ represents the unbiased estimated of r_{t+1}^{2}

3. GARCH Model

   Since the GARCH model can adequately represent a financial time series, especially the ability to solve tail risk. Compared to other approaches, it can produce a better estimation of VaR. This model typically includes two equations, the first one is from the mean regression equation or condition, and the other is the conditional variance equation. Thus, we can calculate the value of volatility within these two equations through algebraic calculation. We begin with the simple GARCH (1,1) model, where $r_t$is the return of the portfolio, $\varepsilon_t$is the error term, μ_t represents the mean or expected return. In this model, we can estimate the values by employing historical data or randomly generated data to obtain parameters α,β,γ (Eq. 3.5) and simulate the model using the Monte Carlo method to forecast possible volatility in the future.

$$r_t = \mu_t + \varepsilon_t \tag{3.3}$$

$$\varepsilon_t = \sigma_t e_t \tag{3.4}$$

$$\sigma_t^2 = \alpha + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 \tag{3.5}$$

Non-parametric Method

1. Historical Simulation

   Under the assumption that the distribution of return is independently and identically distributed, also the risk factors that can cause the volatility of future market are similar to the historical risk factors. We can exploit the change in the actual sample to simulate the rate of return on real assets in the future market. Subsequently, we can rank the ratio sequentially and determine a specified confidence level corresponding to the sub-site to estimate the VaR value.

2. Filtered Historical Simulation

   Filtered Historical Simulation method extends the traditional HS method. Rather than taking historical data, it generates a set of sample data through the mean or correlation of the past returns.

3. Monte Carlo Simulation Method

   The Monte Carlo and Historical Simulation methods are rather similar. The most significant difference is that the MCS method did not directly employ the historical data to estimate the risk value, but used it to simulate the possible distribution of assets returns by applying stochastic processes.

The MCS method represents one of the most effective ways to calculate VaR, which can explain non-linear price risk, volatility risk and risks including those in the model. Moreover, it can manage volatility, fat tail and extreme events. However, the disadvantage of The MCS method is that since the data sequence is generated by a pseudo-random number, it can produce erroneous results. It also refers to large scale computations, which rely on the selected stochastic model and reduce the efficiency of simulation.

3.4 Expected Shortfall

The Basel Committee improved the banking supervision recommendations in 2016. It is worthy to mention that the regulation shifts the quantitative risk metrics system from VaR to ES. The BCBS noted that: “some weaknesses have been identified with using VaR for determining regulatory capital requirements, including its inability to capture tail risk”(BCBS, 2013).

Expected Shortfall can also be termed as conditional VaR, another risk measurement technique that is commonly applied to reduce the possibility of a portfolio incurring enormous losses. In a recent paper concerning risk assessment, ES was proved by several researchers such as Yamai and Yoshiba (2005), Harmantzis et al. (2006) and Wong and Copeland (2008) as a more efficient way to capture the tail risk in the financial market. ES is considered an alternative method since VaR can only measure financial risk with low or without tail risks. If the confidence level is defined as α, ES measures the risk when VaR is breached. In other words, ES represents an alternative approach to estimate the extreme losses that occur beyond VaR under a specified confidence level.

$$ES_{\alpha}(X) = \frac{1}{\alpha}\int_{0}^{\alpha} VaR_{\mu}(X)d\mu \tag{3.6}$$

ES inherits the properties of translation invariance, monotonicity, subadditivity and positive homogeneity from VaR. Hence, ES is a coherent measure of risk. By definition, ES can estimate all risks beyond VaR. Therefore the calculation of ES is based on the value of VaR with regard to the probability of distribution. Under a normal distribution, given the confidence level, ES and VaR are linearly related. Under t distribution, the higher the degree of freedom, the higher is the tail risk.

3.5 The Mathematical Properties of Risk Measurements

3.5.1 Coherence and Related Properties

Artzner et al. (1999) stated that VaR does not represent a consistent measurement method, and it can only measure percentiles of distributions and discards any losses beyond the VaR level. Furthermore, Acerbi and Tasche (2002) discussed the coherence properties of the ES as a financial risk measure. They indicated that ES can be applied to estimate any potential source of risk. Artzner et al. also suggested that a useful risk measure should satisfy properties such as monotonicity, homogeneity, translation invariance and sub-additivity. The first three conditions take consideration that in order to accept the risk, the risk measure defines the amount of capital to be added to the assets while the last situation helps to reduce the risk through facilities diversification.

VaR satisfies most of these conditions as described below except sub-additivity, while ES represents a coherent measurement that could satisfy all the requirements.

Definition 3.5.1. *Artzner et al. (1999) defines that a risk measurement is coherent if it could satisfy all the following conditions* [1]*:*

- Monotonicity

$$X_2 \leq X_1, impliesthat, \rho\left(X_1\right) \leq \rho\left(X_2\right) \tag{3.7}$$

This implies that "if we know that the value of one portfolio will always be greater than that of another portfolio, the portfolio with the higher guaranteed value will always present the less risky alternative".

- Homogeneity

[1] all definitions follows the paper written by Artzner et al. (1999)

The riak measure is homogeneous if for all loss variables X and $\lambda \geq 0$ it holds that

$$\rho(\lambda X) = \lambda \rho(X) \quad forall \quad \lambda \geq 0 \tag{3.8}$$

In other words, doubling the capital implies doubling the risk.

- Translation Invariance

$$\rho(X + cR_0) = \rho(X) - c \tag{3.9}$$

This implies that "the possession of cash also reduces risk by the same amount. This follows automatically from our definition of a risk measure as the buffer capital required to maintain a certain level of risk. Having cash equal to the risk held in a portfolio c=$\rho(x)$ signifies that the total risk equals zero".

- Subadditivity

$$\rho(X_1 + X_2) \leq \rho(X_1) + \rho(X_2) \tag{3.10}$$

This property entails that "the risk value of two combined portfolios should never exceed the sum of the risk of the two portfolios individually".

- Convexity

$$\rho(\lambda X_1 + (1-\lambda)X_2) \leq \lambda\rho(X_1) + (1-\lambda)\rho X_2 \tag{3.11}$$

Essentially, this implies that "diversification and investment in different assets should never increase the risk, but it leads to a reduction".

A risk measure can be considered as a coherent measure of risk as long as it could satisfy the properties of translation invariance, monotonicity, positive homogeneity and sub-additivity. Furthermore, the property convexity and positive homogeneity together imply sub-additivity. In conclude, VaR is not a coherent measure of risk because it satisfies all the properties but subadditive while ES could fulfill all these requirements.

3.5.2 Tail Risks

The definition of tail risk indicates that the distribution of returns is unnormalized, but skewed with fatter tails. The fat tails suggest that there is a small probability that an investment will exceed beyond normal VaR. It has been demonstrated by several studies that ES could capture the tail risks better than VaR method. Yamai and Yoshiba (2005) compared VaR and ES in a specific case and concluded that VaR disregards any loss beyond its level. Harmantzis et al. (2006) examined the performance of VaR and ES using models with heavy tails in returns. They found that ES performs better in fat-tail models. Furthermore, Wong and Copeland (2008) concluded that ES contributes more than VaR especially in the case of tail risks. Emmer et al. (2015) demonstrated that VaR could be more robust in contrast to ES since it does not cover tail risks.

3.5.3 Elicitability

Gneiting (2011) introduced the concept of elicitability in the backtesting of a risk measurement. Elicitability entails a scientific property, fulfilled by some risk measures, that takes into account the positioning of risk models' performance. If a risk measure is elicitable at a point, at that point, there exists a scoring function strictly consistent for the risk measure and can be utilised for relative tests on models.

The comparison between VaR and ES demonstrated that ES is not elicitable under any probability distribution while VaR is.

Definition 3.5.3.1. *A scoring function is a function represented as follows*

$$s: \mathbb{R} \times \mathbb{R} \rightarrow [0,\infty),$$
$$(x,y) \rightarrow s(x,y)$$

where x and y represent the point forecasts and observations respectively.

Definition 3.5.3.2. *(Acerbi and Szekely (2014)) A statistic Y is said to be elicitable if it solves*

$$Y = arg\min_{y} \mathbb{E}[S(y,X)] \tag{3.12}$$

for some scoring function S(y,x)

Elicitability has been demonstrated as a valuable property for model determination, estimation and forecasting simulation. These researchers also suggested that if the scoring function is selected in advance, it could capture the optimal forecast point according to Bayes rule.

Researchers have long debated the association between elicitability and backtestability, fuelled by the appropriation of ES for capital requirements' estimation. The typical relationship was put forward by Gneiting (2011) that the lack of elicitability may increase the difficulty on backtesting. Altough questions have been posed with regard to the backtestability of non-elicitable risk measures, later investigations affirmed the view that lack of elicitability allows the evasion of strict backtesting, even though backtesting is generally possible for non-elicitable risk measures such as ES when some specific conditions are fulfilled.

3.5.4 Backtestability

Backtesting constitutes a mechanism to evaluate the accuracy and effectiveness of risk measures. The BCBS incorporates backtesting into the internal model approach to investigate the minimum capital requirement. A risk measure's ability to take a backtest is associated with its eliciability. A backtest can be applied on VaR because it satisfies the property of elicitability. Backtesting encompasses the comparison of the estimated VaR measure against real gains or losses achieved on the portfolio or assets. Furthermore, a backtest is dependent on the level of confidence assumed in the estimation.

The fact that the discovery of ES was not elicitable in the year 2011. Gneiting (2011) determined that ES is hard to backtest. It is not elicitable signifies that no scoring function can elicit ES. This shortness doomed the popularization and application of ES. However, some studies suggested various approaches to backtest ES. Kerkhof and Melenberg (2004) recommended a framework to backtest ES using the functional delta approach that depends on large data samples to converge to the limiting distributions. They showed that tests for ES with acceptable low levels yielded a better performance as compared to tests for VaR with realistic financial sample sizes. Wong (2010) proposed a mechanism, namely, the saddle-point technique, to backtest the trading risk of commercial banks using ES. This approach derives a small sample asymptotic distribution for ES statistic under standard normal distributions. Moreover, Acerbi and Szekely (2014) proposed three non-parametric, distribution independent ES backtest methods that did not require any asymptotic convergence assumptions. In general, these studies have demonstrated that ES is not non-elicitable, but the backtesting method is not as straight forward as VaR.

3.5.5 Robustness

Robustness represents another essential issue in the assessment of risk measures because risk measurement is meaningless without this property. It is applied to identify risk measures' estimation within the volatility of prices in the underlying assets. Developing a robust risk measure is vital to banks or other financial institutions as they utilise various models and distributions. On the contrary, the application of a risk measure without robustness could lead to the influence of butterfly effect on the output data. From that point forward, small mistakes in the classification of loss distribution could cause a significant impact on the risk measure's estimate. After the financial crisis, regulators started requiring robustness in the internal models employed by financial institutions.

Definition3.5.5.1 presents the concept of robustness in mathematical terms.

Definition 3.5.5.1. *(Cont et al. (2010)) A risk estimator $\hat{\rho}$ is robust at F if for any $\varepsilon > 0$ there exists $\delta > 0$ and $n_0 \geq 1$ such that*

$$G \in C, d(F,G) \leq \delta \Rightarrow d(\hat{\rho}(F), \hat{\rho}(G)) \leq \varepsilon, \forall_n \geq n_0, \tag{3.13}$$

where C is a fixed set of loss distributions and $F \in C$.

The intuitive notion of robustness has been expressed precisely in Definition 3.5.5.1. In this definition, $d(F,G) \leq \delta$ describes that the distortion level of distribution is bounded in certain radius δ, signifying that the variation is so small that the value from risk function will only cause a small change, less than ε.

Cont et al. (2010) introduced another concept of robustness that considers the estimation method. The robustness and sensitivity of the risk measures are examined and utilised as a new foundation of estimation. The result indicated that sensitivity responds to the same risk assessment model significantly. They also found contention between the subadditivity and robustness of a risk measure.

3.6 Summary of Comparison

Table 3.2 presents an overall comparison of VaR and ES. It offers a summary of their fundamental properties.

Table 3.2 Comparison of risk measures

Property	Value at Risk	Expected Shortfall
Calculation	✓	
Coherence		✓
Elicitability	✓	
Backtestability	✓	
Robustness	✓	✓
Tail Risk Capture		✓
Stress Testing		✓

From the summary in the table, it is evident that neither VaR or ES represent perfect risk measures from the point of view of a theoretical analysis, with both presenting advantages as well as disadvantages.

3.6.1 Advantages of Value-at-Risk

As the most popular risk assessment model in recent years, VaR can precisely and efficiently describe the size of the market risk. Furthermore, it is easy to understand for investors who possess less professional knowledge.

Table 3.1 presents variant calculation methods for VaR. Regardless of the data used, there is always a proper approach that can be determined to estimate VaR. Through the calculation of VaR, financial risk can be forecasted in advance.

Several researchers have discussed the relation between elicitability and backtestability such as Gneiting (2011) and Emmer et al. (2015). Some of them indicate that a risk measure can fulfill the property of backtestability as long as it is elicitable. VaR satisfies the property of elicitability because we can obtain the smallest standard error by minimizing the sourcing function. Moreover, VaR is easy to backtest, and the details of backtesting will be demonstrated in the following chapter.

Additionally, VaR is a risk measure that contains robustness. It could be employed to estimate not merely a single financial institution but multiple financial portfolio risks, feature that is different from traditional risk measurement methods.

3.6.2 Problems of Value-at-Risk

Although VaR is utilised as a primary measurement tool for market risk in the current financial system, its application entails considerable limitation. First, VaR does not represents a coherent risk measure due to it is lack of subadditivity. The risks can not be diversified in applying VaR to estimate the portfolio. The Basel Accord requires banks to set aside capital in line with their level of credit, market, and operational risks. From that perspective, an overestimation of market risk will lead to unnecessary utilisation of capital and reduced profits.

Furthermore, although it is easy to backtest VaR, the failure rate is nonnegligible. The reason behind this could be that the VaR method provides inadequate coverage of market risks when the implied volatility is extremely high. In other words, VaR is criticised for its inability to capture information in the lower tail beyond the percentile.

Despite the disadvantages of capturing tail risk, VaR usually underestimates the market risks, especially under conditions of market stress. Yamai et al. (2002) compared VaR and ES under market stress. They indicated that under extreme value distribution, VaR can yield misleading information. The fact that VaR cannot capture the tail risks beyond the quantile renders it more robust than ES. Therefore, VaR is not an accurate risk measure under market stress.

3.6.3 Problems of ES

The popularisation of ES faced some challenges due to some limitation of the method. ES, by definition, is calculated based on the value of VaR. However, it is difficult to select an approach to estimate ES when the distribution of data is unknown.

Furthermore, it is a common concern that ES entails difficulties in back-testing performing capital calculation. Osband et al. (1985) initially introduced the concept of elicitability. In general, an invariant risk measure takes a probability distribution and transforms it into a single-valued point forecast. This implies that the risk measurement can be treated as evaluating forecasting performance. VaR is elicitable because we can obtain a smallest standard error by minimising the sourcing function. The widely contested solution to backtesting difficulties is performing capital calculations using ES and then conduct backtesting using VAR. More specifically, within ES, it is difficult to determine a scoring function such that ES can be defined as the forecast input variable given a distribution output variable that minimises the scoring function.

3.6.4 Advantages of ES

ES inherits the properties of translation invariance, monotonicity, positive homogeneity and subadditivity, hence ES comprises a coherent risk measure. It is important to note that neither VaR nor ES can estimate the maximum loss especially during a financial crisis. Both methods merely indicate a statistic assessment that is valid under normal market conditions. However, ES's ability to catch the tail risks is better as compared to VaR during high volatility. It means that the estimation results using ES is close to the reality. In general, ES does a better job in estimating market risks despite the hard backtesting shortness.

Acerbi and Szekely (2014) introduced three backtesting methods and prove that ES can be back-tested. Those three approaches are all non-parametric, distribution-independent and without any assumption on the asymptotic convergence. They indicated that the tests are easy to implement and generally display better than the Basel backtesting for VaR.

3.7 Conclusion

In this chapter, I have outlined a set of properties that are essential prerequisites for a good risk measure. In general, ES has been described as a risk assessment method theoretically superior to VaR in spite of some limitation presented by its estimation and backtesting, which can be discreetly mitigated.

ES satisfies all the listed coherent properties, especially the sub-additivity that offers investors an upper bound of combined risk. More specifically, lesser capital will be required in proportion to the risk from regulators if ES is applied due to diversification. The overall risk will be smaller in contrast to the sum of individual business and organisations could save the capital for investment.

Furthermore, although neither VaR nor ES can forecast the maximum loss an organisation can experience during a financial crisis, ES is more sensitive to the tail losses as compared to VaR. More significantly, ES offers a more accurate and reliable estimation in unstable financial market conditions.

Chapter 4

Empirical Comparison of Risk Measures

4.1 Introduction

Proper risk measurement and management are crucial for successful banking. In the banking system, banks that are compliant with the Basel standards are required to set aside a certain amount of capital to satisfy the capital adequacy requirement. Although some studies have revealed that the Basel Framework imposes restrictions on banks' development, the essence of the rules is straightforward for the benefit of the financial market. The supervision requires risk capital, which acts as a financial shock absorbers maintained by banks to prepare for unexpected risks.

A considerable amount of money has now been invested in the financial market. There is always uncertainty with regard to investors losing their investment. This uncertainty can be identified, assessed and prioritised through enhanced risk management. Concerning the risk assessment, there are two approaches that can be employed to calculate risk capital; one is the standard model, and the other one is the internal model(e.g. VaR, ES). The internal model aims to identify the amount of capital requirement that must be arranged in advance to ensure there is sufficient capital to cover the loss when risk is incurred. The BCBS evaluates the internal model by backtesting the risk assessment.

The regulation of capital structure has become a crucial issue in banking systems post the financial crisis in 2007. Banks reserve capital requirements to enhance the resilience of the financial system. This measure reduces the probability of default and associated output losses, and furthermore, diminishes the probability of a financial crisis. Several studies have focused on the relationship between bank capital and risks.

Bliss and Kaufman (2002) demonstrated the way in which the constraint of monetary policy is completed through capital as well as reserve requirements. They revealed the compression of capital ratio can cause aggregate shocks on capital requirement and hence impact macroeconomics. Therefore, the capital constraint should be introduced to explain the procyclicality in bank balance sheets.

Alfon et al. (2004) presented the determinant elements for capital. They indicated the amount of capital depends on risk management, market discipline and regulatory environment. Through both quantitative and qualitative analyses, they proposed the outcomes that regulatory requirements impact the amount of capital possessed by banks and building societies, using data from the UK.

Cuoco and Liu (2006) studied the performance of financial institution subject to capital requirements based on a self-reported VaR measure. They paid attention to the problem, although the capital requirement based on the IMA can be effective in curbing portfolio risk and inducing the revelation of risk, it can also lead to an increased probability of default or extreme losses.

Adrian and Shin (2008) stated that monetary policy and financial stability are strongly interlinked in a market-based financial framework. They maintained the view that short-term interest rates are determinants of the cost of leverage and have been found to be important in influencing the size of financial intermediary balance sheets. Moreover, banks effect adjustments in their balance sheet to achieve a target leverage level. Afterwards, a negative capital shock will contribute to a diminishing in credit supply and result in procyclical effects of bank capital management.

Francis et al. (2009) examined the influence of bank capital requirements against credit supply and indicated the way in which the regulator manage the capital requirement by adjusting their lending and other asset components. They also suggested that higher capital requirements may reduce banks' optimal loan growth.

Alessandri and Drehmann (2010) indicated the significance of risk capital by generating a framework to derive risk capital against credit supply and interest rate in the UK banking system.

Hyun and Rhee (2011) applied a simple banking model to demonstrate that banks may prefer to reduce loans rather than issuing new equity to raise the capital ratio at a time of economic downturn if dependent shareholders are to benefit.

Dell'Ariccia et al. (2014) advised that banks can improve their leverage ratio by adjusting the capital structure and reducing real interest rates under a downward sloping loan demand.

They also suggested that when the capital structure is fixed, the degree of leverage will have a significant influence on bank risk.

Gambacorta and Karmakar (2016) highlighted the limitations of risk-sensitive bank capital. Basel III regulatory framework introduces a leverage ratio that is independent of risk measurements to estimate the minimum capital requirement.Consequently, the leverage ratio could replace the risk-sensitive capital requirement properly because it imposes a strict restriction during the financial boom period and a soft constraint in a bust.

Since the previous chapter provides a theoretical comparison of risk measures in relation to various properties, this chapter will undertake the discussion from numerical perspective. Additionally, in this chapter, I will consider the methods not only in terms of the estimated VaR and ES values but also in terms of the distribution of bank capital. The Historical Simulation and Filtered Historical Simulation approaches will be applied to simulate the volatility model.

4.2 Risk Capital Requirement

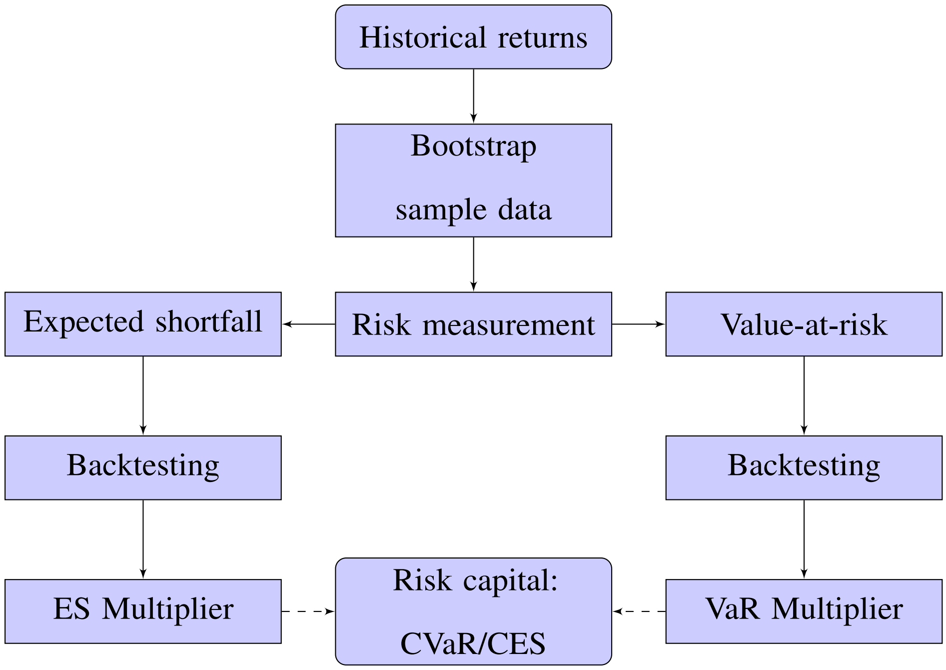
Risk capital requirement (minimum capital requirement or capital adequacy) prescribes that a certain amount of capital of banks (or other financial organisations) should be reserved for rare exigencies. Generally, banks use a capital adequacy ratio of equity to indicate the risk capital, and the risk capital should be in the form of various risk-weighted assets. For the banking system, the BCBS proposed a framework to estimate the minimum capital requirements for market risk following the internal models-approach (IMA). Moreover, the understanding of switching from VaR to ES under market stress has been revised in Basel III.

The Accord indicates that the "use of ES will help to ensure a more prudent capture of tail risk and capital adequacy during periods of significant financial market stress".

Regulators face the problem of determining appropriate minimum capital requirement that could protect regulated banks against adverse market situations as well as prevent them from suffering due to exceptional risks. Furthermore, regulators should leave the banks adequate capital for their core business considering the need for the profitability of financial institutions (Kellner and Rösch, 2016). If this is done, managers would be able to meet the challenge of balancing the investment capital and risk capital requirement.

Figure 4.1 describes a platform overview that briefly explains the estimation of capital requirement in accordance to the Basel Accord. This outline indicates both VaR and ES methods based on historical data.

Fig. 4.1 Risk Capital Calculation



The crucial ingredient in this process is the risk measure approach and multiplication factor that are applied based on the outcomes of the backtesting procedure. The Basel Accord dictates that each bank should fulfill a certain capital requirement on a daily basis, which is expressed as the sum of (BCBS, 2013):

- "the higher of its previous day's risk measure and an average of the daily risk measures on each of the preceding 60 business days, multiplied by a multiplication factor";
- "the higher of its latest available stressed risk measure and an average of the stressed risk measure calculated according to above the preceding 60 business days , multiplied by a multiplication factor".

As required, the multiplication factors range from 1.5 to 2 for ES and 3 to 4 for VaR, or set by individual supervisory authorities based on bank's performance of risk management system.

4.3 Backtesting

Backtesting presents a mechanism to evaluate the accuracy and effectiveness of the risk measurements model. The BCBS incorporates backtesting into the internal models approach to evaluate the market risk capital. The Committee believes that backtesting could provide an opportunity to involve incentives into the internal model approach from the point of consistency.

The framework of backtesting is developed by the Committee that offers a process for all the banks to adopt the internal model to measure the market risks. Backtesting VaR merely involves the comparison of the predicted losses calculated by VaR with the actual damages that take place in the market at a particular time. If the actual losses exceed the VaR values, it implies that, VaR underestimated the market risk. On the contrary, if actual losses are less than VaR, this signifies that VaR effectively measured the market risk during the time horizon. The number of uncovered trading losses is considered as the number of exceptions in backtesting. In addition, VaR should be recalculated if the backtesting result is not satisfactory.

The Committee directs that banks use the recent twelve months of data which is approximately 250 working days for backtesting. With regard to the number of exceptions (out of 250), banks can be divided into three tiers: the green zone, the yellow zone and the red zone. Table

4.1 and Table 4.2 describe the statistic limitations of the three zones regulated by the BCBS for both VaR and ES.

Table 4.1 The Basel Value-at-Risk Penalty Zones

Zone	Number of Exception	Penalty Multiplier
Green	0 - 4	3
Yellow	5	3.4
	6	3.5
	7	3.65
	8	3.75
	9	3.85
Red	10 or more	4

Table 4.2 The Basel Expected Shortfall Penalty Zones

Zone	Number of Exception	Penalty Multiplier
Green	0 - 4	1.5
Yellow	5	1.70
	6	1.76
	7	1.83
	8	1.88
	9	1.92
Red	10 or more	2

The green zone

The BCBS states that banks with 0-4 failures out of the 250-day backtesting period should be placed in the green zone. In the green zone, the stability of test outcomes implies that the risk assessment model is accurate and adequate to capture market risk. Such models that provide 99% confidence level can cover 99% of the 250 results. Since it would be probable for a model that genuinely provides 99% coverage to produce 4 exceptions out of 250 outcomes, the explanation for this backtesting result seems more reasonable. This opinion is enhanced by the statistics in Table 4.1, which states that the acceptance of the backtesting consequences in this range would result in a small likelihood of incorrectly receiving an inaccurate model. The results of the backtesting reveal that when the number of exceptions is up to 4 out of the 250 sample data, the statistic multiplier of VaR should be 3, which comes down to 1.5 for ES.

The yellow zone

Banks with the exception numbers ranging from 5 to 9 are located in the yellow area. Results in this area are plausible for both correct and incorrect models. The Committee states that the exception number indicates the size of potential supervisory and the capital requirement. The tables above indicates that the supervisor requires a multiplier from 3.4 to 3.85 for VaR and 1.7 to 1.92 for ES, increasing with the number of exception. These guidelines help seek a suitable structure of incentives applicable to the internal model approaches.

The red zone

In the red zone, those banks are generally have 10 or more exceptions in backtesting. It is intuitive to extrapolate that a problem exists with a bank's model in this case. If a bank falls into the red zone, the supervisor should increase the statistic multiplier to offset the potential losses. Nevertheless, the supervisor should investigate the reason due to which the bank fell into this zone. During the test period, 10 or more exceptions occur lead to an increase of the multiplication factor to 4 for VaR and 2 for ES.

Penalty multiplier comparison

From Table 4.1 and Table 4.2 it can be observed that the multiplier varies from VaR to ES. For VaR, it ranges from 3 to 4, depending on the area that banks are situated in. Whereas ES takes a penalty multiplier ranging from 1.5 to 2. There are several reasons behind this difference in penalty multipliers between VaR and ES.

1. Definition

   The definition of VaR and ES determines that the value of ES will be usually greater than that of VaR (see Figure 4.2).

   VaR measures the maximum loss given a certain confidence level in a specified period. If the confidence level is 99%, VaR expresses the value of the possible loss within the 99% possibility. For instance, 99% of 1000 is 10, weighting 100% to the 10th quantile; it does not considering other more considerable losses. Therefore, we define the 10th smallest rate of return as the value of VaR. ES can also be referred to as conditional

VaR, another risk measurement technique that is usually utilised to reduce the possibility of a portfolio incurring enormous losses. Under this example, ES measures the average loss when the 1% worst possibilities transpire. ES informs us about the worst possible losses and how much they can amount. Furthermore, ES gives equal weightage to all quantiles greater than the 10th quantile and zero weightage to all quantiles below the 10th quantile. Thus the average value of the ten smallest rate of returns is constituted by the ES.

Fig. 4.2 Probability density function of loss distribution

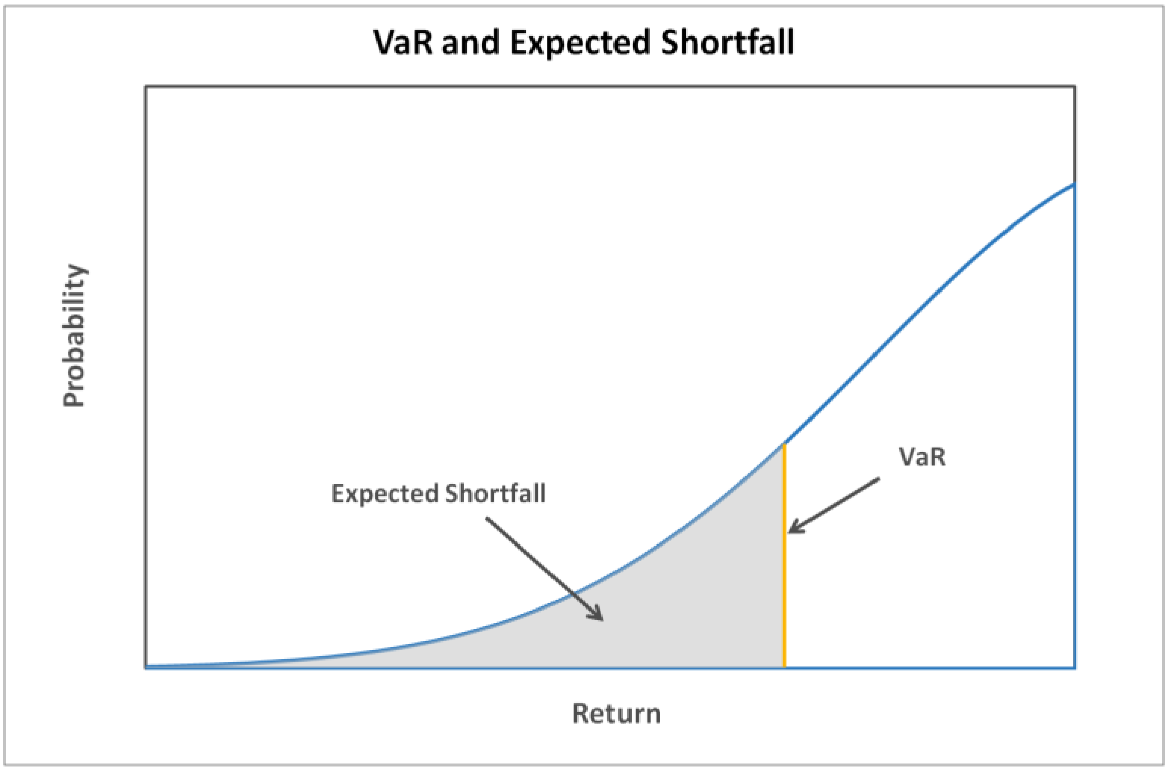


Figure 4.2 briefly explains the definition of VaR and ES. Y-axis describes the probability distribution of the distribution of loss while the X-axis represents the rate of return on assets. In Figure 4.2, VaR is defined as the quantile of the loss distribution under

the confidence level, illustrated with a yellow line, while ES forms the average loss when VaR is breached. Therefore, by definition, under the same risk level, ES always exceeds VaR.

2. Tail risk

   In a recent work about risk assessment, ES was proved by several researchers as a more efficient way to capture tail risk in the financial market. Yamai et al. (2002) found that VaR and ES can underestimate the risk of securities with fat-tailed properties and a high potential for massive losses. Wong and Copeland (2008) tested a basket of the portfolio within derivative assets. In other words, within high tail risk, the measurement results demonstrated that ES can capture the tail risk that VaR fails to capture. They also concluded that ES is more effective in the measurement of portfolios with tail risks as compared to VaR in a crisis-prone world. Figure 4.3 provides an example of the way in which ES can estimate risk beyond VaR (Hull, 2012).

Fig. 4.3 Probability density functions of loss distributions that follow (a) a normal distribution and (b) a distribution with extreme tail behavior

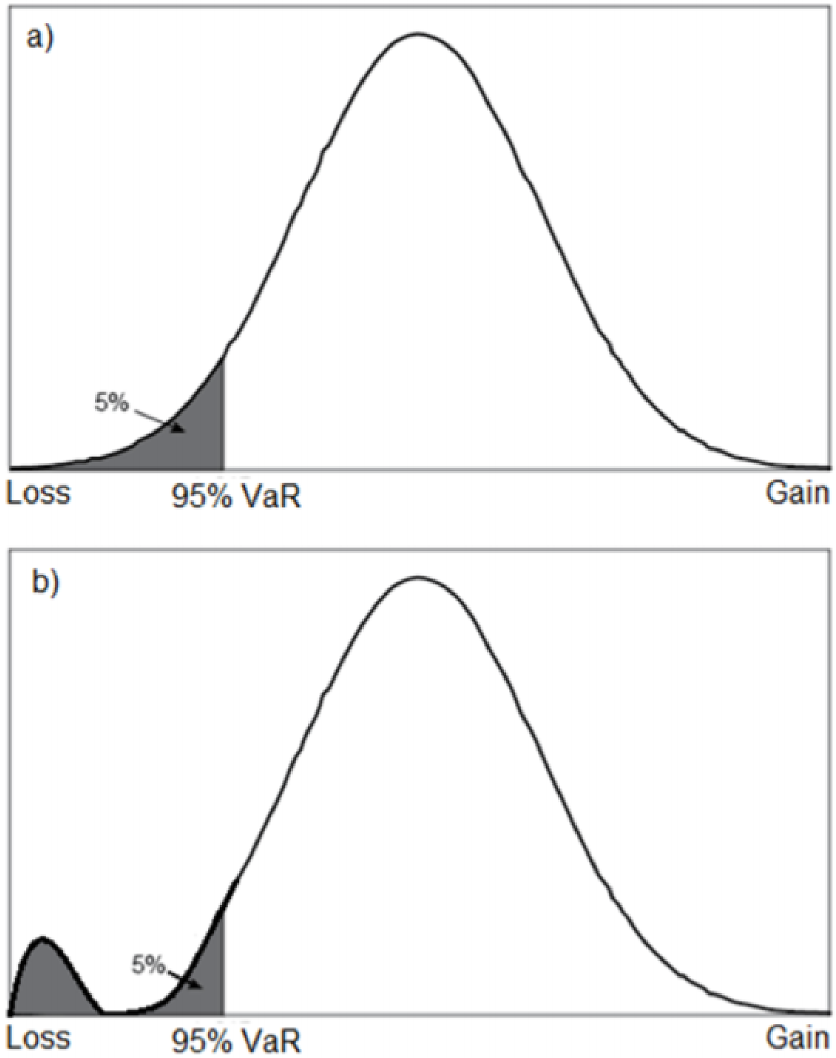


Figure 4.3 describes the probability density functions of loss distributions that follow a normal distribution. It is evident that although both of them offer the same level of VaR, the portfolio in figure (b) with high potential losses presents considerably greater risk as compared to the portfolio in figure (a). Thus, ES is considered as an alternative method since VaR can only measure financial risk that have low or no tail risks.

3. Coherence

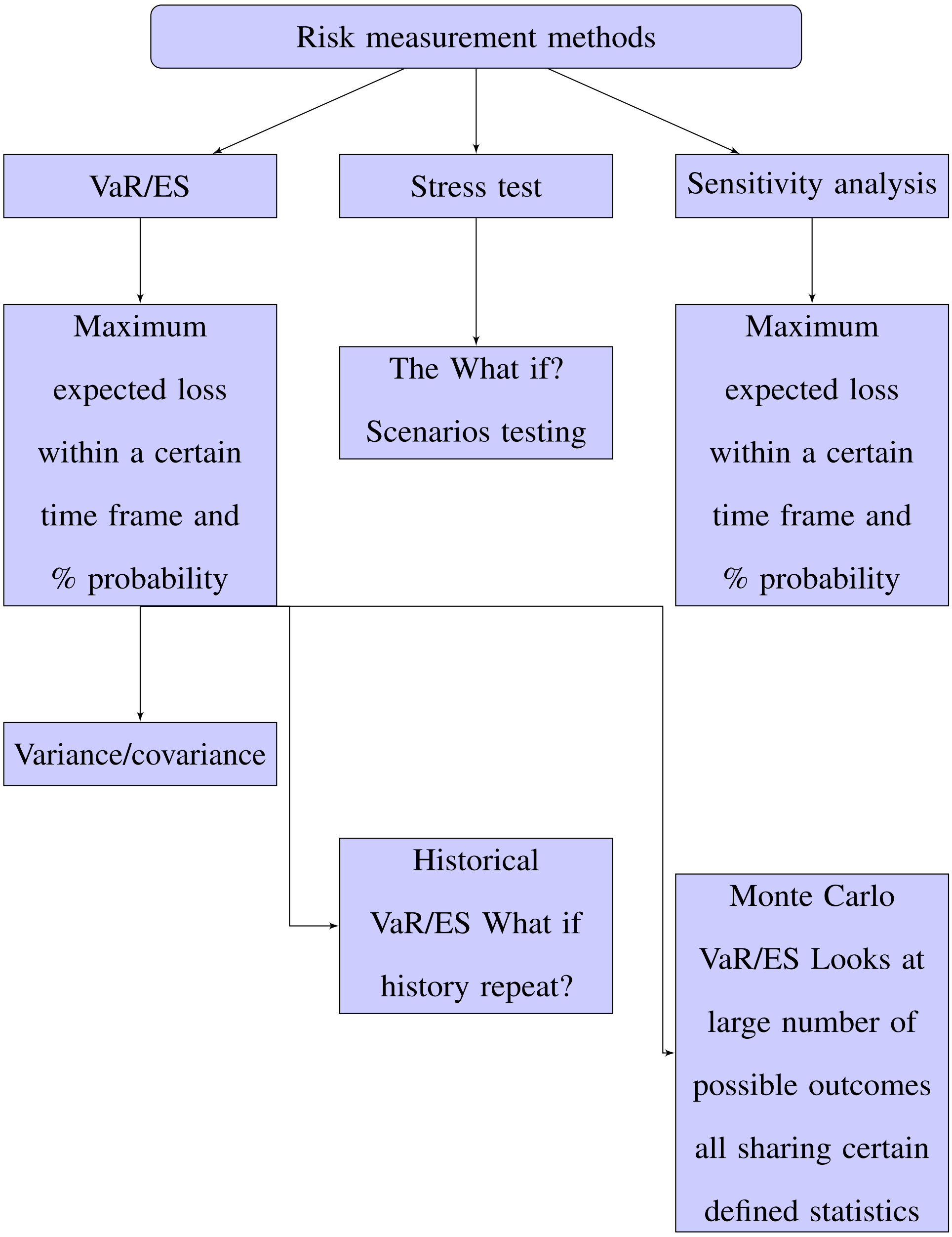
   As introduced in the previous chapter, a coherent risk measurement should fulfill all the properties: monotonicity, homogeneity, translation invariance, convexity and sub-additivity. This property communicates the fact that the risk of a portfolio comprising sub-portfolios will at its maximum be constituted by the sum of the individual risks of the respective sub-portfolios. Sub-additivity is an additional essential property for optimising portfolios. Portfolio diversification aims to reduce the risk under coherence, while diversification can increase the value for measures that violate the notion.

   Furthermore, the property of sub-additivity is important for risk capital requirements in banking supervision. The capital requirement for individual branches depends on its own risk. Moreover, the risk manager should be confident to the estimated risk capital as long as the risk measure fulfils the condition of sub-additivity. However, it may act against the original intention if the measurement method violates the property of sub-additivity. VaR is not a coherent risk measure because it does not satisfy the notion of sub-additivity. Therefore, in the Basel Accord, the basis of penalty multiplier for VaR is set higher than ES.

4.4 Simulation Methods

There are three main approaches to measure market risk: IMA, stress test and sensitivity analysis. The IMA, which involves VaR or ES, can predict the maximum loss within a certain time frame and the confidence level. To estimate Value-at-Risk and Expected Shortfall, several different methods, such as Historical Simulation and Monte Carlo Simulation can be used. All these approaches depend on historical data and the consumption concerning liquidity and the persistence of underlying markets. However, each methodology entails some limitations for the process of risk analysis. Figure 4.4 presents a platform overview of risk measurement and analysis approaches (Bohdalová, 2007).

Fig. 4.4 Risk Measurement Methods



Estimation of VaR or ES usually requires a probability distribution of the changes in portfolio value. The value of a portfolio depends on risk factors such as stock prices, exchange rate and interest rate. Hence the estimation methods are constituted by the distribution of risk factors. According to the underlying distribution, risk measurement approaches can be classified as parametric and non-parametric technique:

1. Parametric
   - Variance-covariance Method
   - GARCH/EGARCH Method

2. Non-parametric
   - Historical Simulation
   - Filtered Historical Simulation
   - Monte Carlo Simulation

To gain precise results, I collected the daily last prices for 25 most representative banks in G7 countries from 1990 to 2016. Thus, the non-parametric techniques (HS and FHS) will be applied due to the distribution of sample data is unclear.

Historical Simulation presents a process that allows constructing future market risk based on previous asset returns of the market. Unlike other simulation approaches, HS is a non-parametric method, signifying that there are no restrictions on both the distribution of data and other parameters such as standard deviation. Under HS, it is assumed that the set of future scenarios could be expressed through a historical window. Moreover, it offers the advantage of providing a more accurate risk assessment with regard to the situation of "fat tails".

Filtered Historical Simulation method extends the traditional HS method. FHS combines non-linear econometric models and the historical returns to innovate the probability distribution of possible returns in the future. In other words, it uses past returns as innovations in modeling the randomness of the asset prices. Filtered Historical Simulation is a semi-parametric model from the statistical perspective.

4.5 Historical Simulation

4.5.1 Definition

A contemporaneous description of HS was initially offered by Linsmeier et al. (1996). The HS method makes a forecast concerning future market risk based on the assumption that the past occurrences will be repeated in the future. For instance, if the risk factor is the change in stock price, to emphasise the reliability of the consequence, I used the data from 25 representative banks from G7 countries for the period 1990 to 2016 regarding their market values. The estimated window and backtesting window were both determined as 250 working days according to the Basel Accords.

It was assumed that the distribution of the rate of return would equal to the distribution of loss rate. Given the confidence level α as 99%, VaR would form the quantile of loss. It is represented by the following equation (Artzner et al., 1999):

$$VaR_{\alpha}(X) = inf\{x \in \mathbb{R} : F_x(x) > \alpha\} \tag{4.1}$$

In Equation 4.1, X represents the rate of return, F(X) defines the cumulative distribution function of X. $VaR_\alpha(X)$ collects the maximum loss within 99% confidence level. More specifically, 99% of 250 working days comprises approximately 3, it weights 100% to the 3rd quantile, and is not concerned about other more significant losses.

Different from VaR, ESmeasures the average loss when the 1% worst events take place. ES informs us about the worst possible events and the associated amount of loss. Besides, ES offers equal weight to all quantiles greater than the 3rd quantile and 0 weight to all quantiles below the 3rd quantile. Thus, the average value of the three smallest rates of return is formed by the ES (see Eq. 4.2).

$$ES_\alpha(X) = \frac{1}{\alpha}\int_0^\alpha VaR_\mu(X)d\mu \tag{4.2}$$

4.5.2 Simulation Procedures

As introduced in the previous section, the risk measurement contribution is not accurate in terms of the randomness of market change. In accordance with the Basel regulation regarding the adequacy capital requirement, banks should arrange sufficient capital to meet the possible loss. This risk capital is a formula based on the risk measurement and does not consider VaR or ES and is also a multiplier that reflects the potential losses. In the Basel regulation, the multipliers are defined as a certain number depending on the risk zone the bank is located in. The higher the multiplier, the worse is the backtesting result. In my thesis, different from the traditional backtesting method, I provide an alternative method to calculate the multiplier in order to cover the entire losses.

Multiplier

Since HS assumes that the past issues will repeat in the future, to offset the maximum losses in the future implies ensuring that the risk capital can counteract the largest loss faced during the previous estimation period. Thus, the calculation of the multiplier is based on one assumption: the capital requirement can provide sufficient capital for any loss that occurs during the backtesting period through ex post.

Suppose in HS, at day 't-1', we can forecast the possible VaR_t for the following day 't'. Based on the assumption that we know the future scenarios of the market, the multiplier ms_t represents a ratio of the real maximum loss over VaR_t.

$$ms_t = \frac{max(L)}{VaR_t} \tag{4.3}$$

where, L represents the real loss (positive value) that took place during the whole estimation window and VaR_t represents the risk estimator (positive value) at time t calculated with HS. This ratio essentially indicates the accuracy of the forecasting VaR_t under the assumption that the historical scenarios can represent the change in future stock price.

Similarly, the multiplier of Expected Shortfall can be expressed as:

$$mc_t = \frac{max(L)}{ES_t} \tag{4.4}$$

where, L is the real loss that took place during the estimation period and ES_t represents the risk estimator at time t calculated through HS.

Capital Requirement

Both VaR and ES should be calculated on a daily basis to estimate regulatory capital. With regard to the Basel Accord, a capital requirement is expressed as the higher of the previous day's aggregate capital charge for market risk or an average of the daily capital measures in the preceding 60 business days. Whereas in this section, to clearly compare VaR and ES in terms of the capital requirement, I calculate the sum of the total VaR and ES in unit for the whole estimation period. Afterwards, the total risk capital requirement in Eq 4.5 and Eq 4.6 should be represented as the multiplication of the total risk measures in unit and the maximum value of all multipliers that have been estimated previously. The risk capital expressed in the two equations could cover the maximum loss during the estimation window because the potential loss has been completely taken into consideration in line with the multiplier.

$$CVaR = \max(ms) \times \sum_{t=1}^{k} VaR_t \tag{4.5}$$

$$CES = \max(mc) \times \sum_{t=1}^{k} ES_t \tag{4.6}$$

CVaR describes the capital requirement for VaR; and CES represents the capital requirement for ES.

4.6 Filtered Historical Simulation

4.6.1 Definition

Although with Historical Simulation, the market risk could be easily estimated without the need for assumptions regarding the distribution of risk factors, there are still some nonnegligible disadvantages that should be considered during the measurement. First, one precondition of the historical method is that the representation of the past can happen again in the future. In order to achieve accurate results, an organisation should collect all possible data concerning risk factors, a task that can be extremely difficult. Meanwhile, the historical method could also lead to a large standard error if the sample size is small. Last but not the least, the assumption itself could be wrong because history events can not replace the future and the market is changing due to the updates in technology, regulatory change, inflation or crisis and altered perceptions in the wake of scandals.

The Monte Carlo Simulation is another popular approach used till now. The critical difference between HS and MCS is that HS uses real data changes in the market whereas MCS generates random numbers based on the standard error.

Barone-Adesi et al. (1999) introduced the FHS that combines the volatility models(GARCH) and the bootstrapping HS method. In other words, they combine the parametric way with the nonparametric techniques. The basic idea is to estimate the GARCH model by considering a set of previous returns. Subsequently, the historical asset returns could be standardised by drawing the estimated standard deviation based on the same day's value. This approach could lead to a standardised sequence of historical rates of return without any assumption regarding their distribution. In this manner, the following day's volatility can be produced at the end of the sample. Risk managers can obtain numerical results by substituting past values of historical standard returns rather than assuming a distribution of future returns. Considered in this way, FHS appears to be superior not only in generating the corresponding number of scenarios but also in taking into account the volatility changes over time. Moreover, it avoids any form of assumption regarding the distribution of returns.

4.6.2 Volatility Model

Normally, an $ARMA-GARCH(1,1)$ model is applied to measure the market risks of return:

$$r_t = c + \theta r_{t-1} + \varepsilon_t \tag{4.7}$$

The time-varying model ARMA(1) states that the returns of a portfolio are based on the information of the last period's market return and the information of the previous financial period, where r_t represents the market return, c is the constant,θ represents the AR(1) term, and ε_t is the random residual.

The GARCH(1,1) model initially introduced by Engle (1982) and Bollerslev (1986) has been presented below to depict the relationship between the current variance and actual sizes of the previous time periods' error terms.

$$\varepsilon_t = \sigma_t e_t, \quad i.i.d. \tag{4.8}$$

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2 \tag{4.9}$$

where the volatility of market return ε_t could be conducted as a function of the conditional variance σ_t and the independent identically distributed random variables e_t. $e_t$could follow a normal distribution or Student's t- distribution, which depends on the data type.

However, within the GARCH(1,1) model, shocks may last only for one period and die out gradually in the following periods. Therefore, the conditional variance could explode even if the process is strictly stationary. Furthermore, coefficient restrictions imposed in GARCH models are usually violated by the evaluated parameters that can hence limit the dynamics of the conditional variance process. Moreover, GARCH model rules out the possible negative correlation between r_t and ε_{t+1}.

Nelson (1991) developed an alternative EGARCH model to overcome the limitation of the GARCH model. It is derived to explain the leverage effect. The leverage effect empirically states that the quantitative results of the rise and fall of financial asset returns have various impact on future volatility in the form of the square. Hence it will affect the future asset returns in the same way. However, it is necessary to abandon the square symmetric function in order to explain the leverage effect efficiently. EGARCH model disposes off the historical data through an asymmetric function to generate the value of future volatility. The EGARCH(1,1) model can be expressed as follows:

$$log(\sigma_t^2) = \omega + \alpha log(\sigma_{t-1}^2) + g(e_{t-1}) \tag{4.10}$$

where,

$$g(e_{t-1}) = \psi e_{t-1} + \phi(\mid e_{t-1} \mid - E(\mid e_{t-1} \mid)) \tag{4.11}$$

in the value of $g(e_t)$ allows the sign and the magnitude of e_t to have separate effects on the volatility.

4.6.3 Simulation Procedures

In this thesis, I utilise the daily last price of the most representative banks in G7 countries from the period 1990 to 2017. These banks were selected based on the market values reported in 2017. The FHS was applied to simulate the volatility in the ARMA model.

- Step 1.

  According to the Basel regulations, risk assessment should be based on the previous 250 working days as well as backtesting. Thus, the VaR and ES are calculated starting from 1991 based on the previous year's data. Within the set of data, the system could be solved by using maximum likelihood estimation, and thus, I obtain $\hat{\omega}$, $\hat{\alpha}$, $\hat{\psi}$ and $\hat{\phi}$.

- Step 2.

  The starting value of the conditional variance $\hat{\sigma_1^2}$ should be set as the equilibrium $\frac{\hat{\omega}}{1-\hat{\alpha}-\hat{\psi}-\hat{\phi}}$. Additionally, e_t are modelled as a standardised Student's t distribution to compensate for the fat tails of daily returns.

- Step 3.

  Within the estimated conditional variance, the standardised returns are calculated using the equation given below:

$$e_t = \frac{\varepsilon_t}{\sigma_t} \tag{4.12}$$

- Step 4.

  FHS bootstraps standardized residuals to generate paths of future asset returns. Hence, I bootstrap e_t 1000 times in relation to the estimated standardise residuals.

- Step 5.

  Within each bootstrapping of e_t, a new data set of asset return could be generate through the AR-EGARCH system by setting up the initial value of r_0 and σ_0.

- Step 6.

  This comprises the calculation VaR and ES using the new data set. As I bootstrap 1000 times, 1000 sets of asset returns could be generated. For each set of data, one VaR or ES could be estimated, and the confidence level is 99%. I derive their mean through the 1000 times estimation.

4.6.4 Backtesting

VaR backtesting

The backtesting in this section follows the Basel Accord presented in section 4.3. The BCBS stipulates that banks should use the data of previous 250 working days to backtest VaR and ES. The basic rationale behind backtesting is to compare the estimated VaR with actual data. The value of the multiplier is determined on the basis of the number of failures according to Table 4.1.

ES backtesting

Since ES lacks eliciability, the backtesting of ES should be generated in virtue of VaR estimation. I consider the methodology proposed by Acerbi and Szekely (2014) to backtest ES without information regarding their distribution. The details of ES backtesting can be found in Appendix A. Subsequently, I summarise the multiplier of ES with regard to its number of failures on the basis of Table 4.2.

4.7 Results and Analysis

In this thesis, I employ data from the 25 most representative banks in G7 countries according to their total assets in the financial market of 2017. The estimated window and the backtesting window are both determined as 250 working days. The model is estimated using in-sample data, and the risk measurement and backtesting is applied using overlapping data.

Table 3.4 displays the result of comparison of the risk capital calculated through VaR and ES respectively. ’CVaR’ and ’CES’ represent the risk capital generated through the basic HS method. ’RCVaR’ and ’RCES’ are estimated through the FHS method.

Table 4.3 Comparison Results of Risk Capital Requirements

Country List					
Country nanme	Bank name	CVaR	CES	RCVaR	RCES
US(USD)	JPM	1234.100	841.957	962.842	686.009
	BAC	1277.600	898.820	1748.270	933.720
	WFC	1110.600	758.719	696.095	537.736
	USB	1011.300	721.326	1088.960	686.655
	CITI	1372.700	967.807	1018.340	796.265
	BK	1173.300	811.911	1260.230	795.649
	PNC	1126.700	784.516	1069.080	695.811
	COF	1342.900	1018.600	1790.420	1003.640
UK(GBP)	HSBC	565.038	394.649	470.549	367.503
	Barclays	1026.000	756.108	1303.385	783.015
	RBS	609.9804	466.4363	1230.5	644.744
	Lloyds	936.344	753.339	1049.350	703.991
France(EUR)	BNP	846.613	572.376	1017.020	565.314
	ACA	746.339	493.599	929.365	488.688
Germany(EUR)	Deutsche	997.289	680.956	873.850	640.110
	CBK	1117.500	766.949	1033.240	696.954
Italy(EUR)	UniCredit	1878.900	1666.200	1454.820	963.053
	ISP	1195.000	794.621	1813.790	804.260
Canada(CAD)	RYCN	636.582	424.475	475.112	372.079
	TDCN	672.590	445.586	495.670	381.274
	BMOCN	656.061	427.513	620.525	408.751
	CMCN	612.264	408.656	598.694	404.113
Japan(USD)	MTU	745.649	469.711	498.290	394.003
	MFG	432.466	289.285	307.734	236.791
	SMFG	438.924	291.858	343.922	273.008

From Table 3.4 it can be observed that the total risk capital requirements vary between different banks in G7 countries. It is evident that CVaR is generally higher than CES, regardless of the bank considered, as well as RCVaR and RCES. In other words, VaR requires more capital to offset possible extra losses. The reason behind these results could be analysed along different directions.

1. Definition

   VaR is defined as the loss level that can not be exceeded with a certain confidence level during a specified period. By definition, ES constitutes the average losses when VaR is breached. Thus, ES should be higher than VaR since ES measures minor probability issues beyond VaR. Furthermore, ES is a superior in capturing tail risks in the market as compared to VaR as demonstrated in the previous section. Consequently, banks that employ ES as a risk assessment could be more confident with their risk management as it covers more losses than VaR.

2. Multipliers

   A possible explanation for this distinction is the calculation of penalty multiplier. First of all, according to the Basel Accord, the multipliers are differentially stated in VaR and ES. Table 3.2 and 3.3 present the regulated multiplier according to the backtesting consequences. The multiplier for VaR starts from 3 plus a plus factor that ranges from 0 to 1 depending on the backtesting results. Meanwhile, ES takes a multiplier only from 1.5 to 2. The reason behind this result can also be analysed with regard to the definition, properties and ability to capture tail risks, as I explained in section 3.3. Additionally, the estimated multipliers using real historical data represent considerably similar results as the regulated multipliers.

3. Risk diversification

   In addition, VaR is not a coherent risk measure because it does not satisfy the notion of sub-additivity. Sub-additivity is necessary for capital adequacy requirements in banking supervision at the point of diversification. More particular, diversification could help to reduce the risks if the measure meets the property of sub-additivity. While for measures such as VaR, diversification may lead to an increase in their value even when mutually exclusive events trigger partial risks.

4.8 Conclusion

The importance of VaR cannot be underestimated as it has been extensively applied in risk management. In the last few decades, VaR has become one of the most popular risk measurement tools in the financial market. However, ES can describe market risk better than VaR, especially under distribution with heavy tails. The only reason that ES lacks popularity is that it is difficult to backtest.

In this chapter I simulate the risk capital of VaR and ES using Historical Simulation and Filtered Historical Simulation. Both methods produce similar conclusions that ES could save the utilization of bank capital, an advantage created mainly by the definition, properties and backtesting outcomes. Banks using ES could help diversify the market risks and save the total risk capital through the property of sub-additivity. Moreover, the multipliers that follow the Basel Accord vary in different risk measures. The result reveals that the multiplier for VaR (m_s) is higher than that for ES (m_c). Furthermore, the backtesting results illustrate that ES is more efficient in evaluating the market risk in practice.

Consequently, the shift in risk assessment model from VaR to ES can help banks save the risk capital and rearrange the distribution of capital by increasing credit supply.

Chapter 5

Global VAR Model

5.1 Introduction

In the previous chapter, it was proved that the application of Expected Shortfall as a risk assessment tool could facilitate saving capital for banks through Historical Simulation and Filtered Historical Simulation. However, the results could only determine that ES is relatively better than VaR for those banks. In other words, the research only focuses on the financial market in the last chapter. In this chapter, the whole economic system will be considered; macro-economy and financial sector should both be involved in this study to support the research aim.

In the formulation of macroeconomic policy, the regulators should take into account the interrelations across markets and countries. Increasing interdependencies between market actors can be caused through global shocks or specific sectoral shocks whose effects are transmitted through various channels. Thus, a relatively comprehensive framework is required to determine the importance of such a specific source in the worldwide economy. Since a proper risk measurement is essential for the banking system, it is worthy to test the various risk assessment models and the ways in which they could affect the entire economy. In the existing literature, researchers studied the comparison of different risk measurement in theoretical and numerical terms, but only rarely papers combined this analysis for various sectors in the economy. Therefore, in this chapter, I will apply a Global Vector Autoregressive (GVAR) model to simulate the relationship and explain how the economic capital change propagates in the economy.

A Global Vector Autoregressive model represents a comprehensive system that is generated based on individual VAR equations. Through a general, practical and worldwide system it directs a quantitative examination of the relative significance of various shocks and channels of transmission components. The GVAR model comprises the vector auto-regression model for individual countries, in which the native variables are linked to foreign elements that have been constructed through the channels of international trade, financial or monetary policy. Moreover, each VAR model is linked consistently, and then the specific GVAR model is estimated in relation to the global economy.

The GVAR model was initially proposed by Pesaran et al. (2004) to determine the interrelationship between national and international factors. They indicated that considering the increasing interdependencies between markets and countries, it is necessary to model the complex high-dimensional system on the global economy in conducting macro-economic policy analysis and risk management. Furthermore, the GVAR model incorporates both the macro section as well as the financial institutions. This paper established the theoretical foundation for the GVAR model.

Dees et al. (2007) asserted that the crux in setting the GVAR model is to systematically clarify the country-specific variables from foreign countries to individual nations to deal with common factor dependencies that exist in the world economy. They associated the domestic variables within the country-specific foreign variables in the vector error-correcting models.

Furthermore, Cologni and Manera (2008) studied the influence of oil price shock on output and prices based on a structural cointegrated VAR model. Moreover, the effect of monetary policies on oil prices has also been studied within this model. GVAR model could also be employed to forecast economic and financial variables (Pesaran et al., 2009).

Chudik and Fratzscher (2011) made an analysis and comparison of the limited liquidity circumstances and the collapse of risk preference in the global transmission of the financial crisis. Through the application of a GVAR model, they attempted to manage the identification of the high dimensionality of the empirical analysis and thus concluded that although the liquidity shocks affect advanced economies, the risk preference shock is crucial for emerging economies.

Gross and Kok (2013) also applied a GVAR model to simulate systemic risk shocks and measure the spill-over potential among sovereigns and banks.

Chudik and Pesaran (2016) summarised the literature and indicated the possible areas of future research. Their study also offered a detailed theoretical description of the GVAR model. The European Central Bank issued a working paper that studies the impact of bank capital on economic activity based on a Mixed-Cross-Section Global VAR model(Gross et al., 2016). They appllied a mixed cross section structural VAR model that ultilises countries, banks and central banks. This cointegration system combined the macroeconomic and financial sector by utilising a weighted parameter within each variable. My research would follow the GVAR model and the shock identification technique based on this working paper.

There are several reasons to support the selection of the GVAR model. First, individual industries in the economy are interlinked in a complicated way, especially the financial market and the macroeconomic elements. Economic capital is a crucial mechanism in the management of market risk, capital structure as well as the daily financial management. Hence an adequate risk assessment model could contribute to the economic activities. Nevertheless, the world economy is now combined; global trading, technological development, labour and capital movement all across from interactions between countries. It is probably a challenge to make a scenario analysis that combines individual economies with a simple model. This model allows long-run relationships consistent with the theory and short-run relationships that are consistent with the data. Lastly, the GVAR model affords an efficient mechanism to model the global economy within high dimensions. It provides a coherent, theory-consistent solution to the difficulty of dimensionality in global economic modelling. This thesis mainly focuses on how the change in economic capital affects the macro-economy and determine the risk measurement method that could lead to higher utility.

5.2 Model and Solution

5.2.1 Model Structure

The GVAR model in this thesis is based on the MCS-GVAR model presented by Gross et al. (2016) that comprises three within and cross-sections. The basic notion is utilising the weighted average as a mechanism to calculate the weight of data within and across sections. For the countries cross-section, Group of Seven(G7) countries[1] where i=1...7 are considered in this model. In the financial institution cross-section, j=1...28 banks of the G7 countries rank among the world top 100 are selected according to their total assets. The central bank cross section contains l=1...7 central banks from G7 nations.

The system contains the following sections:

- Countries cross-section:

$$\begin{aligned} x_{it} = a_i + \sum_{p_0=1}^{P_0} \Theta_{i,p_0} x_{i,t-p_0} + \sum_{p_1=0}^{P_1} \Phi_{i,0,p_1} y_{i,t-p_1} + \sum_{p_2=0}^{P_2} \Phi_{i,1,p_2} z_{i,t-p_2} \\ + \sum_{p_3=0}^{P_3} \Lambda_{i,0,p_3} x^{*,C-C}_{i,t-p_3} + \sum_{p_4=0}^{P_4} \Lambda_{i,1,p_4} y^{*,C-B}_{i,t-p_4} + \sum_{p_5=0}^{P_5} \Lambda_{i,2,p_5} z^{*,C-CB}_{i,t-p_5} + \varepsilon_{it} \end{aligned} \tag{5.1}$$

- Banks cross-section:

$$\begin{aligned} y_{jt} = b_j + \sum_{q_0=0}^{Q_0} \Upsilon_{j,q_0} y_{j,t-q_0} + \sum_{q_1=0}^{Q_1} \Pi_{j,0,q_1} x_{j,t-q_1} + \sum_{q_2=0}^{Q_2} \Pi_{j,1,q_2} z_{j,t-q_2} \\ \sum_{q_3=0}^{Q_3} \Xi_{j,0,q_3} x^{*,B-C}_{j,t-q_3} + \sum_{q_4=0}^{Q_4} \Xi_{j,1,q_4} y^{*,B-B}_{j,t-q_4} + \sum_{q_5=0}^{Q_5} \Xi_{j,2,q_5} z^{*,B-CB}_{j,t-q_5} + \omega_{jt} \end{aligned} \tag{5.2}$$

- Central banks cross-section:

$$\begin{aligned} z_{lt} = c_l + \sum_{r_0=1}^{R_0} \Delta_{l,r_0} z_{l,t-r_0} + \sum_{r_1=0}^{R_1} \Gamma_{l,0,r_1} x_{l,t-r_1} + \sum_{r_2=0}^{R_2} \Gamma_{l,1,r_2} y_{l,t-r_2} \\ \sum_{r_3=0}^{R_3} \Phi_{l,0,r3} x^{*,CB-C}_{l,t-r_3} + \sum_{r_4=0}^{R_4} \Phi_{l,1,r4} y^{*,CB-B}_{l,t-r_4} + \sum_{r_5=0}^{R_5} \Phi_{l,2,r5} z^{*,CB-CB}_{l,t-r_5} + \tau_{lt} \end{aligned} \tag{5.3}$$

[1]G7 is a group which consist United States of America, United Kingdom, Germany, France, Italy, Canada and Japan. The G7 is a consultation for dialogue at the highest level attended by the leaders of the world's most important industrially advanced democracies.

In the countries cross-section, the endogenous variable x_{it} forms the macroeconomic variables such as GDP and housing price index that can describe the state of the country's economy. For the banks cross-section, y_{jt} represent the financial variable collected in the balance sheet such as total assets and leverage. The central banks cross-section define z_{lt} as the endogenous variable to depict the policy rate in each central banks. x_{it}, y_{jt} and z_{lt} are stated with size $k_i^x \times 1$, $k_j^y \times 1$ and $k_l^z \times 1$ in this system. The intercept terms a_i, b_j, c_l are defined as the sizes $k_i^x \times 1$, $k_j^y \times 1$ and $k_l^z \times 1$ respectively. P_O, Q_0, R_0 represent the lag term for the section endogenous variables. In this thesis, due to the complicated model structure and large size of data, the lagged terms are all defined as 1 here. Θ_i, Υ_{j,q_0}, and Δ_l constitute the parameters for endogenous variables with the size of $k_i^x \times k_i^x$, $k_j^y \times k_j^y$ and $k_l^z \times k_l^z$. In this model, x_t, y_t, z_t are not only the endogenous variable for one specific sector but also exogenous variables which could support other sectors. For example, the fluctuation of leverage for JP Morgan and the federal fund rate could contribute to the US GDP. In other word, y_t and z_t affect x_t in the same country "i". Therefore, the endogenous variable in each equation could act as the exogenous variable for the other equations. Similar to the endogenous variables, the lag term P_1, P_2, Q_1, Q_2, R_1, R_2 are all collected as 1. The autoregressive terms of parameter $(\Phi_{i,0,0}...\Phi_{i,0,P_1})$ and $(\Phi_{i,1,0}...\Phi_{i,1,P_2})$ are of size $k_i^y \times k_i^y$ and $k_i^z \times k_i^z$.

Apart from the within-section variables, one important component is the across section participant. An increasing trend of relativities cross countries and the financial market should be taken into consideration by macroeconomic policymakers and people involved in risk management. In the countries cross-section, the star variables $x_{i,t}^{*,C-C}$, $y_{i,t}^{*,C-B}$ and $z_{i,t}^{*,C-CB}$ indicate the influences that foreign countries could exert on the native macro-economy through different channels of transmission, where, 'C-C','C-B' and 'C-CB' distinguish the effects between country to countries, banks to countries and central banks to countries. The coefficient matrix$(\Lambda_{i,0,p_3}$, $\Lambda_{i,1,p_4}$, $\Lambda_{i,2,p_5})$ is of size $k_i^x \times k_i^{*x}$, $k_i^x \times k_i^{*y}$ and $k_i^x \times k_i^{*z}$. The banks cross section involves star variables $x_{j,t}^{*,B-C}$, $y_{j,t}^{*,B-B}$ and $z_{j,t}^{*,B-CB}$ which represent the effects that other countries could have on the native financial market. The superscript 'B-C','B-B' and 'B-CB' demonstrate the influence caused by other countries, banks and central banks. The parameters matrix ($\Xi_{j,0,q_3}$, $\Xi_{j,1,q_4}$, $\Xi_{j,2,q_5}$) are of size $k_j^y \times k_j^{*x}$, $k_j^y \times k_j^{*y}$ and $k_j^y \times k_j^{*z}$. In the central banks cross section, other counties, banks and central banks also influence the native central bank. Star variables $x_{j,t}^{*,CB-C}$, $y_{j,t}^{*,CB-B}$ and $z_{j,t}^{*,CB-CB}$ depict that other countries, banks and central banks could change the current situation of the native central bank. The superscript 'CB-C','CB-B' and 'CB-CB' differentiate the effects from countries to central bank, banks to central bank and other central banks to central bank respectively.The parameters matrix ($\Psi_{l,0,r_3}$, $\Psi_{l,1,r_4}$ and $\Psi_{l,2,r_5}$) are of size $k_l^z \times k_l^{*x}$, $k_l^z \times k_l^{*y}$ and $k_l^z \times k_l^{*z}$.

The cross-section shock vectors ε_{it}, ω_{jt} and τ_{lt} represent structural shocks with the size $k_i^x \times 1$, $k_j^y \times 1$ and $k_l^z \times 1$.

5.2.2 Variable Selection

This paper employs 10 variables with data collected from G7 countries and demonstrate the economic implications of different market risk measures. G7 is a group that include Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. The reason I select G7 group is because these countries currently form the seven largest economies in the world that represent more than 58% of the national net wealth [2].

[2] National net wealth, also known as national net worth, is the total sum of the value of a nation's assets minus its liabilities.

Table 5.1 Model Structure

Cross-Section Type	**Model variables**
Countries	Nominal GDP
	GDP deflator
	Residential property prices
	Long-term interest rate
Banks	Nominal loan volumes
	Leverage
	Interest income/assets(or loan interest rate)
	Interest expense/Liabilities(or deposit rate)
	Probabilities of default
Central banks	Short-term policy rate

This table provides an overview of the model variable selection in three cross-section types.

Cross-countries section

In the cross-countries section, economic activity is represented by the nominal GDP, GDP deflator, residential property prices and long-term interest rate. It can be affected by bank credit, bank lending rate, cost of funding and short-term interest rate. Furthermore, the influence spreads through global trading channels with a decrease in the aggregate demand for domestic market leading to lower imports abroad. This section links G7 countries by setting the weight of each state with regard to their nominal GDP level.

- Nominal GDP

  Nominal GDP is the value of final goods and services that an economy produced under a given period. It is modelled on quarter-to-quarter differences of the log level, which is the GDP growth rate. Theoretically, GDP growth rate is the most crucial indicator that assesses whether the economy is growing or declining and the rate at which it is developing. Hence, regardless of who the economic agent is, the government or the investors should consider the value of GDP growth during the formulation of policies and decisions. Besides, the GVAR model entails a mixed section system involving countries, banks and central banks. To examine how the changes in the financial market affect the economy significantly, the outcome of GDP growth value is the first variable that is considered.

- GDP deflator

  The GDP deflator is an economic indicator which represents the inflation via transforming the measurement of output at current prices into constant-dollar GDP. It is utilised to deflate the effect of inflation from nominal GDP; it also represents the productivity of the economy. In this thesis, GDP deflator is modelled on quarter-to-quarter differences of the log level. Similar to nominal GDP, the GDP deflator represent the aggregate economic activity and could be affected by loan volume from the banking sector. A high credit level will result in a high GDP deflator that will also give rise to the bank's probability of default.

- Residential property prices

  The housing market forms an important factor in the economy because it is closely related to consumer spending and borrowing. An increase in housing prices can contribute to householders' wealth. As a result, it could promote consumption, and in turn, accelerate economic growth. This phenomenon is termed as the wealth effect. People become more confident about spending and borrowing if they can sell the house case of an emergency. Furthermore, the volatility of the housing market can affect the stability of the financial market. Recent research shows that 47% of ownership is mortgaged to become a landlord. The mortgage market will exert a further influence on the way which the central bank makes monetary policy. Lastly, the housing market is related to inflation as well. The housing price is modelled in quarter-to-quarter differences of the log level.

- Long-term interest rate
  The long-term interest rate is defined as the government bonds that are mature in 10 years and are determined by the price of government bonds in the financial market. The long-term interest rate is crucial in business investment that acts as the major source of economic growth. Low-interest rate encourages investment whereas high-interest rates deter and limit it. Long-term interest rate and short-term interest rate are closely related. Short-term interest rate is determined by the central banks whereas long-term interest rate is determined by the price of long-term bonds. If the market believes that short-term interest is higher than expected, the long-term interest rates decline in relation to short-term interest rates and the yield curve flattens. This variable is modelled on quarter-to-quarter differences of its natural level.

Cross-banks section

The cross-banks section include 27 banks from G7 group, the most representative banks with regard to their total assets. The estimation and simulation are performed according to the aggregate banking system data for the G7 countries. Within this section, all variables for each bank are calculated through the weighted aggregate data according to their market capitalisations.

- Nominal loan volumes

  Nominal credit at bank level is a key element that can affect both the financial market and macro-economy. Gross et al. (2016) explained that the nominal credit at bank-level is represented as a function of nominal GDP, inflation, bank lending rates as well as bank leverage. Besides, loan volume can also affect house prices via the wealth effect channel. Tsatsaronis and Zhu (2004) indicated that residential property prices are sensitive to short-term rates. They also pointed out that the type of mortgage with floating rate is more popular and acceptable in the housing market. In this way, housing price values can affect the bank capital and finally contribute to the change in loan interest rate through the wealth effect.

- Bank leverage

  Leverage at bank level represents the percentage of debt contained in the capital structure of a bank. Debt is utilised to increase the production volume, the higher debt, the larger leverage is. Meanwhile, it illustrates the profitability of a bank if it uses limited capital. Leverage ratio is also an indicator of risk. Banks with high leverage ratio may be beneficial in times of economic boom, while this leverage can lead to serious problems in cash flow when a recession happens. Bank leverage is an important variable in this GVAR system due to the research aim. In the previous chapter, I proved that switching the risk measurement model from VaR to ES could lead to reduced capital requirement. This influence would be acted through the financial leverage channel. In this thesis, the leverage ratio is defined as a function of bank credit, probability of default and is modelled in quarter-to-quarter differences of it's natural level.

- Loan interest rate

  Loan interest rate actually indicates the banking lending rate is defined as the fraction of interest income and total assets. Gross et al. (2016) conclude that the banking lending rate can be affected by GDP, house price, long-term interest rate, bank leverage, cost of funding and short-term policy rates. I study the worldwide economy hence the interest income and asset return may be driven by macroeconomic and financial conditions of other countries in the global system. Furthermore, a higher interest rate signifies that less projects can be founded as a result of lower bank credit and finally affect the macroeconomic (Bernanke et al., 1991). This variable is modelled in quarter-to-quarter differences of it's natural level.

- Deposit rate

  In this model, deposit rate is defined as the interest bank promises to pay when people store their deposit in the bank. The bank deposit rate could be affected by variables such as GDP, long-term interest rate, policy rate and bank leverage. Gross et al. (2016) represented the deposit rate as the cost of funding. They defined the deposit rate using the fraction of interest expense and liabilities. Babihuga and Spaltro (2014) considered determinants of bank funding costs with regard to a set of international banks' data. They suggestted that increased capital buffer can potentially support banks' lending to the real economy by reducing bank funding costs. The cost of funding is literately correlated across banks, which are essentially driven by leverage. The higher the leverage, the lower the cost of funding. This variable is modelled in quarter-to-quarter differences of it's natural level.

- Probability of default

  This ratio describes the likelihood of a default that may occur during a certain time period in a financial institution. More specifically, it offers an estimation that the borrowers cannot make their debt obligations. Probability is an important indicator in risk management since it is closely related to the expected loss. When the assessed risk increases, the probability also increases. This variable is allowed to be a function of macroeconomic information such as GDP growth rate, house price indices or obligor specific information such as loan growth and leverage ratio based on the stress condition. The Basel commitment states that a default can happen if it is unlikely that the obligor will be able to repay their debt to the bank without sacrificing any pledged collateral or the obligor is more than 90 days past due on a material credit obligation.This variable is modelled in quarter-to-quarter differences of it's natural level.

Cross-central banks section

- Short-term policy rate

  The short-term policy rate implies the interest that needs to be paid between financial institutions when borrowing and is generally determined by domestic central banks. For instance, the Federal Reserve Board's Open Market Committee determine the federal funds rate in the US. In addition, there is a direct connection between short-term interest rate, long-term interest rate, inflation as well as GDP. A low short-term interest rate conducts expansionary monetary policy and results in high inflation while a high rate produces contractionary monetary policy that affects aggregate demand and employment. In term of the GVAR model structure, each country can only have one central bank. Thus, I consider the weights of the cross-central bank sector same as the cross-country sector for the central banks of each country. This variable is modelled on quarter-to-quarter differences of its natural level.

In term of the complex model structure, this thesis allows one lag in both the exogenous and endogenous variables. The model is estimated using the quarterly data from 1999Q1 to 2016Q4. Before estimation, I use the Unit Root Test to examine the stationary of each variable. The test results which are shown in Appendix C indicate most variables are stationary after modelled. Besides, the individual equations are estimated by the Ordinary Least Squares method since the stability of data is confirmed. The estimated parameters are summarised in Appendix D.

5.2.3 Global Solution of GVAR Model

The GVAR model presented contains time-contemporaneous relationships. Thus the system needs to be understood before entering the simulation procedure.

For the bank section, the 28 banks from the G7 countries are classified by countries aggregate banking system, as well as central banks. The reason I model in the group of the country is due to the research aim. Although different banks may respond heterogeneously to similarly sized shocks, the target of this chapter is to compare the consequence of switch risk measurements. Estimating the model based on the banking system level could help simulate the macroprudential capital buffer according to banking systems. Furthermore, it better captures the diverse responses across countries. In addition, the size of time series data varies between different banks, and sample data for 28 individual banks from G7 countries cannot be considered entirely representative.

Step 1: Rewrite the model according to countries

Since different nations now distinguish between the group of variables, the indicators represented for different banks(j) and central banks(l) should be replaced with the symbol of countries(i). Besides, the period of lagged terms have been defined as 1, implying in the time of serious regressions, the current value of variable depends on information from the previous period.

Then the equation system can be re-written as follows:

- Countries cross-section:

$$\begin{aligned} x_{it} &= a_i + \Theta_{i,1}x_{i,t-1} + \Phi_{i,0,0}y_{i,t} + \Phi_{i,0,1}y_{i,t-1} + \Phi_{i,1,0}z_{i,t} + \Phi_{i,1,1}z_{i,t-1} \\ &+ \Lambda_{i,0,0}x^*_{i,t} + \Lambda_{i,0,1}x^*_{i,t-1} + \Lambda_{i,1,0}y^*_{i,t} + \Lambda_{i,1,1}y^*_{i,t-1} + \Lambda_{i,2,0}z^*_{i,t} + \Lambda_{i,2,1}z^*_{i,t-1} + \varepsilon_{it} \end{aligned} \tag{5.4}$$

- Banks cross-section:

$$\begin{aligned} y_{it} &= b_i + \Upsilon_{i,1}y_{i,t-1} + \Pi_{i,0,0}x_{i,t} + \Pi_{i,0,1}x_{i,t-1} + \Pi_{i,1,0}z_{i,t} + \Pi_{i,1,1}z_{i,t-1} \\ &+ \Xi_{i,0,0}x^*_{i,t} + \Xi_{i,0,1}x^*_{i,t-1} + \Xi_{i,1,0}y^*_{i,t} + \Xi_{i,1,1}y^*_{i,t-1} + \Xi_{i,2,0}z^*_{i,t} + \Xi_{i,2,1}z^*_{i,t-1} + \omega_{it} \end{aligned} \tag{5.5}$$

- Central banks cross-section:

$$\begin{aligned} z_{it} &= c_i + \Delta_{i,1}z_{i,t-1} + \Gamma_{i,0,0}x_{i,t} + \Gamma_{i,0,1}x_{i,t-1} + \Gamma_{i,1,0}y_{i,t} + \Gamma_{i,1,1}y_{i,t-1} \\ &+ \Psi_{i,0,0}x^*_{i,t} + \Psi_{i,0,1}x^*_{i,t-1} + \Psi_{i,1,0}y^*_{i,t} + \Psi_{i,1,1}y^*_{i,t1} + \Psi_{i,2,0}z^*_{i,t} + \Psi_{i,2,1}z^*_{i,t-1}\tau_{it} \end{aligned} \tag{5.6}$$

Step 2: Generate model in the form of matrices

Time-contemporaneous relationships exist between variables in this GVAR model. The endogenous variables x_t,y_t, z_t and their lagged terms are all involved in every single equation. Thus it is necessary to solve the system using the matrix form.

Reallocating the simultaneous equations, the following can be obtained:

$$\begin{pmatrix} I & -\Phi_{i,0,0} & -\Phi_{i,1,0} \\ -\Pi_{i,0,0} & I & -\Pi_{i,1,0} \\ -\Gamma_{i,0,0} & -\Gamma_{i,1,0} & I \end{pmatrix} \begin{pmatrix} x_{i,t} \\ y_{i,t} \\ z_{i,t} \end{pmatrix} = \begin{pmatrix} a_i \\ b_i \\ c_i \end{pmatrix} + \begin{pmatrix} \Theta_{i,1} & \Phi_{i,0,1} & \Phi_{i,1,1} \\ \Pi_{i,0,1} & \Upsilon_{i,1} & \Pi_{i,1,1} \\ \Gamma_{i,0,1} & \Gamma_{i,1,1} & \Delta_{i,1} \end{pmatrix} \begin{pmatrix} x_{i,t-1} \\ y_{i,t-1} \\ z_{i,t-1} \end{pmatrix}$$
$$+ \begin{pmatrix} \Lambda_{i,0,0} & \Lambda_{i,1,0} & \Lambda_{i,2,0} \\ \Xi_{i,0,0} & \Xi_{i,1,0} & \Xi_{i,2,0} \\ \Psi_{i,0,0} & \Psi_{i,1,0} & \Psi_{i,2,0} \end{pmatrix} \begin{pmatrix} x^*_{i,t} \\ y^*_{i,t} \\ z^*_{i,t} \end{pmatrix} + \begin{pmatrix} \Lambda_{i,0,1} & \Lambda_{i,1,1} & \Lambda_{i,2,1} \\ \Xi_{i,0,1} & \Xi_{i,1,1} & \Xi_{i,2,1} \\ \Psi_{i,0,1} & \Psi_{i,1,1} & \Psi_{i,2,1} \end{pmatrix} \begin{pmatrix} x^*_{i,t-1} \\ y^*_{i,t-1} \\ z^*_{i,t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{it} \\ \omega_{it} \\ \tau_{it} \end{pmatrix} \tag{5.7}$$

Step 3: Define parameter matrices

For the model provided above, I define each parameter to obtain a more straightforward expression.

$$Q = \begin{pmatrix} I & -\Phi_{i,0,0} & -\Phi_{i,1,0} \\ -\Pi_{i,0,0} & I & -\Pi_{i,1,0} \\ -\Gamma_{i,0,0} & -\Gamma_{i,1,0} & I \end{pmatrix} \tag{5.8}$$

$$G_0 = Q^{-1} \begin{pmatrix} a_i \\ b_i \\ c_i \end{pmatrix} \tag{5.9}$$

$$G_1 = Q^{-1} \begin{pmatrix} \Theta_{i,1} & \Phi_{i,0,1} & \Phi_{i,1,1} \\ \Pi_{i,0,1} & \Upsilon_{i,1} & \Pi_{i,1,1} \\ \Gamma_{i,0,1} & \Gamma_{i,1,1} & \Delta_{i,1} \end{pmatrix} \tag{5.10}$$

$$G_2 = Q^{-1} \begin{pmatrix} \Lambda_{i,0,0} & \Lambda_{i,1,0} & \Lambda_{i,2,0} \\ \Xi_{i,0,0} & \Xi_{i,1,0} & \Xi_{i,2,0} \\ \Psi_{i,0,0} & \Psi_{i,1,0} & \Psi_{i,2,0} \end{pmatrix} \tag{5.11}$$

$$G_3 = Q^{-1} \begin{pmatrix} \Lambda_{i,0,1} & \Lambda_{i,1,1} & \Lambda_{i,2,1} \\ \Xi_{i,0,1} & \Xi_{i,1,1} & \Xi_{i,2,1} \\ \Psi_{i,0,1} & \Psi_{i,1,1} & \Psi_{i,2,1} \end{pmatrix} \tag{5.12}$$

Step 4: Define variable matrices

Subsequently, the variables could also be written in the matrix form:

$$s_{i,t} = \begin{pmatrix} x_{i,t} \\ y_{i,t} \\ z_{i,t} \end{pmatrix} \tag{5.13}$$

$$s^*_{i,t} = \begin{pmatrix} x^*_{i,t} \\ y^*_{i,t} \\ z^*_{i,t} \end{pmatrix} \tag{5.14}$$

$$\phi_{i,t} = Q^{-1} \begin{pmatrix} \varepsilon_{it} \\ \omega_{it} \\ \tau_{it} \end{pmatrix} \tag{5.15}$$

Step 5: Global solution

The reduced form of the model can then be expressed as follows:

$$s_{i,t} = G_0 + G_1 s_{i,t-1} + G_2 s^*_{i,t} + G_3 s^*_{i,t-1} + \phi_{i,t} \tag{5.16}$$

The global system can now be applied for purpose of simulation and forecast. Additionally, the weights vary according to the time as indicated by the definition,

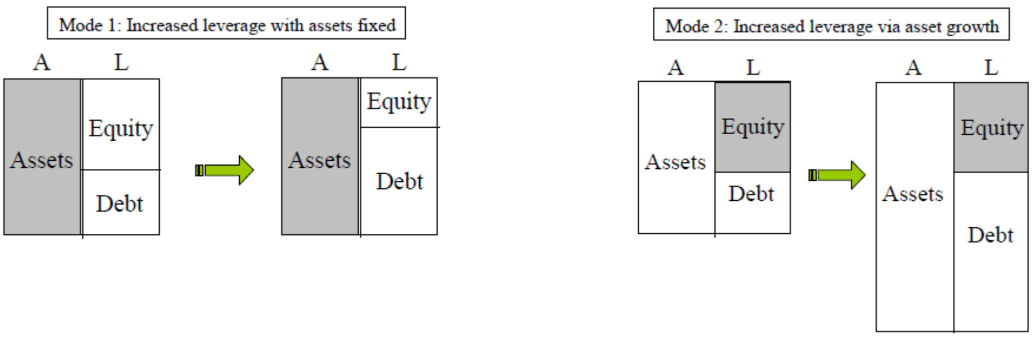
5.3 Shock Identification

5.3.1 Shock Type Identification

In the discussion of capital or capital ratio, the term "leverage" has a strong presence. The leverage ratio is one of the key indicators for financial institutions. It measures the amount of capital generated from loans and its contribution to profits. Organisations depend on this indicator not only because it provides a way to finance their operations on a mixture of equity and debt but also set an alert on the amount of debt companies need to pay off and ensure it falls within their capacity. Adrian and Shin (2010) found that marked-to-market leverage is strongly procyclical and leverage growth has a negatively correlation with total asset growth. Adrian and Shin (2013) suggestted that leverage growth is negatively aligned with unit Value at Risk growth for banks. Financial leverage can be defined in different ways, the ratio used in this thesis is the equity multiplier which is expressed as a ratio of total assets and total equity.

Leverage ratio is also closely related with risk as well as risk measures. By definition, the leverage comprises a ratio of total assets and total equity. Figure 5.1 clearly explain two modes to enhance leverage ratio (Adrian and Shin, 2013). Banks can increase their leverage ratio either by improving credit supply or diminishing the amount of equity.

Fig. 5.1 Two modes of leveraging up



In mode 1, the firm maintains assets fixed but replaces equity with debt. In mode presented on the right, the firm keeps equity fixed and increases the size of total assets.

In the last chapter, I have proved that switching from VaR to ES could bring a reduction on the capital requirement through both Historical Simulation and Filtered Historical Simulation. In this case, banks could reach higher leverage when using ES as the internal model via mode 2. Take an example of JP Morgan, and I collect data from 1999 to 2016, bank leverage and risk measures [3] are positively correlated.

[3] Here I take the absolute value of risk measures.

Fig. 5.2 JP Morgan Leverage Correlation with Risk Capital

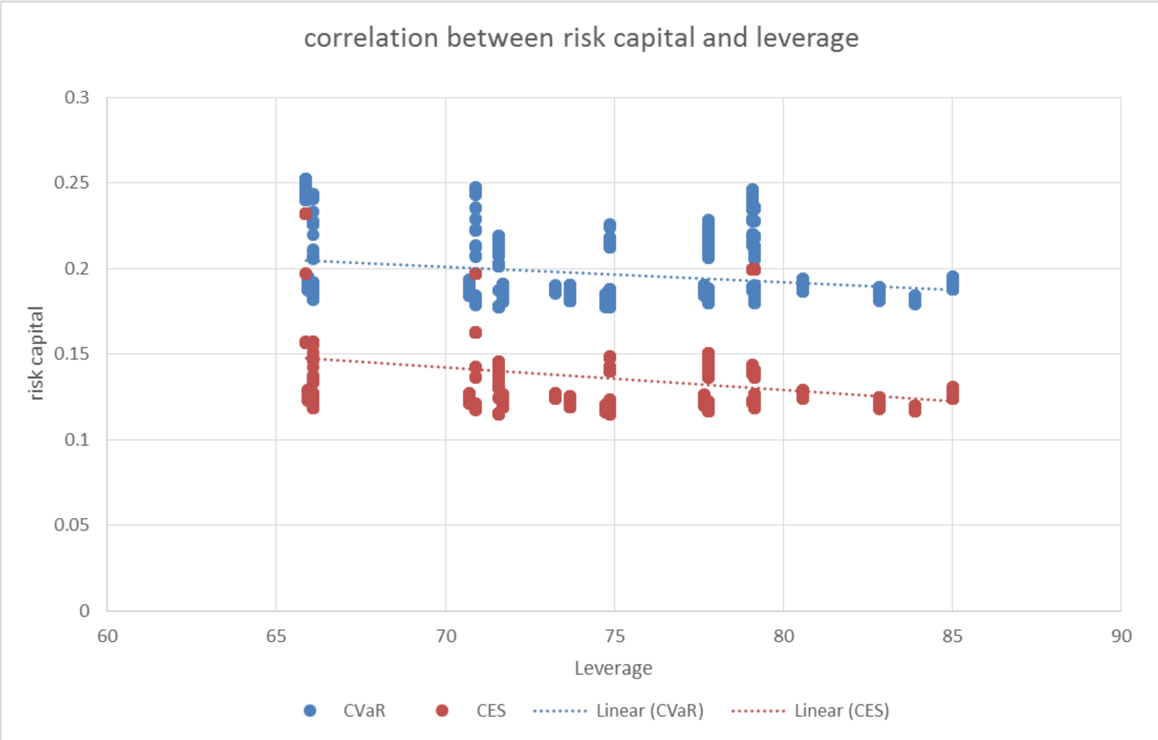


Figure 5.2 describe the correlation between risk capital and leverage ratio of JP Morgan from 1999 to 2016 and "CVaR" and "CES" are the risk capital requirements for VaR and ES respectively. It is noticeable that the leverage ratio is negatively related to risk capital. Leverage will go up when there is a decrease in risk capital. Since ES could help to diminish the risk capital requirement by better capturing the tail risks, using ES can improve the leverage ratio for banks. Under such a case, the saved capital could be either invested as the credit supply to increase the total asset or deduced from the equity. Thus, I can identify two shocks through the assumptions.

Credit Supply Shock

Under the assumption of constant capital, a reduction in the risk capital requirement implies increased capital investment. Therefore, a positive credit supply shock can be issued. Banks could achieve a higher leverage ratio by increasing their assets.

Capital Shock

Under the assumption of an unchangeable debt, a decrease of risk capital requirement constitutes diminished capital. Again, it can lead to a higher leverage ratio. Thus, a negative capital shock can be observed here.

However, when the minimum capital requirement declines due to a changing in the risk assessment model, most companies would rather shift the capital buffer into investments rather than cut down the capital to reduce risks.

5.3.2 Shock Size Calibration

Since the leverage ratio is conducted through risk capital requirement change when switching from VaR to ES, each unit growth of leverage will decrease the risk capital by the value of correlation. Meanwhile, VaR requires more capital to cover the risk than ES under same leverage value. Therefore, the shock size should be calibrated using the difference of correlation between risk capital requirement and leverage ratio. [4]

$$\Delta = \psi^{ES} \times m_c - \psi^{VaR} \times m_s \tag{5.17}$$

where Δ represents the shock size calibrated for the leverage shock. ψ^{ES} is the correlation between each bank's leverage and ES, and ψ^{VaR} marks the correlation between each bank's leverage and VaR. Additionally, m_c and m_s constitute the penalty multipliers for ES and VaR respectively according to the data for each bank. More specifically, $\psi^{ES} \times m_c$ represent the correlation between leverage and the minimum capital requirement for ES while $\psi^{VaR} \times m_s$ demonstrate the correlation between leverage and risk capital requirement for VaR. In general, the shock size indicates the extend to which the leverage ratio will change when VaR is replaced with ES.

I collect data for the 28 banks which has been introduced before in G7 countries. Through Eq. 5.17, I take shock size for each country as a weighted average of Δ of individual banks with regard to their total asset value. The shock sizes are calibrated in the table below:

Table 5.2 Shock Size Calibration

Countries	US	UK	France	Germany	Italy	Canada	Japan
Shock Size	0.0391	0.0695	0.1059	0.1067	0.0335	0.0219	0.0676

One assertion that requires to be made here is that shock size evaluates the amount of risk capital change, which could either be served to improve the credit supply or to deduce the equity.

[4]For example, if the bank leverage increases by 1, CVaR will decrease by 0.293 while CES reduce by 0.236. The difference between correlations (0.057) is the shock size.

5.3.3 Sign Restriction

Sign restriction is applied to identify the structural shock in a GVAR model. This approach was originally proposed by Faust (1998), Canova and De Nicolo (2002), and Uhlig (2005) in the context of monetary policy applications. This method has been increasingly applied to structural VAR identification in several studies subsquently. The sign restriction method is different from the other identification approaches. In this identification technique, the number of shocks does not requested to be equalised with the number of variables and the sign of restrictions are imposed directly on the impulse responses.

Faust (1998) initially introduced a new approach to identify shocks in the SVAR model to examine the measure of forecast error that can contribute to monetary policy shocks. In his paper, he proposed that restrictions on shock identification could be estimated as both formal restrictions, such as some linear restrictions and informal restrictions. Informal restrictions in VAR identification assert that people hold preformed opinions regarding the economy's dynamic response to a particular shock. For instance,a supply shock could increase the quantity and price of goods while a demand shock could decrease both. This research imposed a minimal set of restrictions with regard to a monetary policy shock.

Canova and De Nicolo (2002) researched on the importance of monetary disturbances for cyclical fluctuations in real activity and inflation by applying a macroeconomic model populated by 5 types of agents: those from households, firms, financial intermediaries, fiscal authority and monetary authorities. Similarly, they identified monetary shocks by describing theoretical sign restrictions.

Uhlig (2005) further estimated the effects of monetary policy shocks on output by imposing sign restrictions on the impulse response of prices. This approach is asymmetric as part known sign restrictions on fiscal policy shock. More specifically, he assumed that people are agnostic with regard to the response of output but not of certain other variables.

Mountford and Uhlig (2009) studied the impact of fiscal policy shocks using vector autoregressions. The sign restriction technique was also applied in this study to identify government revenue and expenditure shocks.

Peersman and Straub (2009) tested the impact of various shocks such as technology shock, labour supply shock, monetary policy shock and aggregate spending shock on hours worked in the Euro area. The vector autoregressions and sign restriction were used in this research. The results revealed a positive response of hours to technology shocks.

The outcomes from the last chapter demonstrate that the risk capital requirement differs from VaR and ES. Therefore, a positive leverage shock will occur when banks switch their risk assessment model from VaR to ES. In this thesis, I concentrate on the degree of the leverage shock that can affect the macroeconomics using a GVAR model, hence the sign restriction is imposed with regard to the following 10 variables: GDP, inflation, residential property price, the long-term interest rate in the macroeconomic sector; loan volume, leverage, lending rate, deposit rate and probability of default in the banking sector; policy rate in central bank level.

Since I have obtained the reduced GVAR model

$$s_{i,t} = G_0 + G_1 s_{i,t-1} + G_2 s^*_{i,t} + G_3 s^*_{i,t-1} + \phi_{i,t} \tag{5.18}$$

$\phi_{i,t}$ is a vector of structural shocks ε_{it}, ω_{it} and τ_{it}

$$\phi_{i,t} = Q^{-1} \begin{pmatrix} \varepsilon_{it} \\ \omega_{it} \\ \tau_{it} \end{pmatrix} = Q^{-1} \times e_{i,t}{}^{5} \tag{5.19}$$

Assume the structural shocks are uncorrelated, Ordinary least squares (OLS) approach can be applied to estimate the system because only lagged values of endogenous variables appear on the right-hand side. When all parameters are obtained, the variance of structural shock can be calculated as:

$$\begin{aligned} \Sigma_{\phi} &= (Q^{-1}e_{i,t})(Q^{-1}e_{i,t})^{'} \\ &= Q^{-1}Q^{-1\prime} \end{aligned} \tag{5.20}$$

Assume P is a lower triangular matrix in the case of usual Cholesky decomposition that satisfies $P^{'} = chol(\Sigma_{\phi})$.

$$\begin{aligned} \Sigma_{\phi} &= P^{'}P \\ &= P^{'}S^{'}SP \\ &= \bar{P}^{'}\bar{P} \end{aligned} \tag{5.21}$$

where S is an orthonormal matrix. The procedure continues in the following way. S is randomly drawn using the QR decomposition, then the restriction matrix Q is computed through the formula:

$$Q^{-1} = \bar{P}^{'} \tag{5.22}$$

The following step would be computing the impulse responses and evaluating whether they satisfy the restrictions imposed directly on the shape of the impulse responses. If the impulse responses satisfy the given restrictions, then the impact matrix P is saved. If not, then delete the impact matrix P.

Random drawing should be continued until N accepted draws are achieved. Then sort the models by impulse response distance to the median according to the given sign restrictions.

[5] $e_{i,t} \sim i.i.d$

Finally, choose the model which represents the median impulse responses. Matrix B which represents the median impulse responses is defined as the one that produces responses to the identified structural shocks. It should be observed that there does not exist a unique B. Regarding our model, we have drawn randomly until we have identified 1000 impact matrices and hence 1000 different SVAR models in the structural VAR identification procedure. The sign restrictions that were used to sort the model and select the median one will be discussed in the following section.

In our model, the sign restrictions on impulse responses have been illustrated in Table 5.3. I consider two types of shocks in the GVAR model, a negative capital shock and the a positive credit supply shock. In this thesis, both of these two shocks are in line with the leverage shock. Gross et al. (2016) indicated that credit supply growth is combined with a negative sign restriction on the loan interest rate. While Uhlig (2005) stated a contractionary monetary policy should raise the federal funds rate. Mumtaz et al. (2015) proposed that increased credit will lead to higher inflation and policy rate. Furthermore, an increased likelihood of default negatively constrains GDP growth while liquidity has a significantly positive effect on capital buffer (Stolz, 2007). Moreover, a decline in capital supply can lead to an increase in credit supply, leverage ratio and the probability of default. In addition, Alessandri and Drehmann (2010) found that higher risk capital levels impact the bank's profit by lowering the total interest payments on liabilities.

Table 5.3 Sign restriction on impulse responses

	VARIABLES									
SHOCK	GDP	IPD	HPI	LTIR	LOAN	LEV	LIR	DR	POD	STPR
Credit Supply (+)		+			+	+	-		+	+

Relations between macroeconomic variables, such as GDP and housing price index, should be left without any information restriction. In contrast to other identification approaches, sign restriction brings several advantages to the model. One advantage of this method is that the restriction is imposed through impulse responses rather than the identification of the structural parameters. Furthermore, the evenness of structural impulse response functions can be restricted by the covariance of prior responses. In addition, it is not necessary to apply the Bayesian approach to estimate the model because sign restriction does not demand any prior for the sign matrix Q.

5.4 Results and Discussion

Recalling the previous chapter, the risk assessment model can affect the capital buffer of banks in the financial sector. This chapter aims to determine the way in which it contributes to the entire economy. Hence, a sign-identified GVAR model is generated to simulate the impulse response under a positive capital shock. Meanwhile, from 5.1 the leverage could increase through the growth of credit supply. Thus the positive capital shock is imposed with a positive leverage shock from the perspective of sign restriction technique. This system offers the advantage of combining different departments and involves information restrictions from the real world. The results of shock simulation will be presented for both impulse response and forecasting scenario.

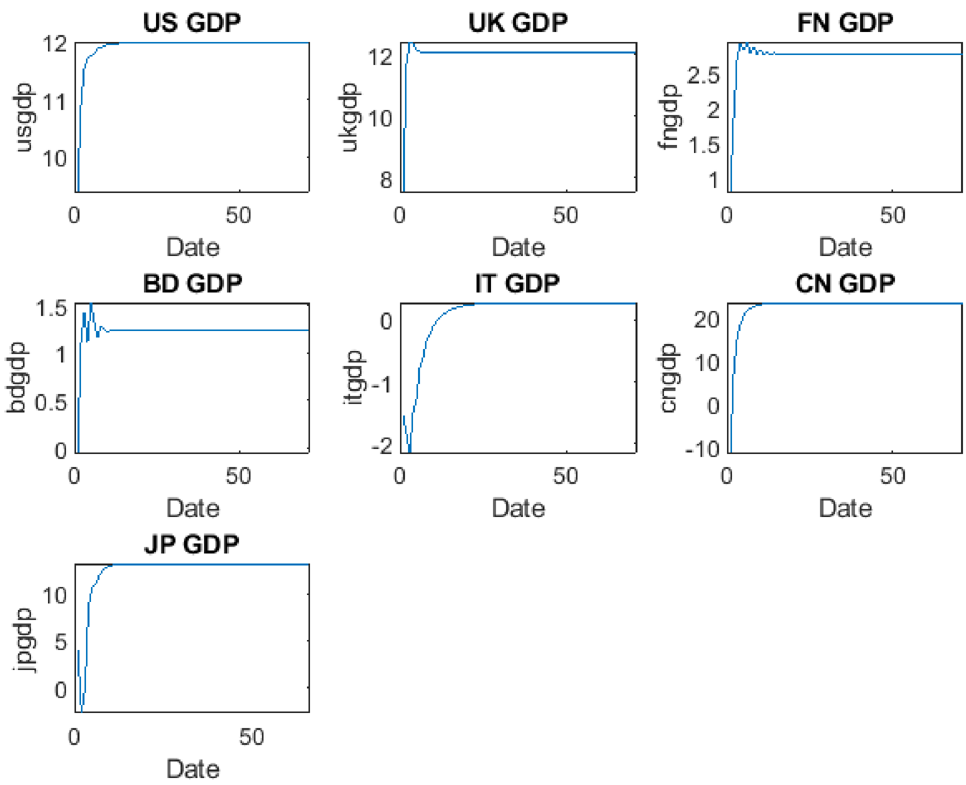
5.4.1 Impulse Response

In economics, the term impulse response is applied to describe how the economy reacts to various type of shocks during different market conditions. These shocks, caused by exogenous factors, are modelled through contemporary economic systems. The form of exogenous variables used for simulation in this study differ from those used in the estimation procedure. GDP, GDP deflator, residential property price and loan volume are considered in the log of their natural level. The leverage ratio, long-term interest rate, loan interest rate, deposit rate, the probability of default and short-term policy rate are simulated in their natural level.

GDP impulse response to leverage shock

The impulse response of GDP to a positive leverage shock of G7 countries have been collected and presented in the figure below:

Fig. 5.3 GDP impulse response from G7 countries

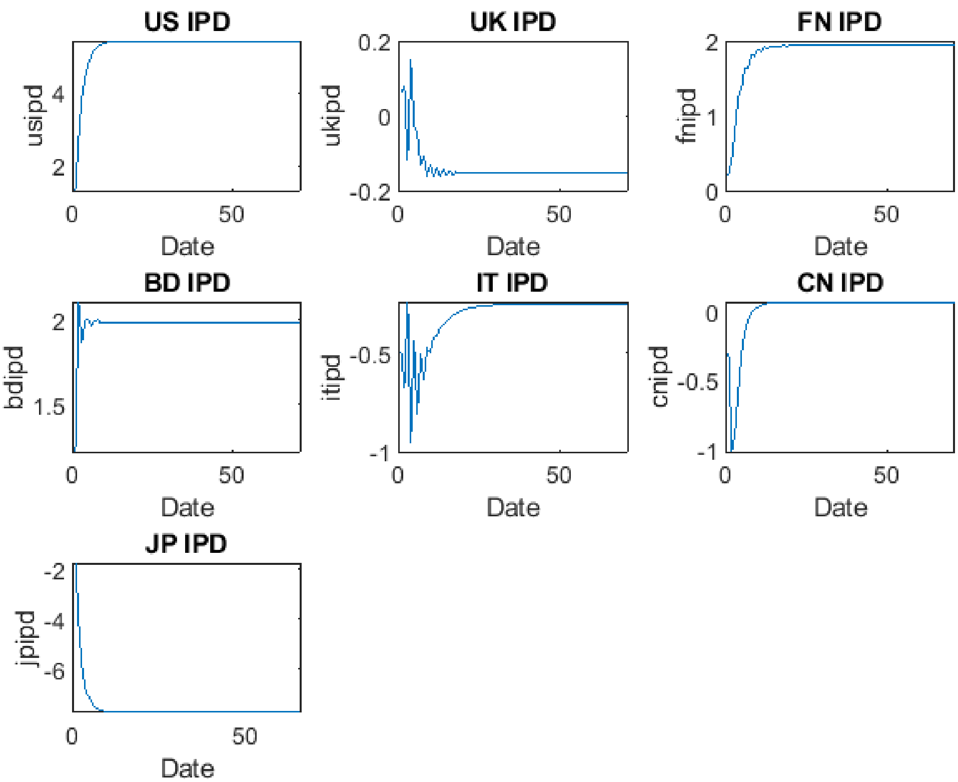


In general, these figures demonstrate a temporary increase on the impulse response function of real GDP in response to positive capital shocks, especially in the US, the UK, France, Germany and Canada. While the other countries, such as Italy and Japan show a slight decline during the first few periods and then increase afterwards. Evidently, the shock drives GDP to a higher level in all countries. The reason for this increase might be a spillover effect transmitted through the channel of consumption. More specifically, a positive capital shock will cause an increase in credit supply and encourage consumption.

Inflation impulse response to leverage shock

Figure 5.4 offers the overall impulse response of GDP deflator against the leverage shock in G7 countries. GDP deflator is an index that measures price inflation or deflation for a specific country for a certain time. In the sign restriction, I have left the relation between capital shock and IPD blank as no general trend that could be concluded from those impulse response figures.

Fig. 5.4 IPD impulse response from G7 countries

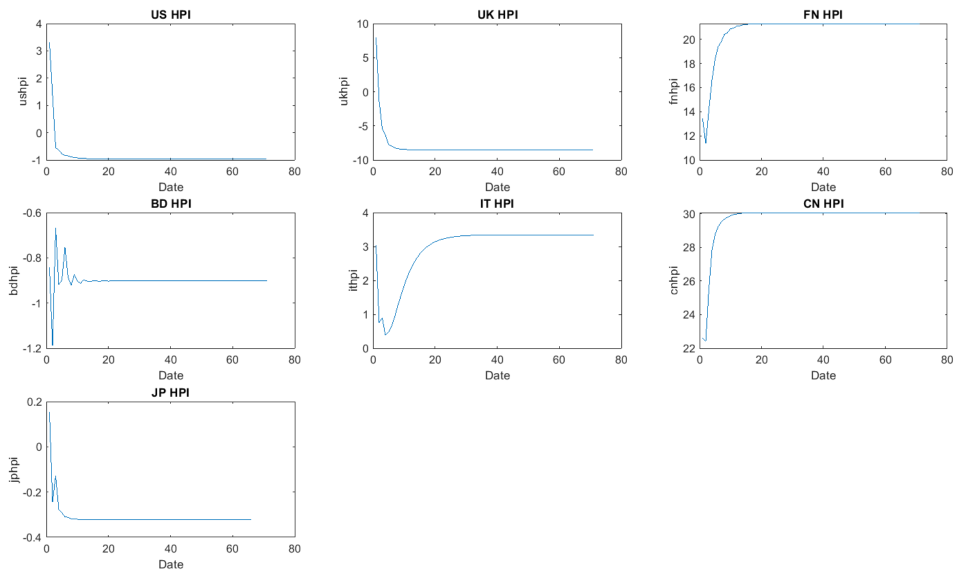


From the results, we can see that the US, France, Germany and Italy's responses to the capital shock are significantly positive although there was some fluctuation when the shock began. This fluctuation is caused by the negative estimated parameter before IPD. However, inflations in UK and Japan response negatively and decline to a lower steady-state when aftershocks happen. Canada witnesses a slight decrease in capital shock due to inflation and increasing afterwards. Rather like the similar trend in GDP response, various responses in inflation might be caused due to different reasons. Generally, an increasing credit supply encourages consumption, which can lead to an increase in inflation.

Residential property price impulse response to leverage shock

The figures bellow represent the impulse responses of capital shock on residential property price in G7 countries.

Fig. 5.5 HPI impulse response from G7 countries

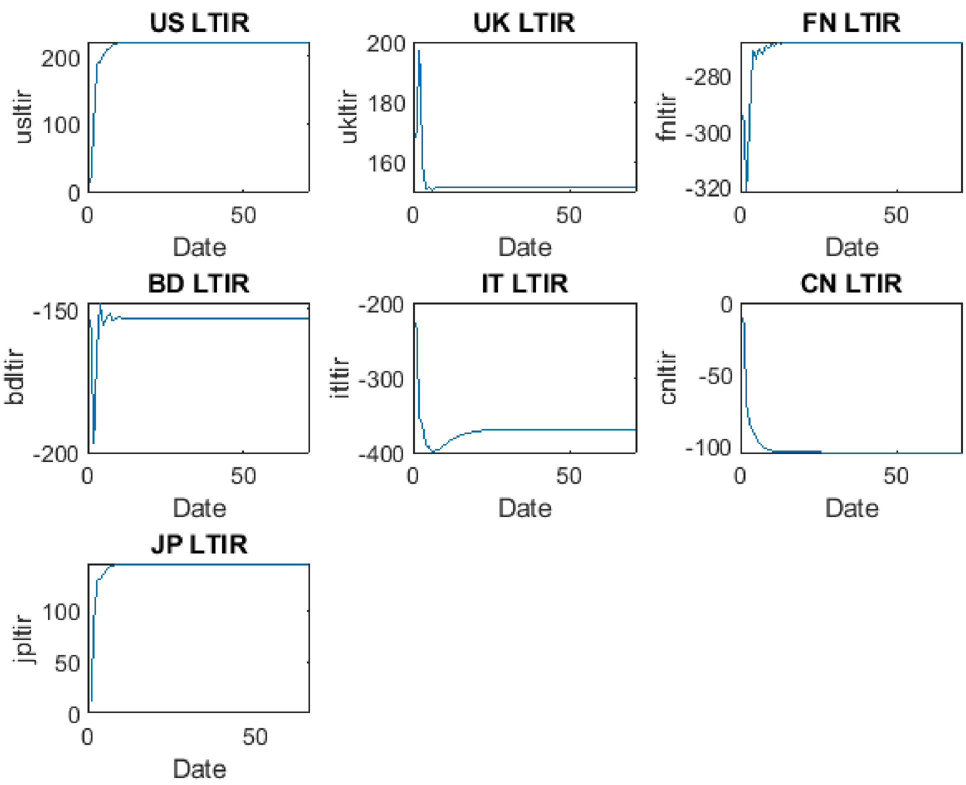


A decrease in HPI occurs aftershocks in the US, the UK and Japan, this decrease takes the steady state of HPI to a lower level in the long run. While the other countries show a general, increasing trend of response after the shock happens despite some volatilities. From the figure, it can be observed that most countries show increased responses to a positive leverage shock on the housing price index. This is because greater credit supply will increase the demand in the housing market, and finally drive the houses to increase.

Long-term interest rate impulse response to leverage shock

Figure 5.6 presents the response of long-term interest rate to the leverage shock. The long-term interest rate, as defined in the variable structure, is the interest rate of 10-year government bond. It is affected by capital shock as well.

Fig. 5.6 LTIR impulse response from G7 countries



From the figures, it can be observed that countries such as the US, France, Germany and Japan response positively against the leverage shock whereas a reduction can be seen for countries like the UK, Italy and Canada.

5.4.2 Implication from IRF

The impulse responses manifest the positive leverage shock will bring positive influences on GDP for most countries in G7. This consequence further state that the shift from VaR to ES could be conducive to economic development.

The BCBS has been revising their accords on market risk framework since 2012, and it is expected to be implemented by 2018. The VaR will be retired by that time and ES will be applied to calculate the market risk capital requirement as an internal model. My research started before the BCBS changed their rule in 2016, but this behaviour virtually supports my idea about VaR and ES. It is necessary to point out that neither VaR or ES can forecast the actual maximum loss in the future market. However, by construction, ES will always be more conservative than VaR. Therefore, the risk capital requirement for ES has regulated smaller than which for VaR because of their potential losses. In addition, people will lose information about the individual risk drivers and their possible effects when they assemble results from a large number of risk factors via a simple measure.

The replacement of VaR by ES also reflects the fundamental change of risk management, especially after the financial crisis. Banks used to aim for surviving in normal market situations now tend to ensure survival in stressed market conditions by better capturing the tail risks using ES. By far, VaR is still extensively used to evaluate market risk, and its importance is unlikely to diminish. While for efficient and robust risk management, banks and regulators should be familiar with the properties of ES and they will benefit significantly from the new risk measure sooner or later.

5.4.3 Counter-factual Experiment

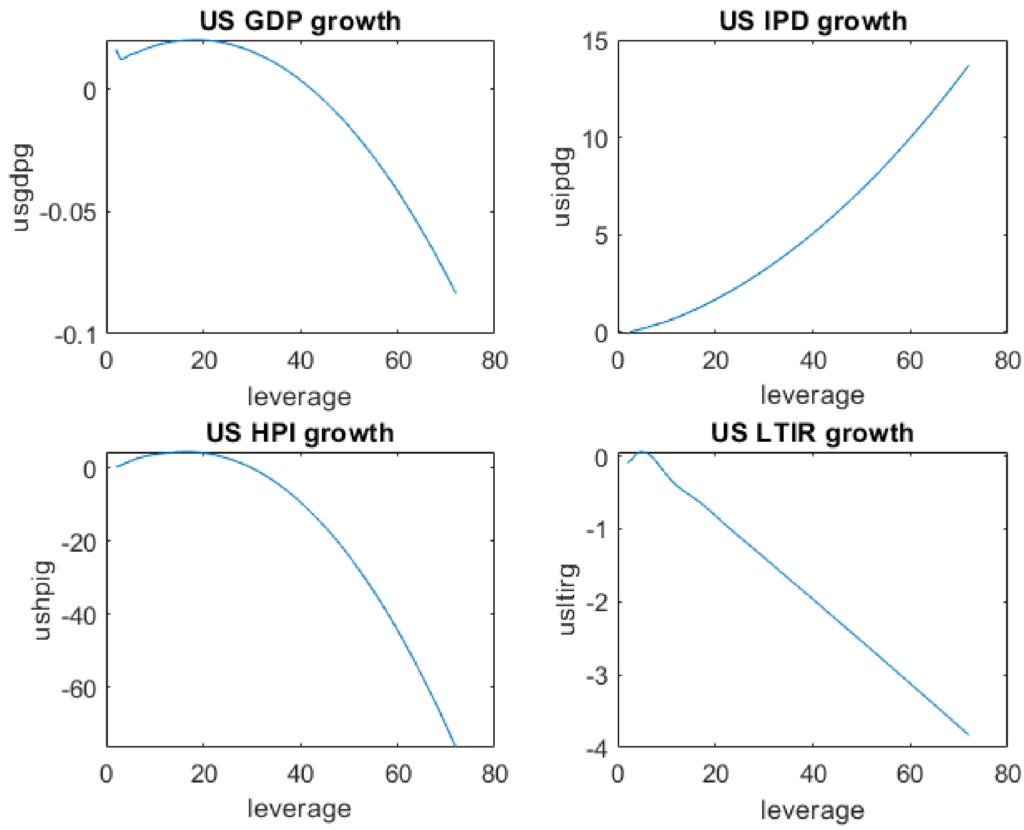
Determining capital requirements is a major concern for bank policymakers. The recently settled Basel III framework will direct banks to allocate increased equity capital to finance their assets than was previously required. In the earlier literature, researchers examined the optimal bank capital from the view of cost (Miles et al., 2013). While this thesis argues the question from the perspective of the arrangement of bank capital.

Leverage amplifies the level of risk. By the results of impulse responses, a positive leverage shock will encourage the economic growth. Whereas, this acceleration will not last invariably with the increasing value of leverage. I examine the connection between leverage and the economy across the GVAR model by giving a set of values in leverage. Instead of using natural level data, this experiment takes first difference quarterly on data to simulate the trend. In other words, all variables are applied to their growth rates. This is because this counter-factual experiment aims to figure out the real relation between the leverage ratio and the growth of the economy.

Another variable should be added into the simulation process is the square of leverage. Leverage growth has been proved to be negatively aligned with VaR growth rate (Adrian and Shin, 2013). With all conditions remaining equal, companies that have higher leverage indicate a greater ability to earn profits. However, the relationship between leverage and risk cannot be monotonic; a highly leveraged financial system is one that is prone to collapse. This is because a financial leverage ratio forms the variation of the debt to equity ratio. The company with a considerable amount of debt is more likely to not pay back the debt, which increase the probability of default. It is worthy to observe that the leverage square is involved in the GVAR model to describe the non-monotonic relationship between leverage and GDP growth, which make the GVAR model more effective for achieving the research aim, compared to the based model by Gross et al. (2016).

Figure 5.7 shows the simulation scenarios of the leverage ratio and the macroeconomic variables from the cross-countries section. The simulation of macro-economy in the US is generated by inputting a set of value into X-axis[6] in bank leverage ratio. And all the output are shown in the y-axis as the simulation results.

Fig. 5.7 US Simulation



[6]The value of leverage ratio is defined monotonically increasing within a range from '1' to '72' during the 72 periods.

GDP growth

From the simulation results, the relation between GDP growth and the leverage ratio is worthy of explore. Under the increase in leverage ratio, GDP growth rate increases till the peak point and then fall. By definition, financial leverage represents the utilisation of debt in the bank's financial structure. The higher the leverage ratio, the larger is the debt the company borrowed to fund investment. Assume the financial leverage raise due to the increase of credit supply for banks. The leverage ratio is a critical index for banks, managing risks by controlling leverage is the most important thing for risk managers. The result also reflects the balance between profits and risk.

Housing price growth

Similar to GDP growth, the housing price growth simulation forms a convex curve with a peak point. Housing price is affected by several factors such as inflation and interest rate (Tsatsaronis and Zhu, 2004). However, it has been observed that housing loan is the key element and is highly related to the volatility of housing price (Oikarinen, 2009). Since it is assumed that banks raise the amount of capital to extend the corresponding amount into loans, this could lower the interest rate to stimulate current and future economic activities. Consequently, a higher housing price will be expected under increasing loan value.

However, the relation based on the results does not appear to be monotonic. Within the amplification of the leverage ratio, housing price growth reduces continuously till the last period. It is also reasonable from the perspective of real economy that excessive credit will be detrimental for the market. A good example of this is considered the most recent global financial crisis caused by the loan losses across US banks, which led to a downturn in macroeconomics.

Inflation growth

IPD is an indicator that represents inflation at the corporate and government level. Additionally, inflation constitutes the spillover of the price on the products and service by increasing the quantity of money or credit. Essential conditions growth in inflation are caused from two sides: demand pull inflation and cost-push inflation. A positive credit supply shock will stimulate consumption and drive up the demand for products and service. Thereby, demand increases inflation through more consumption. Figure 5.7 certainly demonstrates this relation between inflation and credit supply. The leverage increases in the company with the growth of inflation.

Long-term interest rate growth

The long-term interest rate can be affected by many factors such as inflation, short-term policy rate and economic growth. From Figure 5.7 we can see the long-term interest rate has a slight increase then decline with leverage ratio growth.

The leverage ratio is a useful mechanism to indicate the risk for financial organisations even for the policymakers. The BCBS has set the framework to track the leverage ratio and the underlying components since 2011 for banks and keeps revising afterwards. Now the leverage ratio becomes a mandatory part of Basel III requirements. For the managers, the arrangement of bank capital should be reasonable and take account of the underlying risks. Too high leverage level could be harmful to not only the financial institution but also the whole economy.

Economic Implication

Several reasons can be introduced here to explain the non-monotonic relationship between economic growth and leverage ratio. Financial leverage represents the utilisation of debt in the financial structure, the higher the leverage the larger is the debt borrowed to fund investment. The rapid growth of leverage promotes the development of the capital market which could contribute to the economic growth in the short run through high financial market liquidity (Adrian and Shin, 2010). However the trend is not monotonic in the long term. High credit supply and demand will add instability of the financial market which could damage GDP growth (Kelly et al., 2013).

Inflation refers to the price of goods and service in the market. The inflation growth rate rises when the leverage ratio increases. A high leverage ratio illustrates that financial institutions have more capital to invest which will encourage economic growth and further enhance the inflation (Hochman and Palmon, 1985). Also, an increase in inflation would bring a decline in the purchasing power of money which further decrease consumption and GDP level which fit the simulation result of GDP growth.

A housing price index is determined by many elements such as GDP, inflation, interest rate and credit level. High inflation will increase the HPI via the high price level. The HPI growth may increase when more investments are made in the market due to the wealth effect, however long periods of elevated inflation followed by a sharp deceleration of price growth may bread misalignments between house prices and longer-term determinants of residential real estate values (Tsatsaronis and Zhu, 2004).

The long-term interest rate can be affected by many factors such as inflation, short-term policy rate and economic growth. Interest rates and inflation tend to be inversely correlated in general. People prefer to spend more money under a low-interest rate rather than investing in the long-term government bond. Meanwhile, long-term interest rates are one of the determinants of business investment. Low long-term interest rates encourage investment in new equipment, and high-interest rates discourage it. It further strengthens the economy to grow and inflation to increase. Stable growth of leverage ratio and the long-term interest rate is inversely correlated from the simulation result. It is because a long-term accelerating leverage ratio will improve the inflation level and certainly will reduce the long-term interest rate growth.

Although the US simulation results can be explained using economic theory, it must admit that other countries from Group Seven cannot easily access such a consequence, especially in the GDP response. The US has been positioned as the world largest economy since 1871, and it has been affecting the economic development of other countries through political and international trade. The GVAR model represents a comprehensive system that comprises the vector auto-regression model for individual states, in which the native variables are related to corresponding foreign variables that have been constructed exclusively to comply with the international trade, financial or monetary policy requirements. Therefore, other countries in the group received the leverage effect from the United States. As a result, the estimation of the GVAR model provides an effective measure of the leverage effects in the US while it cannot capture the reality of other countries sufficiently.

5.5 Conclusion

In this chapter, I further analyse the comparison of VaR and ES from the perspective of their influence on macroeconomics. The research is conducted by applying a GVAR model that links the three elements macro-economy, financial market and central banks together. The sign restriction approach is used in the identification of structural shocks.

The banking sector is found to play a critical role in facilitating credit and economic growth. At the same time, capital requirement is designed to offset the possible risks by business practices and risk-taking behaviour. Risk managers tend to provide suggestions to adjust debt and assets, in order to attain a target level of leverage. A starting point of link this chapter and the previous chapter together is that by switch the two risk assessment method, an adjustment of capital requirement could occur due to the property of expected shortfall. Thereby, a capital shock brings the whole economy to the next level.

The results provide consistent trends on the effects that capital requirement could make on GDP, housing price, inflation and long-term interest rate. In consequence of shock simulation, GDP is generally benefiting from a positive capital shock and the steady state is driven to a higher level afterwards. However, an increasing leverage ratio could only contribute to GDP growth when their value is limited. After that, high leverage ratio could be very harmful to the economic growth. Meanwhile, except for Japan, there is a positive response of capital shock on inflation in all other countries. Besides, the leverage ratio is positively related to inflation growth in the long run. The impulse responses of housing price index vary from different countries. But forecasting simulation states a convex curve relation between leverage ratio and housing price growth in the US. Last but not least, I cannot summary the effects on long-term interest rate through countries results, but most countries have been negatively affected by a positive capital shock. In addition, leverage ratio and long-term interest rate growth are negatively correlated.

Chapter 6

Conclusion

Many researchers in the past years have studied the topic of comparing Value at Risk and Expected Shortfall. Most of them agree that ES is a better risk measure than VaR whereas some of them argue that the backtesting for ES is difficult. In this thesis, I compare VaR and ES from different respects: intellectual properties, risk capital requirement and the influence on the macroeconomics.

First of all, a list of properties has been made as the standards for proper risk measures. Value at Risk can precisely and efficiently describe the size of market risk whereas it does not work well under market stress especially during a financial crisis. Meanwhile, VaR does not satisfy sub-additivity hence it is not a coherent risk measure. The risk cannot be diversified when applying VaR to estimate the portfolio. Moreover, although VaR meets the property of elicitability, the failure rate of backtesting result for VaR estimation is nonnegligible. It illustrates that VaR is not an efficient risk measure tested by the real market losses. In addition, VaR usually underestimates the market risk, and it is unable to capture tail risks compared by ES.

ES is an alternative risk measure, and it estimates all market risks beyond VaR. ES fulfils all the properties of coherence including the sub-additivity. The risk can be diversified when using ES as the risk measure to estimate the market risk. Banks could benefit not only from evaluating market risk efficiently but also from the view of saving capital. Besides, ES is sensitive to the tail risks and also works better under market stress than VaR. This property also leads to a better test result when backtesting ES. Although the previous literature argues that it is hard to backtest ES, some papers still demonstrate the possibility and feasibility of backtesting.

In chapter 4, a new idea to compare VaR and ES is introduced from the view of bank capital requirement. I collect the last stock price for 25 most representative banks in G7 countries according to their total assets value and follow the Basel Accords to estimate their minimum capital requirement. Historical Simulation and Filtered Historical Simulation have been applied on account of unknown data distribution. Both methods conclude similar consequences that ES could save the minimum capital requirement and make effective utilisation of bank capital. Banks using ES could diversify the market risks and save capital because ES is a coherent risk measure. Moreover, by both backtesting methods via real losses or Basel Accords, the multiplier for VaR is larger than which for ES.

The comparison is taken place not only from the financial market itself but also through the interaction between individual sections among the whole economic system. In chapter 5, I further study the comparison by applying a GVAR model which associates macroeconomics, financial market and central banks together. Sign restriction approach is used here to identify the structural shocks. Since the banking sector is now playing a critical role in facilitating credit and economic growth, it is worthy to test the effects of changing risk measure from VaR to ES on the macroeconomics through banking channel. The connection between risk measure and the banking sector is conducted via the leverage ratio. Under the consequence that switching from VaR to ES will reduce the capital requirement, the leverage will go up due to increased assets value. And the degree of growth depends on the correlation difference between risk capital and leverage ratio. The result provides consistent trends on the effects that capital requirement could make GDP, housing price, inflation and long-term interest rate. GDP is generally benefiting from a positive leverage ratio shock, and the steady state is driven to a higher level afterwards. However, the contribution is not monotonic where the increasing leverage value will be harmful to the economy by reason of high-risk level.

Combine the consequences of each chapter, ES is concluded as a better risk measure than VaR in spite of some backtesting difficulties. This result supports the dominant point about the topic of comapring VaR and ES. Nevertheless, the research angle differs from the previous studies. The comparison is conducted not simply from the risk measure values but via their risk capital requirements. The risk management aims to optimise the utilisation of capital to achieve high profit. Therefore, from the view of bank capital to compare risk measures conform the object of risk management.

Macroeconomic policy and risk management require taking account of the increasing interdependencies that exist across markets and countries. It is worthy to test risk measures via how it affects the whole economy. GVAR model is a comprehensive system generated based on individual VAR equations. It conducts the quantitative analysis of the relative importance of different shocks and channels of transmission mechanisms by providing a general, practical and global modelling framework. This chapter further substantiates the superiority of using ES across the influence that it may exert on the macroeconomics.

In conclusion, this thesis finds out that ES seems the better risk measure for use in general and practice compared with VaR. The BCBS has changed the internal risk assessment model from VaR and ES and required banks to follow the rule by this year. The backtesting of ES has always been a problem for the popularisation of ES. However, many studies have shown that the shortness of hard backtesting ES can be carefully mitigated. Hopefully, in the near future, ES can take the place of VaR and help risk management to achieve better results.

Although the significant consequences have been detected in this thesis, some potential limitations of this study are noticeable. In a typical GVAR model, the weight of each variable should be drawn from a weight matrix which is estimated according to certain variables. Whereas in my GVAR model, I take the weighted average as the weight due to the high dimension and complex model structure. The weight could change the calculation of each variable and make an influence on the model estimation result. Therefore, it could affect the regression results by reducing the sensitivity of the GVAR model.

Furthermore, it has been proved that the shift in risk assessment model from VaR to ES can help banks save the risk capital requirement and rearrange the distribution of capital by increasing credit supply using Historical Simulation and Filtered Historical Simulation. During the calculation, a multiplier is required as a penalty indicator for both VaR and ES. In Basel Accord, the multiplier should be the higher of backtesting result or stressed test result. While in this thesis, due to the difficulty of the stressed test, I directly use the backtesting result as the multiplier. Although in most cases the results of backtesting and the stressed test may show a similar tendency, it could still affect the comparison results by simplifying the testing procedures.

This thesis studies the influence of various risk measures on the macroeconomy through a Global Vector Autoregression model. The result confirms the assumption that ES is a better risk measure method not only for the financial market but also for the whole economy. In the future study, deeper and broader topics are worth to explore around risk assessment and management. Firstly, various models can be applied to find out the interdependency between the financial market and macroeconomy such as factor model and the DSGE model. Furthermore, the risk measure method is not just located among the probability distribution. Credit risk, operation risk and other risks such as war and oil prices are worthy to study in the future.

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Appendix A

ES Backtesting

The backtesting of ES uses the reference by Acerbi and Szekely (2014), and is based on the VaR backtesting results. The test statistic is given as:

$$Z = \frac{1}{Np_{VaR}} \sum_{t=1}^{N} \frac{R_t I_t}{ES_t} + 1 \tag{A.1}$$

where,

N is the number of time periods in the test window.

R_t is the rate of return.

p_{VaR} is the confidence level.

I_t is the VaR failure indicator on period t.

The expected value for this test statistic is 0, any negative value determines that ES underestimates the market risk. The backtesting takes advantage of stability of the unconditional test statistic, and the backtesting result of VaR could contribute to compute the statistic as an indicator. Moreover, Z is sensitive to both the severity and number of VaR failures relative to

ES measure. Thus, a single but large VaR failure relative to ES may cause the rejection of a model in a certain period while a large loss on a test day when ES estimation is also large may not impact the test results as much as ES is smaller.

Appendix B

Variable Form

Different variables are modeled in log level or quarter to quarter different form regard to their values. An augmented Dickey–Fuller test is applied to examine the stationary of data.

Table B.1 Variable Form

US	Log	First Difference	Stationary	Non-stationary
GDP	✓	✓	✓	
IPD	✓	✓	✓	
HPI	✓	✓	✓	
LTIR		✓	✓	
LOAN	✓	✓	✓	
LEV		✓	✓	
LIR		✓	✓	
DR		✓	✓	
POD		✓	✓	
STPR		✓	✓	

Table B.2 Foreign Variable Form

US	Log	First Difference	Stationary	Non-stationary
GDP	✓	✓	✓	
IPD	✓	✓	✓	
HPI	✓	✓	✓	
LTIR		✓	✓	
LOAN	✓	✓	✓	
LEV		✓	✓	
LIR		✓	✓	
DR		✓	✓	
POD		✓	✓	
STPR		✓	✓	

Appendix C

Unit Root Test

US

Null Hypothesis: USGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.520678	0.0000
Test critical values:	1% level	-3.524233	
	5% level	-2.902358	
	10% level	-2.588587	

Null Hypothesis: USHPI has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.167104	0.2200
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

Null Hypothesis: USLOAN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.55288	0.0001
Test critical values:	1% level	-3.524233	
	5% level	-2.902358	
	10% level	-2.588587	

Null Hypothesis: USLIR has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.649022	0.0071
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: USPOD has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.483716	0.0000
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

Null Hypothesis: USIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.888949	0.0001
Test critical values:	1% level	-3.524233	
	5% level	-2.902358	
	10% level	-2.588587	

Null Hypothesis: USLTIR has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.971644	0.0000
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

Null Hypothesis: USLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.817369	0.0000
Test critical values:	1% level	-3.524233	
	5% level	-2.902358	
	10% level	-2.588587	

Null Hypothesis: USDR has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.987981	0.0001
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

Null Hypothesis: USCB has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.135131	0.0285
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: USFGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.809892	0.0002
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: USFIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.832004	0.0000
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: USFHPI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.622337	0.0000
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: USFLTIR has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.123160	0.0000
Test critical values:	1% level	-3.528515	
	5% level	-2.904198	
	10% level	-2.589562	

Null Hypothesis: USFLOAN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.06226	0.0001
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: USFLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.236824	0.0000
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: USFLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.790343	0.0000
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: USFDR has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.791169	0.0649
Test critical values:	1% level	-3.531592	
	5% level	-2.905519	
	10% level	-2.590262	

Null Hypothesis: USFPOD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.238015	0.0000
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: USFCB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.472973	0.0000
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

UK

Null Hypothesis: UKGDP has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.238075	0.0011
Test critical values:	1% level	-3.514426	
	5% level	-2.898145	
	10% level	-2.586351	

Null Hypothesis: UKIPD has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.736485	0.0000
Test critical values:	1% level	-3.514426	
	5% level	-2.898145	
	10% level	-2.586351	

Null Hypothesis: UKHPI has a unit root
Exogenous: Constant
Lag Length: 6 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.026847	0.2750
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: UKLTIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.992142	0.0000
Test critical values:	1% level	-3.512290	
	5% level	-2.897223	
	10% level	-2.585861	

Null Hypothesis: UKLOAN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.822230	0.0041
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: UKLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.154487	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: UKLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.830416	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: UKDR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.37786	0.0001
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: UKPOD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.508070	0.0000
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

Null Hypothesis: UKCB has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.784796	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: UKFGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.831646	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: UKFHPI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.605530	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: UKFLOAN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.927892	0.0000
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Null Hypothesis: UKFLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.30899	0.0001
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Null Hypothesis: UKFPOD has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.995897	0.0000
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: UKFIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.606048	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: UKFLTIR has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.942757	0.0000
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Null Hypothesis: UKFLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.68863	0.0001
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Null Hypothesis: UKFDR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.575967	0.0000
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Null Hypothesis: UKFCB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.451987	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

France

Null Hypothesis: FNGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.202113	0.0012
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: FNHPI has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.340298	0.1625
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

Null Hypothesis: FNLOAN has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.876439	0.0036
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

Null Hypothesis: FNLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.732699	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: FNPOD has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.741786	0.0723
Test critical values:	1% level	-3.528515	
	5% level	-2.904198	
	10% level	-2.589562	

Null Hypothesis: FNIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.876423	0.0001
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: FNLTIR has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.263305	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: FNLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.905653	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: FNDR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.352822	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: FNCB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.692045	0.0002
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: FNFGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.602426	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: FNFIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.184537	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: FNFHPI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.843199	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: FNFLTIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.283831	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: FNFLOAN has a unit root
Exogenous: Constant
Lag Length: 7 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.932330	0.3158
Test critical values:	1% level	-3.531592	
	5% level	-2.905519	
	10% level	-2.590262	

Null Hypothesis: FNFLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.53469	0.0001
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: FNFLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.03011	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: FNFDR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.528426	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: FNFPOD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.600460	0.0000
Test critical values:	1% level	-3.524233	
	5% level	-2.902358	
	10% level	-2.588587	

Null Hypothesis: FNFCB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.117428	0.0000
Test critical values:	1% level	-3.512290	
	5% level	-2.897223	
	10% level	-2.585861	

Germany

Null Hypothesis: BDGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.684356	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: BDHPI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.909212	0.0001
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: BDLOAN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.178827	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: BDLIR has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.995439	0.0000
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Null Hypothesis: BDPOD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.597284	0.0000
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

Null Hypothesis: BDIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.469354	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: BDLTIR has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.610669	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: BDLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.366399	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: BDDR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.265355	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: BDCB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.698617	0.0002
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: BDFGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.666073	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: BDFHPI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.759556	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: BDFLOAN has a unit root
Exogenous: Constant
Lag Length: 7 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.927369	0.3181
Test critical values:	1% level	-3.531592	
	5% level	-2.905519	
	10% level	-2.590262	

Null Hypothesis: BDFLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.32562	0.0001
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: BDFPOD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.649290	0.0000
Test critical values:	1% level	-3.524233	
	5% level	-2.902358	
	10% level	-2.588587	

Null Hypothesis: BDFIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.796060	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: BDFLTIR has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.176479	0.0000
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Null Hypothesis: BDFLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.91894	0.0001
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: BDFDR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.755986	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: BDFCB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.373421	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Italy

Null Hypothesis: ITGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.744118	0.0002
Test critical values:	1% level	-3.513344	
	5% level	-2.897678	
	10% level	-2.586103	

Null Hypothesis: ITHPI has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.431198	0.5628
Test critical values:	1% level	-3.517847	
	5% level	-2.899619	
	10% level	-2.587134	

Null Hypothesis: ITLOAN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.01783	0.0001
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: ITLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.09008	0.0001
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: ITPOD has a unit root
Exogenous: Constant
Lag Length: 7 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.137843	0.0287
Test critical values:	1% level	-3.536587	
	5% level	-2.907660	
	10% level	-2.591396	

Null Hypothesis: ITIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.37349	0.0001
Test critical values:	1% level	-3.513344	
	5% level	-2.897678	
	10% level	-2.586103	

Null Hypothesis: ITLTIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.723649	0.0000
Test critical values:	1% level	-3.512290	
	5% level	-2.897223	
	10% level	-2.585861	

Null Hypothesis: ITLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.713427	0.0057
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: ITDR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.00819	0.0001
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: ITCB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.068356	0.0001
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: ITFGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.580824	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: ITFHPI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.814288	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: ITFLOAN has a unit root
Exogenous: Constant
Lag Length: 7 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.930712	0.3165
Test critical values:	1% level	-3.531592	
	5% level	-2.905519	
	10% level	-2.590262	

Null Hypothesis: ITFLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.875323	0.0035
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: ITFPOD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.848542	0.0000
Test critical values:	1% level	-3.524233	
	5% level	-2.902358	
	10% level	-2.588587	

Null Hypothesis: ITFIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.093374	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: ITFLTIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.277618	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: ITFLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.59593	0.0001
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: ITFDR has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.233692	0.1965
Test critical values:	1% level	-3.524233	
	5% level	-2.902358	
	10% level	-2.588587	

Null Hypothesis: ITFCB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.339152	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Canada

Null Hypothesis: CNGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.799682	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: CNIPD has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.371752	0.0000
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Null Hypothesis: CNHPI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.731576	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: CNLTIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.544000	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: CNLOAN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.209544	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: CNLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.098868	0.7124
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: CNLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.894907	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: CNDR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.188810	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: CNFPOD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.673857	0.0000
Test critical values:	1% level	-3.524233	
	5% level	-2.902358	
	10% level	-2.588587	

Null Hypothesis: CNCB has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.178886	0.0000
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

Null Hypothesis: CNFGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.456713	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: CNFIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.293651	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: CNFHPI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.792330	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: CNFLTIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.287327	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: CNFLOAN has a unit root
Exogenous: Constant
Lag Length: 7 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.928187	0.3177
Test critical values:	1% level	-3.531592	
	5% level	-2.905519	
	10% level	-2.590262	

Null Hypothesis: CNFLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.61428	0.0001
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: CNFLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.856812	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: CNFDR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.778543	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: CNPOD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.250387	0.0000
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

Null Hypothesis: CNFCB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.264909	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Japan

Null Hypothesis: JPGDP has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.698972	0.0000
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Null Hypothesis: JPIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.954480	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: JPHPI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.458278	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: JPLTIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.686606	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: JPLOAN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.868629	0.0000
Test critical values:	1% level	-3.533204	
	5% level	-2.906210	
	10% level	-2.590628	

Null Hypothesis: JPLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.04954	0.0001
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: JPLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.272849	0.0000
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: JPDR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.399516	0.0000
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: JPPOD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.576734	0.0000
Test critical values:	1% level	-3.527045	
	5% level	-2.903566	
	10% level	-2.589227	

Null Hypothesis: JPCB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.694303	0.0000
Test critical values:	1% level	-3.519050	
	5% level	-2.900137	
	10% level	-2.587409	

Null Hypothesis: JPFGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.873447	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: JPFIPD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.775611	0.0000
Test critical values:	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Null Hypothesis: JPFHPI has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.249472	0.1911
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Null Hypothesis: JPFLTIR has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.227752	0.0000
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Null Hypothesis: JPFLOAN has a unit root
Exogenous: Constant
Lag Length: 7 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.934282	0.3150
Test critical values:	1% level	-3.531592	
	5% level	-2.905519	
	10% level	-2.590262	

Null Hypothesis: JPFLEV has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.583406	0.0003
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: JPFLIR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.861403	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: JPFDR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.418207	0.0000
Test critical values:	1% level	-3.520307	
	5% level	-2.900670	
	10% level	-2.587691	

Null Hypothesis: JPFPOD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.946321	0.0000
Test critical values:	1% level	-3.524233	
	5% level	-2.902358	
	10% level	-2.588587	

Null Hypothesis: JPFCB has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.250942	0.0210
Test critical values:	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Appendix D

Estimated Parameters

Table D.1 US Estimated Parameters

	GDP	IPD	HPI	LTIR	LOAN	LEV	LIR	DR	POD	STPR
Coefficient	0.008	0.002	0.006	0.109	0.068	0.098	-0.031	0.013	-0.001	-0.071
GDP_{t-1}	-0.003	0.020	0.083	-0.033	-2.320	-5.273	5.080	1.091	9.107	6.156
IPD_{t-1}	-0.838	0.336	-0.466	-21.035	5.133	-27.622	-8.322	-5.743	-54.418	-15.660
HPI_{t-1}	0.102	0.028	0.974	2.895	0.698	2.454	0.553	0.292	0.674	4.714
$LTIR_{t-1}$	-0.005	-0.003	-0.014	-0.114	-0.099	0.166	-0.089	-0.051	0.077	-0.011
$LOAN_{t-1}$	-0.019	0.003	-0.011	0.360	-0.113	3.264	0.239	-0.020	-1.698	0.638
LEV_{t-1}	0.001	0.000	0.000	-0.063	-0.033	-0.012	-0.012	-0.005	0.259	-0.055
LIR_{t-1}	-0.007	0.001	0.002	0.404	-0.157	-2.605	-0.202	-0.163	-0.346	0.956
DR_{t-1}	0.010	0.003	0.004	-0.006	0.513	3.353	0.072	0.329	-0.240	-0.709
POD_{t-1}	0.000	0.000	-0.003	0.069	0.075	0.009	-0.058	-0.022	-0.010	-0.190
$STPR_{t-1}$	0.006	0.000	0.007	0.190	-0.020	0.467	0.067	0.090	0.086	0.453
$FGDP_t$	0.266	-0.043	0.059	-3.012	-0.028	-30.753	-4.348	-1.592	0.044	-10.246
$FIPD_t$	-0.428	0.152	-0.500	6.783	-11.239	-5.502	9.579	-0.196	5.900	-5.040
$FHPI_t$	0.052	0.004	-0.014	0.463	0.021	8.452	0.247	0.382	9.718	3.570
$FLTIR_t$	0.003	0.000	0.005	1.453	0.049	-0.184	-0.030	-0.014	0.099	1.048
$FLOAN_t$	0.002	0.007	0.019	-0.057	-0.263	-3.952	-0.760	-0.334	1.189	-0.363
$FLEV_t$	0.001	0.000	0.000	0.016	-0.003	-0.063	0.012	-0.002	0.004	0.005
$FLIR_t$	-0.003	0.005	0.000	-0.574	-0.186	2.835	0.261	0.172	0.166	-0.227
FDR_t	0.001	-0.006	0.003	0.681	0.328	-3.288	-0.565	-0.209	-0.216	0.282
$FPOD_t$	-0.012	0.002	-0.004	0.047	0.210	-2.582	-0.630	-0.165	-0.275	-0.491
$FSTPR_t$	0.000	0.000	-0.003	-0.034	0.043	-0.383	0.040	0.023	-0.015	-0.044
$FGDP_{t-1}$	0.195	0.014	-0.534	-9.826	0.559	50.460	3.037	2.386	7.672	-1.043
$FIPD_{t-1}$	-0.009	0.208	0.158	7.642	-8.902	-50.152	10.046	4.270	1.917	27.380
$FHPI_{t-1}$	-0.012	0.009	-0.006	-0.411	0.104	-2.296	0.131	-0.217	3.945	1.713
$FLTIR_{t-1}$	-0.001	0.005	0.012	-0.218	0.109	-0.092	0.105	-0.004	-0.313	-0.695
$FLOAN_{t-1}$	-0.004	-0.002	-0.004	-0.069	-0.163	1.828	-0.337	-0.103	0.759	-0.193
$FLEV_{t-1}$	-0.001	0.000	0.000	-0.017	-0.003	-0.046	0.008	0.006	-0.081	-0.005
$FLIR_{t-1}$	-0.026	0.003	-0.027	0.527	-0.207	-1.405	-0.043	0.079	1.078	2.176
FDR_{t-1}	0.028	-0.002	0.035	-0.392	0.104	2.044	0.069	-0.129	-0.644	-1.789
$FPOD_{t-1}$	0.005	0.004	-0.012	0.363	0.252	0.993	-0.021	-0.001	-0.127	0.087
$FSTPR_{t-1}$	0.001	0.000	0.002	-0.023	-0.032	-0.036	-0.128	-0.035	0.257	-0.022

Table D.2 UK Estimated Parameters

	GDP	IPD	HPI	LTIR	LOAN	LEV	LIR	DR	POD	STPR
Coefficient	0.000	0.004	0.000	-0.099	-0.001	-1.590	-0.026	-0.028	0.101	-0.137
GDP_{t-1}	0.291	0.115	-0.112	-4.661	1.412	21.850	0.408	0.290	-8.205	-5.372
IPD_{t-1}	-0.369	-0.110	0.353	-1.306	0.851	-3.446	-3.296	-3.476	2.441	-5.942
HPI_{t-1}	0.009	0.002	0.421	1.538	1.181	6.577	-0.816	-0.675	1.746	0.147
$LTIR_{t-1}$	0.007	-0.004	0.005	-0.130	0.268	5.431	-0.237	-0.178	0.283	-0.332
$LOAN_{t-1}$	0.000	0.001	0.003	0.056	-0.885	-1.749	0.190	0.144	0.137	0.175
LEV_{t-1}	0.000	0.000	0.000	0.009	0.004	-0.250	0.008	0.014	0.007	0.014
LIR_{t-1}	-0.019	-0.039	0.129	0.342	0.036	-4.288	0.298	0.512	0.325	0.948
DR_{t-1}	0.018	0.025	-0.175	-0.168	-0.312	-1.462	-0.145	-0.438	0.010	-0.633
POD_{t-1}	0.001	-0.001	0.009	0.014	0.072	-0.086	0.007	0.018	-0.075	0.023
$STPR_{t-1}$	-0.001	-0.001	-0.012	0.219	-0.232	-5.617	0.175	0.108	-0.353	0.402
$FGDP_t$	0.462	-0.108	1.151	-2.227	3.546	11.732	-0.670	1.562	-8.446	4.021
$FIPD_t$	1.049	0.062	-1.464	17.276	4.459	2.295	4.754	9.353	-18.609	17.178
$FHPI_t$	-0.049	-0.026	0.499	1.845	0.473	13.834	-0.699	-1.392	2.936	2.908
$FLTIR_t$	0.002	0.000	-0.001	1.140	-0.003	0.617	-0.085	-0.088	0.137	1.069
$FLOAN_t$	-0.030	0.014	0.083	0.047	-0.096	-8.346	0.152	0.068	0.139	0.106
$FLEV_t$	0.000	0.000	0.000	0.005	-0.004	-0.092	0.001	0.000	0.001	0.002
$FLIR_t$	-0.010	0.023	0.017	0.232	-0.031	3.789	-0.335	-0.345	0.030	0.032
FDR_t	-0.011	0.020	0.051	-0.197	0.033	-0.414	-0.048	-0.051	-0.018	-0.287
$FPOD_t$	-0.002	-0.002	-0.007	0.042	-0.031	1.371	-0.022	-0.054	-0.073	0.128
$FSTPR_t$	0.000	0.001	0.006	-0.188	0.050	-0.677	0.089	0.054	0.017	-0.053
$FGDP_{t-1}$	0.216	-0.152	0.215	0.734	-0.780	9.051	0.533	1.954	7.198	4.691
$FIPD_{t-1}$	-0.434	0.293	0.528	23.044	-6.231	-5.416	6.966	5.918	-22.816	26.610
$FHPI_{t-1}$	-0.021	0.054	-0.344	-2.180	-1.386	4.975	-0.056	-0.861	0.187	-2.262
$FLTIR_{t-1}$	-0.005	0.003	0.024	0.169	-0.019	-0.283	0.108	0.163	-0.032	0.256
$FLOAN_{t-1}$	0.019	0.022	0.071	-0.570	0.360	-2.069	0.023	-0.069	-0.368	-0.403
$FLEV_{t-1}$	0.000	0.000	-0.001	-0.003	0.000	-0.014	-0.001	0.000	-0.005	-0.005
$FLIR_{t-1}$	0.005	0.011	0.003	0.040	-0.001	-0.525	0.063	0.095	-0.243	0.174
FDR_{t-1}	-0.008	0.012	0.018	-0.242	-0.109	-3.218	-0.001	-0.027	0.151	-0.227
$FPOD_{t-1}$	-0.003	0.007	-0.016	-0.111	0.015	-1.433	-0.097	-0.094	0.024	-0.281
$FSTPR_{t-1}$	0.000	-0.003	-0.010	-0.022	0.009	1.451	-0.072	-0.078	0.143	-0.061

Table D.3 FN Estimated Parameters

	GDP	IPD	HPI	LTIR	LOAN	LEV	LIR	DR	POD	STPR
Coefficient	0.001	0.001	-0.012	-0.006	0.037	0.369	-0.043	-0.041	-0.046	-0.109
GDP_{t-1}	0.490	0.070	0.796	15.826	-0.286	3.927	-3.015	-2.558	16.354	32.794
IPD_{t-1}	-0.366	0.473	1.368	2.309	1.903	2.617	9.491	5.544	-2.422	3.272
HPI_{t-1}	0.070	0.020	0.487	0.215	0.576	2.426	0.427	0.427	8.203	-0.354
$LTIR_{t-1}$	0.000	-0.001	0.013	0.219	0.097	0.747	-0.010	-0.003	0.114	-0.038
$LOAN_{t-1}$	0.004	0.005	-0.018	-0.051	-0.834	2.032	0.002	0.068	-0.175	0.623
LEV_{t-1}	0.000	0.000	0.000	-0.003	0.006	-0.518	-0.002	-0.002	0.010	0.014
LIR_{t-1}	-0.019	0.011	0.273	0.232	-0.122	-3.272	-0.313	-0.195	3.217	5.038
DR_{t-1}	0.021	-0.005	-0.333	-0.781	0.057	3.934	0.365	0.275	-2.881	-5.354
$PODt-1$	-0.001	0.000	-0.008	-0.021	-0.021	-0.137	-0.027	-0.027	-0.058	-0.067
$STPR_{t-1}$	-0.003	0.000	-0.007	-0.256	-0.055	-3.065	-0.036	-0.016	-0.168	0.302
$FGDP_t$	-0.024	0.032	-0.207	0.558	-0.866	-9.489	4.192	3.900	-5.264	-1.767
$FIPD_t$	0.034	-0.114	2.029	-2.521	-9.063	3.188	4.526	5.353	-32.560	3.070
$FHPI_t$	-0.025	-0.011	0.020	0.439	-0.881	18.357	0.203	0.127	-2.775	-1.899
$FLTIR_t$	-0.002	-0.001	-0.001	-0.053	0.119	3.512	-0.062	-0.072	0.224	-0.153
$FLOAN_t$	0.005	0.002	0.087	-0.476	1.655	-0.355	-0.686	-0.492	0.275	-2.485
$FLEV_t$	0.000	0.000	0.000	-0.001	0.005	0.028	0.001	0.002	0.002	0.003
$FLIR_t$	-0.009	-0.001	-0.004	-0.319	0.095	-8.567	-0.325	-0.349	0.087	-0.129
FDR_t	-0.004	-0.001	0.016	0.110	0.234	-1.138	0.481	0.492	-0.475	-0.794
$FPOD_t$	0.007	0.001	0.014	-0.094	0.005	0.085	-0.005	0.011	0.192	0.147
$FSTPR_t$	0.003	-0.001	-0.002	0.362	-0.019	-3.567	0.034	0.034	0.020	0.427
$FGDP_{t-1}$	0.080	-0.034	0.291	-6.261	-1.474	-2.282	-2.202	-1.675	9.977	4.600
$FIPD_{t-1}$	-0.082	0.151	-0.603	-18.094	3.760	-16.287	-4.212	-4.449	-0.538	-17.596
$FHPI_{t-1}$	0.004	0.015	0.039	-1.542	-0.108	-24.595	-0.358	-0.208	-2.585	0.684
$FLTIR_{t-1}$	-0.001	-0.001	0.007	-0.121	-0.043	6.652	0.007	0.018	0.151	-0.009
$FLOAN_{t-1}$	0.007	0.001	0.197	0.530	1.313	-4.685	-0.385	-0.387	2.190	0.425
$FLEV_{t-1}$	0.000	0.000	0.000	0.005	0.006	-0.009	-0.002	-0.001	0.003	0.000
$FLIR_{t-1}$	-0.004	0.001	-0.013	0.409	0.349	-3.955	-0.222	-0.231	0.575	-0.578
FDR_{t-1}	-0.003	-0.002	0.055	0.194	0.063	-9.018	-0.066	-0.087	-0.283	0.563
$FPOD_{t-1}$	0.001	-0.001	0.005	0.017	0.010	-1.029	0.060	0.065	-0.341	-0.022
$FSTPR_{t-1}$	0.003	0.001	0.004	-0.176	-0.114	-0.156	0.115	0.111	-0.122	0.203

Table D.4 BD Estimated Parameters

	GDP	IPD	HPI	LTIR	LOAN	LEV	LIR	DR	POD	STPR
Coefficient	0.003	0.001	0.000	0.014	0.010	0.283	-0.009	0.012	0.218	-0.007
GDP_{t-1}	-0.006	0.008	0.242	3.876	-0.650	7.268	-2.914	-2.271	2.214	6.404
IPD_{t-1}	0.246	0.199	0.326	7.252	2.317	-1.926	1.575	-9.232	8.199	-2.146
HPI_{t-1}	-0.157	0.091	0.285	1.567	-0.169	-9.412	-5.886	0.357	-2.155	-0.424
$LTIR_{t-1}$	-0.004	-0.002	0.002	0.236	0.028	2.389	-0.096	0.020	-0.171	-0.067
$LOAN_{t-1}$	0.014	0.001	0.025	-0.085	0.158	3.482	0.737	0.086	-0.089	0.154
LEV_{t-1}	-0.001	0.000	0.000	-0.010	0.004	0.092	0.005	-0.006	0.024	0.008
LIR_{t-1}	0.005	-0.002	0.004	0.153	0.057	-2.443	-0.156	-0.119	-0.093	0.411
DR_{t-1}	0.019	-0.001	0.009	-0.818	-0.131	3.755	0.221	-0.118	1.983	0.005
POD_{t-1}	-0.004	-0.001	0.002	0.023	0.031	3.409	-0.054	-0.075	-0.247	0.061
$STPR_{t-1}$	0.012	-0.002	-0.002	-0.053	0.076	0.340	0.040	0.085	-0.188	0.156
$FGDP_t$	-0.014	-0.004	0.009	3.717	-1.821	-1.070	4.814	-0.308	-6.049	-1.822
$FIPD_t$	-0.096	0.061	0.346	-19.755	-1.806	2.296	15.411	5.047	-16.960	-5.350
$FHPI_t$	-0.059	-0.002	0.015	-0.238	-0.371	1.537	0.519	0.263	-2.691	-0.807
$FLTIR_t$	-0.002	-0.003	-0.001	-0.090	-0.030	0.588	0.168	0.104	0.255	-0.090
$FLOAN_t$	0.010	0.022	-0.018	0.064	0.453	-1.607	-0.456	0.379	-1.882	0.057
$FLEV_t$	0.000	0.000	0.000	0.008	0.001	0.046	-0.008	-0.004	-0.011	-0.002
$FLIR_t$	-0.013	0.006	-0.002	-0.349	0.114	-1.086	-0.106	0.079	-0.007	-0.438
FDR_t	0.003	0.001	0.001	0.297	0.148	-3.091	-0.278	0.261	-0.282	0.416
$FPOD_t$	0.012	0.004	-0.002	-0.017	-0.072	-5.385	-0.097	0.086	0.242	0.212
$FSTPR_t$	0.001	-0.002	-0.002	0.444	-0.002	-1.366	0.098	-0.046	0.053	0.329
$FGDP_{t-1}$	0.002	-0.044	-0.086	-8.151	-0.782	1.317	0.575	-2.634	9.701	3.734
$FIPD_{t-1}$	0.200	0.264	-0.078	-3.847	7.510	-1.380	-24.077	4.681	-3.449	-20.389
$FHPI_{t-1}$	0.025	0.013	0.005	-0.890	-0.198	-2.537	-0.444	0.069	-1.137	0.067
$FLTIR_{t-1}$	-0.004	0.000	0.000	0.021	-0.017	2.361	-0.171	-0.033	-0.327	-0.249
$FLOAN_{t-1}$	-0.019	0.002	-0.031	1.588	0.413	8.947	-0.324	0.425	-0.969	0.912
$FLEV_{t-1}$	0.000	0.000	0.000	0.005	0.002	0.015	-0.002	0.001	0.008	0.000
$FLIR_{t-1}$	-0.011	0.002	-0.004	0.283	0.141	2.721	0.024	0.200	-0.393	-0.132
FDR_{t-1}	-0.011	0.001	-0.001	0.223	0.040	-2.738	-0.069	-0.005	-0.734	0.108
$FPOD_{t-1}$	0.001	0.002	-0.004	0.103	-0.026	-3.440	0.015	0.079	-0.332	0.145
$FSTPR_{t-1}$	0.002	0.001	-0.002	-0.277	-0.104	0.015	0.158	-0.037	0.218	0.077

Table D.5 IT Estimated Parameters

	GDP	IPD	HPI	LTIR	LOAN	LEV	LIR	DR	POD	STPR
Coefficient	0.001	0.006	-0.002	0.082	0.074	0.233	-0.289	0.323	0.352	0.063
GDP_{t-1}	0.704	0.025	0.295	-2.535	2.589	-4.492	13.633	8.714	5.953	10.765
IPD_{t-1}	0.051	-0.527	-0.055	-10.459	8.927	8.450	6.359	23.149	-2.033	-3.312
HPI_{t-1}	0.087	0.190	0.725	6.463	2.961	-11.395	-3.168	-13.394	15.824	4.273
$LTIR_{t-1}$	0.000	-0.001	0.000	0.286	-0.058	-0.214	0.147	0.127	-0.355	0.115
$LOAN_{t-1}$	0.001	-0.001	0.009	0.596	-0.255	-0.930	-0.754	-0.734	0.010	-0.290
LEV_{t-1}	0.001	0.000	0.000	0.048	-0.027	0.248	0.066	-0.044	0.073	0.036
LIR_{t-1}	0.004	0.000	0.004	0.092	0.001	-0.639	-0.595	-0.268	-0.018	-0.003
DR_{t-1}	0.000	0.001	0.003	-0.026	-0.036	-0.456	-0.226	-0.280	-0.103	0.087
POD_{t-1}	0.001	0.001	0.003	0.025	0.008	0.248	0.144	0.125	-0.503	-0.062
$STPR_{t-1}$	-0.006	0.002	0.000	0.199	-0.147	0.481	-0.171	0.045	-0.274	0.276
$FGDPt$	-0.060	0.046	0.014	8.311	-2.199	4.635	-9.896	-0.534	-0.606	1.987
$FIPD_t$	-0.527	-0.167	-0.251	0.292	-26.872	-7.337	1.171	-9.473	-0.902	-2.869
$FHPI_t$	-0.006	-0.015	-0.024	2.928	-1.439	6.117	-4.639	1.030	-0.772	-2.184
$FLTIR_t$	-0.008	0.000	-0.006	-0.038	0.037	0.899	0.468	-0.066	0.264	-0.065
$FLOAN_t$	-0.030	0.001	0.072	-1.257	0.062	2.548	-2.054	-5.105	-4.078	-0.179
$FLEV_t$	0.000	0.000	0.000	0.007	-0.002	0.024	-0.018	0.012	-0.023	0.006
$FLIR_t$	-0.017	0.018	0.139	-1.277	-0.377	5.770	2.945	-1.329	-3.301	-0.761
FDR_t	0.023	-0.024	-0.116	-0.371	0.767	-1.230	-1.507	1.320	2.262	0.812
$FPOD_t$	0.002	-0.004	-0.006	-0.251	0.033	-0.197	0.143	0.403	0.402	0.199
$FSTPR_t$	0.002	0.000	0.004	0.439	0.030	-0.284	-0.135	-0.215	0.034	0.621
$FGDP_{t-1}$	0.003	0.004	-0.033	-14.164	0.517	-3.160	-6.918	-4.091	-3.595	0.709
$FIPDt-1$	0.384	-0.058	0.522	-25.496	7.445	0.871	33.158	7.329	-11.316	-29.309
$FHPI_{t-1}$	0.009	0.017	0.031	-1.113	-0.642	0.752	-1.278	-0.286	-0.772	-0.507
$FLTIR_{t-1}$	-0.003	0.002	0.006	-0.183	0.007	-0.203	0.316	-0.132	-0.521	0.009
$FLOAN_{t-1}$	0.030	-0.014	0.041	0.061	-0.430	-7.321	-2.850	-0.193	-3.353	0.578
$FLEV_{t-1}$	0.000	0.000	0.000	-0.004	0.000	0.008	0.001	0.011	-0.013	-0.004
$FLIR_{t-1}$	0.023	-0.050	-0.105	0.707	-0.590	-0.554	-8.684	3.978	-2.725	0.250
FDR_{t-1}	0.011	0.017	0.063	0.204	0.633	0.588	2.622	-0.281	3.843	-1.009
$FPOD_{t-1}$	0.000	-0.004	0.006	0.019	0.031	-0.156	-0.186	0.069	-0.668	0.093
$FSTPR_{t-1}$	0.002	-0.002	-0.006	-0.515	0.076	0.045	0.552	0.494	-0.039	0.053

Table D.6 CN Estimated Parameters

	GDP	IPD	HPI	LTIR	LOAN	LEV	LIR	DR	POD	STPR
Coefficient	0.007	0.004	-0.001	0.044	-0.009	-0.350	0.014	-0.013	0.088	-0.048
GDP_{t-1}	0.082	0.043	0.021	0.483	-0.201	-0.401	-0.214	-0.102	1.633	1.051
IPD_{t-1}	0.341	0.211	0.433	-2.622	1.446	2.905	0.164	0.623	-4.959	1.936
HPI_{t-1}	0.169	-0.038	0.032	-1.230	1.156	-0.656	0.159	0.089	1.045	-0.804
$LTIR_{t-1}$	-0.014	0.006	-0.034	0.338	-0.029	-1.466	0.106	0.029	0.151	-0.710
$LOAN_{t-1}$	0.000	0.014	-0.033	-0.008	0.031	0.269	0.318	0.137	1.419	-0.026
LEV_{t-1}	0.004	0.000	0.005	-0.006	0.016	0.240	0.008	0.003	-0.252	-0.031
LIR_{t-1}	-0.066	-0.005	0.082	0.359	0.426	-7.898	-0.413	-0.196	-2.972	2.325
DR_{t-1}	0.081	0.023	-0.250	-0.794	-0.726	11.863	0.618	0.484	6.999	-3.522
POD_{t-1}	-0.043	-0.002	-0.012	0.022	0.004	-0.861	0.048	0.017	0.199	0.113
$STPR_{t-1}$	-0.039	0.001	-0.001	-0.001	-0.005	-0.076	-0.012	0.021	-0.339	0.327
$FGDP_t$	1.173	0.127	-0.292	2.065	-1.155	12.868	0.354	0.557	3.232	-8.023
$FIPD_t$	-3.226	-0.376	2.118	19.364	3.860	-3.152	4.789	3.592	-6.640	-9.173
$FHPI_t$	0.203	0.040	-0.088	-0.568	-0.054	-0.269	0.184	0.097	-1.137	-0.078
$FLTIR_t$	-0.008	0.002	0.020	0.849	0.011	-0.757	0.021	0.014	-0.292	0.063
$FLOAN_t$	0.067	0.050	0.070	0.285	-0.242	-1.221	-0.114	-0.162	0.822	-0.213
$FLEV_t$	0.001	0.000	0.000	0.003	-0.005	0.014	-0.001	-0.001	0.006	-0.017
$FLIR_t$	0.076	0.022	-0.038	0.139	-0.141	-0.920	0.126	-0.014	1.000	-0.874
FDR_t	0.012	-0.002	0.018	0.331	-0.075	-1.791	0.189	0.044	-0.324	0.194
$FPOD_t$	0.037	0.003	0.026	-0.098	0.066	0.619	-0.063	-0.015	-0.402	-0.003
$FSTPR_t$	-0.038	-0.002	0.005	-0.030	0.039	-0.012	-0.004	0.034	-0.048	0.583
$FGDP_{t-1}$	-0.880	-0.077	0.436	-3.367	1.378	-0.521	-1.832	-0.780	-1.479	3.478
$FIPD_{t-1}$	-2.176	-0.214	1.596	-18.265	-1.515	4.787	-7.155	-1.189	9.370	15.164
$FHPI_{t-1}$	0.283	0.001	-0.025	-0.786	0.378	0.389	0.020	0.012	-1.813	-1.912
$FLTIR_{t-1}$	-0.014	-0.009	0.036	-0.118	-0.020	0.845	-0.100	-0.034	-0.261	0.762
$FLOAN_{t-1}$	0.281	0.025	0.124	0.170	-0.197	2.100	0.038	0.122	0.481	1.117
$FLEV_{t-1}$	0.002	0.000	-0.001	0.002	0.000	-0.005	-0.002	-0.002	-0.002	0.001
$FLIR_{t-1}$	0.054	0.009	-0.032	-0.168	-0.137	1.049	0.002	-0.042	-0.229	-0.431
FDR_{t-1}	0.066	0.012	0.021	0.175	-0.249	0.692	0.089	0.078	-0.138	-0.001
$FPOD_{t-1}$	0.013	-0.002	-0.006	0.125	-0.051	0.492	-0.031	-0.031	-0.151	-0.030
$FSTPR_{t-1}$	0.008	-0.001	0.017	0.053	0.030	0.309	0.012	0.011	0.001	-0.134

Table D.7 JP Estimated Parameters

	GDP	IPD	HPI	LTIR	LOAN	LEV	LIR	DR	POD	STPR
Coefficient	0.000	0.001	0.000	-0.041	-0.155	-9.771	0.037	0.015	-0.648	0.989
GDP_{t-1}	0.087	-0.005	-0.001	0.158	-1.000	6.213	0.118	-0.057	1.048	6.231
IPD_{t-1}	-3.706	0.165	-0.013	-0.814	3.239	-1.534	1.273	0.806	-1.218	-2.145
HPI_{t-1}	13.315	-0.251	0.008	-2.586	-3.969	3.873	-0.759	-1.952	-16.868	19.519
$LTIR_{t-1}$	0.037	-0.009	0.000	-0.020	-0.153	16.426	-0.022	-0.024	-0.495	-0.182
$LOAN_{t-1}$	0.000	0.006	0.002	-0.114	0.249	3.735	-0.035	-0.016	0.563	-0.637
LEV_{t-1}	0.000	0.000	0.000	0.000	0.001	-0.345	0.000	0.000	0.005	0.001
LIR_{t-1}	-0.087	-0.003	0.007	0.135	-1.285	-63.858	0.023	0.127	-2.650	-4.319
DR_{t-1}	0.152	0.033	-0.006	-0.668	1.944	84.587	0.021	-0.067	3.217	12.417
POD_{t-1}	-0.016	-0.003	0.000	0.099	-0.038	-3.788	0.016	0.005	0.091	0.096
$STPR_{t-1}$	0.002	0.000	0.000	-0.010	0.006	-0.793	-0.006	-0.001	0.100	0.224
$FGDP_t$	-0.342	0.016	0.020	-0.351	2.249	5.134	-1.674	-0.989	45.728	-24.644
$FIPD_t$	1.006	-0.867	0.007	1.975	7.098	20.321	-4.766	-3.157	15.900	-12.678
$FHPI_t$	-1.651	-0.107	-0.001	-2.249	4.678	-50.305	0.387	-0.798	-2.255	3.071
$FLTIR_t$	-0.008	0.001	0.000	0.342	-0.147	30.492	0.003	0.003	-0.220	-0.252
$FLOAN_t$	-0.267	-0.022	0.000	0.303	0.242	-18.970	0.129	0.036	2.854	-4.711
$FLEV_t$	0.008	0.000	0.000	0.015	-0.026	-6.985	0.006	0.005	-0.084	0.136
$FLIR_t$	0.066	0.004	0.001	0.020	-0.010	-38.362	-0.007	0.018	-0.027	2.815
FDR_t	-0.078	-0.005	0.000	0.141	-0.127	14.732	0.082	0.036	0.223	-1.803
$FPOD_t$	-0.023	0.003	0.000	-0.140	0.227	-24.514	-0.049	-0.045	0.733	-0.174
$FSTPR_t$	-0.001	0.001	0.000	-0.032	-0.046	-4.591	0.027	0.022	-0.203	0.560
$FGDP_{t-1}$	1.433	0.096	-0.009	-1.873	-2.430	54.600	-1.036	-0.392	-7.280	-1.508
$FIPD_{t-1}$	-2.373	0.179	-0.022	7.003	22.130	-21.960	2.731	3.407	-10.772	-8.669
$FHPI_{t-1}$	1.448	0.171	0.010	2.061	-5.496	33.996	-0.061	0.757	-2.219	7.179
$FLTIR_{t-1}$	-0.024	0.004	0.001	-0.076	0.237	-17.255	0.008	0.000	0.388	-0.255
$FLOAN_{t-1}$	-0.103	-0.022	0.000	0.098	1.557	34.337	-0.221	-0.179	9.704	-6.927
$FLEV_{t-1}$	0.002	0.000	0.000	0.000	0.024	-2.356	0.002	0.002	0.004	0.152
$FLIR_{t-1}$	-0.028	0.012	0.000	-0.177	-0.457	-7.304	0.114	0.041	0.700	0.293
FDR_{t-1}	0.033	-0.007	0.000	-0.152	0.027	-27.990	-0.044	0.014	1.134	-1.446
$FPOD_{t-1}$	0.019	0.002	0.000	-0.092	0.009	-9.735	0.005	0.015	0.052	0.871
$FSTPR_{t-1}$	-0.018	-0.001	0.000	-0.010	0.061	6.045	-0.043	-0.027	-0.062	0.795